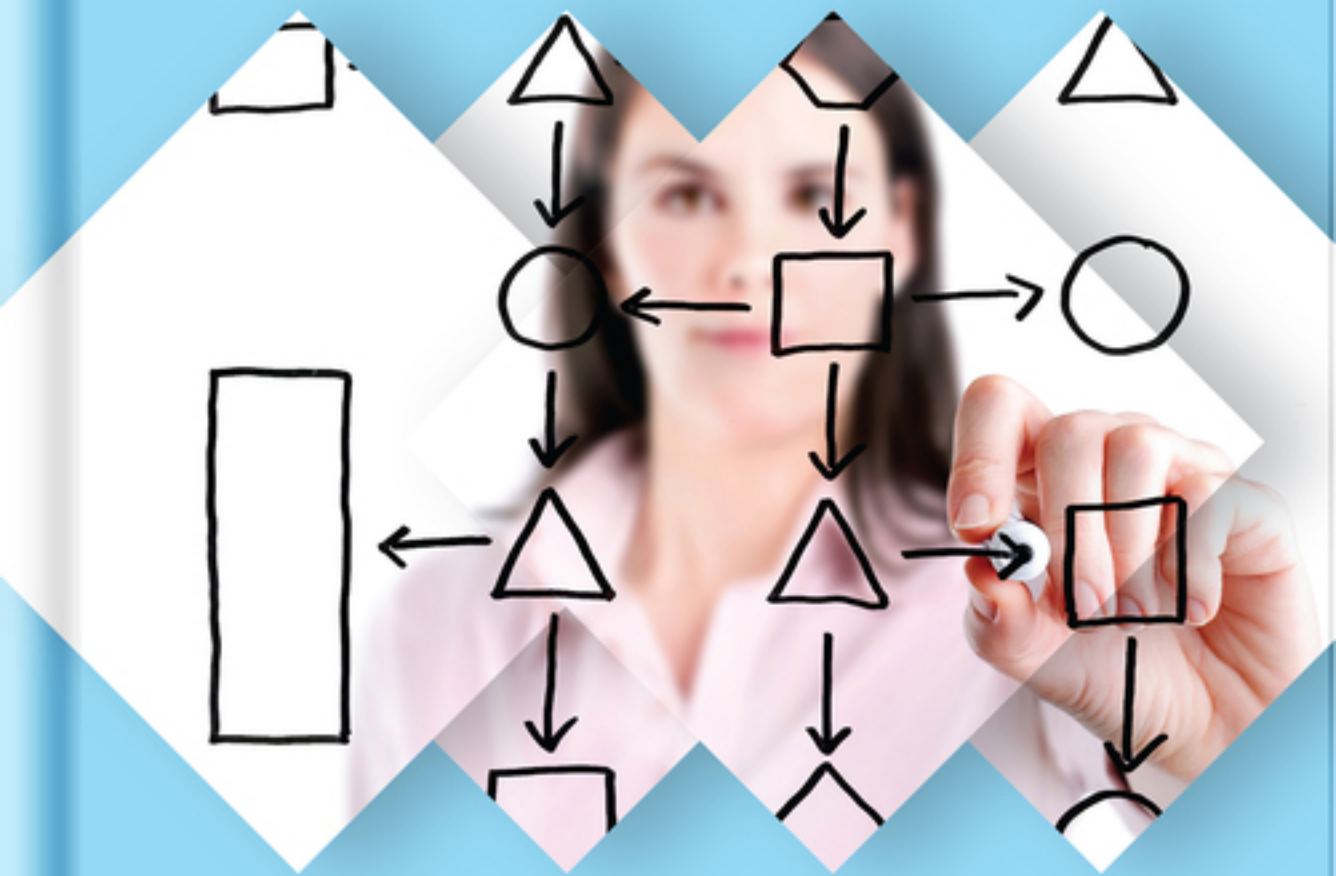
Research Insights

Bayesian Networks for Managing Learner Models in Adaptive Hypermedia Systems

Emerging Research and Opportunities



Mouenis Anouar Tadlaoui, Mohamed Khaldi, and Rommel Novaes Carvalho

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Bayesian Networks for Managing Learner Models in Adaptive Hypermedia Systems:

Emerging Research and Opportunities

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Preface

INTRODUCTION

Overview

The technological landscape of modern e-learning is dominated by so-called learning management systems. The latter, being powerful integrated systems, support a number of activities carried out by teachers and learners during the e-learning process. Teachers use e-learning systems to develop course notes and web-based activities to communicate with learners on one side, and monitor and classify their progress on the other. Learners use it for learning, communication and collaboration.

Adaptive e-learning systems often employ learner models. A learner model is an internal representation of the user's properties through which the system is based in order to adapt to the needs of each user. Before this model can be used, it must be built. This process requires a lot of effort to collect the required information and ultimately generate a learner model. Thus, an adaptive e-learning system takes all the properties of adaptive systems. To meet the needs of the application in the field of e-learning, adaptive e-learning systems adapt the learning material using user templates.

The behavior of an adaptive system varies depending on the data from the learner model and the learner's profile. Without knowing anything about the learner who uses the system, a system would behave in exactly the same way for all learners.

In general, the adaptation process can be described in three steps: the first is the collection of information about the user, the second, the processing of information to initialize the user's model, finally, updating the model of the initialized user and its use to provide adequate adaptation. In the process of adaptation, it is possible to distinguish between two different characters: on the one hand, we have the learner or the student with his goal of acquiring

knowledge, on the other hand, the teacher. The goal of a teacher is the mediation of knowledge covered by a course to learners. Therefore, both points of view must be present in an e-Learning system.

The user model is an essential element in adaptive e-learning systems. The adaptation of an e-learning system primarily involves the selection and presentation of each successive teaching activity based on the full scope of the learner's knowledge, the subject taught and other relevant characteristics of the course. All information about the learners is held in a learner model. As a result, it is used to modify the interaction between the system and the learner to meet the individual needs of the learner.

Problematic

In the context of learner modeling in adaptive hypermedia systems, the representation of all learner actions is a central concept. Although there are already approaches that provide some form of modeling in adaptive hypermedia, some problems remain unresolved. We were interested in the following main issues:

- There are various attempts to model the learner in different adaptive educational hypermedia; these are the static representations of this model, representations that are generally based on information given by the learner himself when he enters the system. This gives the end a static view of the learner model. The learner model is characterized by a dynamic aspect, the knowledge of the learner evolves in the same module, and its characteristics change during a learning situation. This requires a dynamic vision for the management of this model;
- The learner model behaves in two broad areas, the specific information domain that represents learner-related data and is named in Adaptive Educational Hypermedia by the learner profile. And the independent information domain that represents learner-related data but also takes into consideration the environment and the type of learning situation. There are several studies during the last twenty years that aim at modeling the learner in adaptive hypermedia, but they always concern one domain while forgetting the other, which does not give a complete, dynamic and probabilistic vision of this one. model during its development during an educational journey;

- The learner model is divided into three phases: data collection, initialization and updating of the developed model. There are several methods, techniques and models for each phase, but the problem lies in choosing the appropriate method that can handle uncertainty in all three phases. Are only one method and one technique sufficient for managing this model? Or is the solution in the combination of several methods to achieve a complete and formal management for adaptive educational hypermedia?

Faced with the problems mentioned above, the problem addressed here is reduced to specify the one hand, a dynamic modeling of learning a formal model for adaptive educational hypermedia systems and also to ensure that management of the model developed that addresses both information domains and includes the three phases of the learner modeling process.

Proposed Approaches

The approaches in this book and the work resulted reside in the modeling framework of the learner in an adaptive educational system. That is, the representation and specification of (largely defined) knowledge about the learner.

Different approaches were used to manage the learner model with multiple objectives, from assessing the learner's knowledge to recognizing the plan followed in solving problems. In order to monitor the learner's behavior in real time during the training, we need to adopt a dynamic modeling approach to learning model management.

Despite the various learner modeling attempts that are dynamic, we still struggle to achieve this goal. The proposed approaches give us just a static view of the learner model, but this model is still in development (the learner's knowledge evolves in the same module), which is why a dynamic vision is essential. All actions of the learner in a learning situation are not limited to valid or invalid (true / false) actions, but are the actions that characterize his or her learning path and training. From this observation, we cannot represent each learner's system information using relative data. We need to locate our work in a probabilistic context because of changes in the learner model during training.

The main hypothesis of this research insight is the use of Bayesian networks and methods as a probabilistic formalism for the management of the learner model in adaptive hypermedia. During all stages of the development of this model, since the initialization of the learner model based on the combination of Bayesian networks, and the method of stereotypes and during the update, in which we propose to integrate the networks Bayesians with the overlay model for complete probabilistic management of this model.

Features and Contributions

The idea developed in this book lies in the design and management of a valid learner model for all adaptive hypermedia systems. This management of all phases of development and updating of the learner model is based on Bayesian networks and multi-entity Bayesian networks to manage the dynamic aspect of this model. Thus, the contributions of our work are as follows:

- Presentation of a *comparative study* in which we presented the different functionalities and characteristics of a learner model in the adaptive educational systems.
- Presentation of a *comparative study* in which we presented the different methods and approaches for the management and modeling of the learner model in the adaptive educational systems and their level of intervention according to the components of the learner model and during the development process and model update.
- Presentation of a *learner model* for adaptive hypermedia based on e-learning standards and standards and using the unified modeling language use case diagram.
- Presentation of *the transformation rules* of use case diagrams into Bayesian networks, respecting all the existing modeling cases in the unified modeling language.
- Presentation of the *Bayesian network* of the learner model developed from the use case diagram presented, based on our transformation rules.
- Presentation of a dynamic and probabilistic learner model for adaptive hypermedia based on e-learning standards and standards and using *multi-entity Bayesian networks*.

- Presentation of *tests and experiments* for all stages of learner modeling, from data collection, initialization of the learner model and its update, using a customized version of *UnBBayes* software to validate our model of learner and our approaches to managing it.

ORGANIZATION OF THE BOOK

This book is divided into two major sections. The first section concerning the analysis of the state of the art, the first two chapters aim at presenting two comparative studies. The first study concerns the functionalities and composites of a learner model and its development in AHES. The second study aims at presenting the methods and models used to develop the learner model. Both studies present several arguments in which we have based our work for choosing the Bayesian methods as a probabilistic formalism to manage the learner model in AHES. The second section, composed of five chapters. In each chapter we present the process that we have used to develop a dynamic learner model in AHES.

Chapter 1: A Comparative Study of the Functionalities and Characteristics of a Learner Model in Adaptive Hypermedia Educational Systems

This chapter will cover the description of the learner model and adaptive e-Learning systems. We will begin by presenting the learner model in Adaptive Hypermedia Educational Systems (AHES), its main role and categories that will form the context of this chapter. The focus then will shift to the study of the main functionalities of the learner model. We will divide these functionalities into six categories and we will present a study in 10 different hypermedia to conclude in which functionalities they're based. Then, we will put emphasis on the different phases to develop and model the learner model in adaptive educational hypermedia systems, and illustrate the range of application of each functionalities and aspect and it focus area. We aim in this paper at presenting a comparative study of each aspect and functionalities of the learner model in different adaptive educational systems, and at showing their level/degree of intervention in relation with the components of the learner model and development process.

Chapter 2: A Comparative Study of the Modeling techniques and Models of a Learner Model in Adaptive Hypermedia Educational Systems

In this chapter, we will come back to the process of developing the learner model and the different types of its components and content. Then, we will present the different methods and approaches of management and modeling of the learner model in the adaptive educational systems and this by illustrating the field of use of each of these methods as well as its field of intervention. Finally we will present a comparative study of these modeling methods and its level of intervention according to the components of the learner model and during the development process and the model update.

Chapter 3: Development of Bayesian Networks From Use Case Diagrams for Managing the Learner Model

The objective of this chapter will be to develop a Bayesian network since the unified modeling language (UML) in the objectives is to represent the learner model. In this chapter, we will try to offer a combination of these two approaches, starting with specifying the transformation rules on which we have based our work. We will then demonstrate how to transform use case diagrams into a Bayesian network based on these rules. Finally, we will present the formal structure for this consideration.

Chapter 4: A Learner Model Based on Bayesian Networks in Adaptive Educational Hypermedia Systems

The objective of this chapter will be to use Bayesian networks as a probabilistic formalism to solve the problem of managing and dynamically updating the learner model. We will begin by presenting the meta-model of the learner model that we used as a reference to develop our use case diagram of the learner model. Then we will move on to the specifics of the transformation rules of our use case diagram to a Bayesian network based on these rules. Finally, we will present experiments to test our hypothesis by testing all the nodes of our developed Bayesian network.

Chapter 5: The Determination of Learning Styles in a Learner Model Using the Combination of Bayesian Network and the Overlay Model

In this chapter, we will first see the concepts and definitions of the learner model and the learning styles on which our work will be based. Next, we will define the Bayesian networks and the overlay model. Once done, we will focus on the combination rules from which we have based our work to integrate Bayesian networks with the overlay model. We will then demonstrate, using an example of a learning situation, the validity of this combination. Finally, we will describe a formal structure for defining each learning style for a learning situation.

Chapter 6: The Combination of Bayesian Networks and Stereotypes to Initialize the Learner Model in Adaptive Educational Hypermedia Systems

In this chapter, we will explain our approach to the initialization of the learner model based on a combination of stereotyping method and Bayesian networks, specifying the field of intervention of each method and these expected results. Finally, and with the objective of dismantling the validity of our hypothesis, we will present the experiments and the tests carried out. The results obtained following these experiments presented in this work will represent arguments in favor of our hypothesis. This realized combination also promotes its reuse in the step of updating the learner model in different adaptive educational hypermedia systems.

Chapter 7: A Learner Model Based on Multi-Entity Bayesian Networks in Adaptive Hypermedia Educational Systems

In this last chapter of our manuscript, we will present our probabilistic learner model based on multi-entity Bayesian networks. We will return to begin with the learner model that we modeled in the beginning using the Unified Modeling Language Use Case Diagram, and then introduce the Bayesian network of the learner model that we developed. Then, we will explain the approach followed in this chapter for modeling the learner model with Bayesian multi-entity networks, starting with the presentation of MEBNs and their composition,

explaining the notions of fragments and MTheories. Finally, and in order to demonstrate the validity of our hypothesis; we will present the fragments of each node of our network, these random variables, and then we will perceive our multi-entity Bayesian network in a complete way.

CONCLUSION

The approach that we followed in this research insight is marked initially by the modeling of the learner model in three levels: we started with the conceptual level of modeling with the unified modeling language, followed by the modeling of the model based on Bayesian networks to be able to lead to probabilistic modeling in the three phases of learner modeling. Finally, we have proposed in this last chapter a dynamic and probabilistic modeling of this model using multi-entity Bayesian networks.

This approach is considered very useful for the learner model, especially in the case of a large number of data stored in the system. The transformation of the nodes for fragments gives us the possibility of a separate management of the data of each fragment, keeping at the same time all types of relations of each fragment with the other fragments by using the random variables which exist in several fragments within an m-theory of the learner model.

We presented, firstly, a conceptual modeling of the learner, based on an e-learning meta-model of adaptive hypermedia. Using the use case diagram of the unified modeling language, we have developed based on this diagram, the Bayesian network that represents the learner model through specific transformation rules. A transformation based on our work of development of Bayesian networks since the unified modeling language presented in the second chapter.

We then presented a combination of the overlay model with Bayesian networks for domain-specific information management. We took as examples the learning styles to test this combination, testing our Bayesian network of learner model with precise metrics. And for the initialization stage of the learner model, we have based our hypothesis on the combination of the stereotype method to create a learner profile since the collection of independent information about the learner, and the Bayesian networks that represent the initial tests that the learner must take before he enters a learning situation in adaptive hypermedia.

The elaborate learner model could be reused and adapted for other environments in various domains while using an engineering approach, which provides a better framework for design. The choice of Bayesian multi-entity networks as formalism to manage the uncertainty of this model becomes more beneficial especially for environments with many examples. The model could also help the teacher to better adapt his teaching to the learner. Nevertheless, learner participation largely influences the effect of using our model.

Acknowledgment

"Making the world a better place" is a phrase that we are used to hearing every year around the world in different languages. This phrase was the driving force to write this book. We believe that changing the world and making it a better place, is only possible by developing education and making it much easier for everyone around the globe.

I want to dedicate this book to my mother, my force and my rock. She always was with me in every difficult moment in my life. And without her, this work wouldn't see the light.

I want to thank my father, the only math teacher that I liked. Not just because he is my father. But especially because he is the one that made me love mathematics and encourage me daily to push myself into the limits.

I want to thank my beautiful sister, who I love the most in this world. Here you go. This book is dedicated to you!

Section 1

Chapter 1
A Comparative Study of the Functionalities and Characteristics of a Learner Model in Adaptive Hypermedia Educational Systems

ABSTRACT

Today's adaptive hypermedia systems are putting more and more emphasis on the intelligence of the system. One of the most important factors in assessing the quality and usability of the system is the level to meet the needs of the user, the learner. So, the learner model, the component that backs up and manages learner information, becomes more important. The learner model is an essential component for adaptive e-learning systems. The term adaptation in e-learning systems involves the selection and manner of presentation of each learning activity as a function that examines the entity of knowledge, skills, and other information given by each subject taught. The chapter aims at studying the functionalities of the learner model in different adaptive hypermedia educational systems in the three stages of developing and managing this model. The authors present in this comparative study a full analysis of the learner model used in 10 major hypermedia to come up with most appropriate method to treat the dynamic aspect of this model.

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INTRODUCTION

In general, the adaptation process can be described in three steps: retrieving user information, processing information to initialize the user model, and updating the initialized user model; finally, the use of the user model to provide the adaptation. In this chapter, we will only use the user's model term, which is used because the user profile is simply considered the process of collecting raw data from the user (Kobsa, 1993)

In the process of adaptation, it is possible to distinguish between two different characters. At the beginning, the learner or student with his goal of acquiring knowledge, second: the teacher. The goal of a teacher is to mediate the knowledge covered by a course to learners. Therefore, both points of view must be present in an e-Learning system (Brusilovsky, 2000)

To be able to adapt the presentation of learning and navigation content to the needs of the user, a user model is needed, including objectives or tasks, knowledge, pre-requisites and user preferences. These user properties are used to make adaptive decisions by adaptive hypermedia systems. In addition, the user's recent templates also store the interests and individual traits.

In this chapter, we will begin by presenting the learner model in Adaptive Hypermedia Educational Systems (AHES), its main role and categories that will form the context of this chapter. The focus then will shift to the study of the main functionalities of the learner model. We will divide these functionalities into six categories and we will present a study in 10 different hypermedias to conclude in which functionalities they're based. Then, we will put emphasis on the different phases to develop and model the learner model in adaptive educational hypermedia systems, and illustrate the range of application of each functionalities and aspect and it focus area. We aim in this chapter at presenting a comparative study of each aspect and functionalities of the learner model in different adaptive educational systems, and at showing their level/degree of intervention in relation with the components of the learner model and development process.

LEARNER MODEL IN ADAPTIVE HYPERMEDIA EDUCATIONAL SYSTEMS

In this section, we will present the categories of a learner model in adaptive hypermedia educational systems. And then will present the main functionalities of the learner model, and a comparative analysis of their existence in 10 existing hypermedia.

The Categories of a Learner Model in AHES

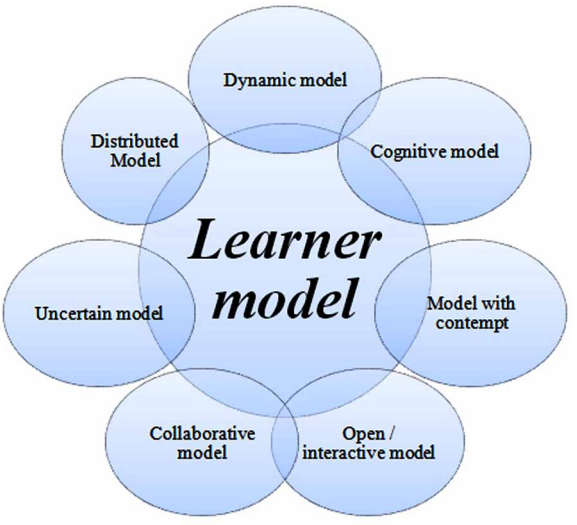
Today's AHES are putting more and more emphasis on the intelligence of the system. One of the most important factors in assessing the quality and usability of the system is the level to meet the needs of the user, the learner. So the learner model, the component that backs up and manages learner information, becomes more important.

A Learner model is one of the major components of an AHES. It allows to keep information about the learner, for example his level of knowledge on a given subject (performance), his frequent errors / misunderstandings, his psychological characteristics, etc. A learner model can be defined as a set of structured information about the learning process, and this structure contains values about the characteristics of the learner. It provides the necessary data for the other modules in order to adapt the teaching to the learner. (Han, 2003; Zhou et al., 1999)

Figure 1 represents the different categories of a learner model existing in different AHES. Each learner model must belong to one or more of these main categories:

- ***Dynamic Model:*** This category of learner model accumulates and records in real time the information about the learner. This information could be modified or updated dynamically depending on the interaction between the learner and the system. E.g. system visits, answers to questions, etc. As a result, the system actively adapts the teaching to the learners; in particular it supports the dynamic navigation in quantity of educational materials.
- ***Cognitive model:*** The cognitive model means that the cognitive aspects of the learner are considered in modeling. For example, the principles of cognitive psychology are adapted and incorporated in the modeling, to follow the state of the memory of the learner, in order to

Figure 1. The categories of a learner model in AHES



adapt pedagogical strategies to the needs of the learner among others by offering him relevant contents to be revised at the appropriate time. Many researchers have applied cognitive theories to modeling in a variety of ways. In addition, cognitive characteristics of the learner, for example, the attitude of learning, the time that a fact remains in the memory, the capacity of memory, are frequently included in this category of a learner model.

- ***Model with contempt:*** In this category, the learner model mainly retains the errors or the frequent misunderstandings of the learners and also the causes or explanations of these errors. Normally, this list of errors is a result of empirical studies involving many students and tutors in concrete cases in schools. This type of model is often used to simulate a learner's problem-solving process to diagnose possible errors. In addition, the misunderstanding model could be used for the automatic construction of exercises, for example in the case of multiple-choice questions, to automatically produce the most common erroneous answers given by students.
- ***Open / Interactive Model:*** This new approach to learner modeling allows learners to have some control over diagnostic inspection and model modification. The model is built jointly by the system and the learner. The system then accumulates its own points of view and those of the learner on the knowledge of the learner. The open model is used

to encourage learners to reflect on their learning, as well as for tutors to tailor instruction to the individual or group. The openness of the model could also make it easier for learners to compare their own progress over time or their own progress with peers in the same group or other groups.

- ***Collaborative model:*** This model is used in the context of collaborative learning. Collaborative learning is a new paradigm that broadens a classical AHES by involving concepts of collaboration. The success of a student could help the success of other members of the group. The learner could also search for an online peer, the system that matches students according to relevant attributes, to solve a problem. The collaborative model is also useful for finding peers who could or would like to receive feedback about some aspects of their work.
- ***Uncertain Model:*** This category of learner model focuses on dealing with the uncertainty of the learner's knowledge. Descriptions of knowledge or levels of knowledge are often inaccurate in the actual situation. Knowledge modeling can represent, train and update this uncertain knowledge. The treatment of uncertainty could also help to reach certain conclusions about learner knowledge or pedagogical strategies, based on incomplete information.
- ***Distributed Model:*** This learner model is often used in the distributed environment. There is no monolithic model associated with each student. Knowledge about a specific student is distributed among agents who communicate with that student. Modeling is a process of assembling and summarizing fragmented learner information from potentially diverse sources. This information could be raw data recorded by an application, partially calculated models, and learner options recorded by a tutor or peers, or a history of the learner's actions.

We briefly presented the characteristics and usefulness of the different categories of learner model. It is difficult to attribute rigid and definitive boundaries to these categories. Some concrete learner models have several characteristics, that is, they belong to several different categories. We could find in some situations, the same learner model in some AHES is in the same time a dynamic, distributed and collaborative model. To determine the most appropriate learner model category, one needs to thoroughly analyze the practical needs and real situations. And to achieve this purpose, we will try to conduct this comparative study with 10 different AHES.

The Existing Adaptive Hypermedia Educational Systems

In this study to comprehend the main functionalities of a learner model in adaptive hypermedia educational systems, we have chosen 10 AHES from different domains of intervention. We will compare each one of them based on some well defined metrics to define a proper path to construct and initialize a learner model using a combination of methods/model.

- ***AHA!,*** the "Adaptive Hypermedia Architecture", was originally developed to support an on-line course with some user guidance through conditional (extra) explanations and conditional link hiding. It consists of a set of concepts, some of which are linked to pages or objects (or fragments). Concepts can be used to represent topics of the application domain. (De Bra et al., 2003)
- **The *ADAPTWEB*** environment is an adaptive hypermedia system providing the same content adapted to different students groups. ADAPTWEB is an open source environment in operation in different universities. (Warpechowski et al., 2004)
- ***AVANTI*** is a system designed for a range of users with different needs. This system combines in the stages of data collection and initialization of the learner model stereotypes and superposition method to create initial assumptions, and to maintain the knowledge of the user. (Anouar Tadlaoui et al., 2016)
- ***ANATOM-TUTOR*** Developed for teaching anatomy of the brain at university level, ANATOM-TUTOR's hypertext component makes use of a user model to adapt hypertext lessons at both the link and the text level. Hypertext is one of three learning modes offered by ANATOM-TUTOR. (Beaumont, 1994)
- **The *AHM*** system, in which the adaptation depends on the level of expertise on the concepts of the field know the system is a subset of all the user's domain concepts. (Hardman, 1997)
- **The *ELM-ART*** system is an Adaptive distance Tutor system, which support learning Lisp programming language. It uses different techniques for initializing and updating its learning model: overlay model, the complex machine learning methods and Bayesian networks to represent episodic learning model. (Weber et al., 2001)
- ***INSPIRE*** is an adaptive hypermedia that emphasizes the fact that learners perceive and process information in very different ways,

and integrates ideas from theories of instructional design and learning styles. INSPIRE, throughout its interaction with the learner, dynamically generates learner-tailored lessons that gradually lead to the accomplishment of learner's learning goals. (Papanikolaou et al., 2003)

- **In *HYPERADAPT***, a specialized approach utilizing an aspect-oriented programming is used. This hypermedia places the adaptivity into separate modules called adaptation aspects. The aspects are not applied on a model level, but on XML documents. (Niederhausen et al., 2009)
- ***HYNECOS*** is adaptive hypermedia that demonstrates the applicability of the Hypertext Design Model HDM for design of hypertext-based information systems from relational databases. HYNECOS contains textual and graphical data about patients (administrative data, reports, x-rays etc.), hospital staff (names, telephones and shift-information about all staff members), a medical encyclopedia (diseases, treatments, and prognosis) and the location of the wards (room-plans, beds, occupancy etc.). (Schwabe et al., 1990)
- **The *METADOC*** system is an adaptive hypermedia mainly used in medicine, it's not only has hypertext capabilities but also has knowledge about the documents it represents. This knowledge enables the document to modify its level of presentation to suit the user. METADOC builds and dynamically maintains a user model for each reader. (Boyle et al., 1998)

The Fonctionalites of a Learner Model in Existing AHES

The intelligence of an AHES is mainly attributed to its ability to adapt to a specific learner during the teaching process; adaptation depends on the individual learner's knowledge of the subject taught and other relevant characteristics of the learner; relevant knowledge and information of the learner is often managed in a learner model. (Anouar Tadlaoui et al., 2014; Anouar Tadlaoui et al., 2015)

The learner model category plays an important role in the implementation of intelligence and personalization of AHES. Specifically, a learner model can help personalize learning, assess learner knowledge, track learner progress, etc.

In Table 1, we identified six essential functionalities of a learner model: Personalizing learning, assessment of the learner's knowledge, follow-up and

Table 1. Comparative table between the functionalities of a learner model in existing AHES

The functionalities of a learner model	AHA	ADAPTWEB	AVANTI	ANATOMTUTOR	AHM	INSPIRE	HYPADAPTER	ELM-ART	HYNECOS	METADOC
Personalizing learning	X	-	X	X	X	X	-	X	-	-
Adaptation of teaching	X	X	X	-	-	-	-	-	-	-
Adapted presentation of teaching materials	X	-	-	X	-	X	-	-	-	-
Planning and organization of activities or educational contents	-	-	-	X	-	X	-	-	-	-
Selection of relevant teaching methods / strategies	-	-	X	-	-	-	-	X	-	-
Personalized help / advice	-	-	-	-	-	-	-	X	X	X
Adaptive assessment	-	X	-	-	X	-	-	-	-	-
Planning learning activities	X	-	X	-	-	-	-	-	-	-
Adaptive navigation	X	X	-	-	-	-	X	X	-	-
Assessment of the learner's knowledge	-	-	-	X	X	-	-	-	X	X
Analyzes of learner responses / beliefs	X	-	X	-	X	-	-	-	-	-
Diagnosing the mistakes of the learner	-	-	X	X	X	-	-	-	-	-
Planning the diagnostic dialogue	-	-	X	-	X	X	-	-	-	-
Adaptive explanations	-	-	X	-	-	-	-	-	X	-
Resolving ambiguities of error explanations	-	-	-	-	-	-	-	X	X	-
Follow-up and/or presentation of progress and actions of the learner	-	-	-	-	-	X	-	-	X	-
Search for appropriate peers to get help	-	-	-	-	-	-	-	X	X	-
Management of the learner information	-	-	-	-	-	-	-	-	X	X
Automatic construction of exercises	-	-	X	-	-	-	-	X	-	-

presentation of progress and actions of the learner, search for appropriate peers to get help, management of the learner information and automatic construction of exercises. And we will compare the existence of these functionalities in the AHES we took into our comparative study.

According to this table, we can conclude that two features are very common. Systems provide personalized learning by adapting teaching to the needs of the learner, giving relevant advice. Planning own learning activities, etc. Appropriate exams or tests are built according to the learner's performance. In addition, adaptive navigation has long been a technique used to achieve adaptation of learning. More specifically, to adapt teaching, teaching materials can be presented according to the level of knowledge and according to the learner's personal preference. Educational planning can also be organized according to the learner's knowledge, psychological characteristics or preferences. Pedagogical strategies can be selected according to the psychological characteristics and the learner's performance.

Learner model is also an essential component in assessing the learner's knowledge. For example, learner responses can be analyzed to infer beliefs, in other words, correct, erroneous, or incomplete knowledge. We can diagnose errors or misunderstandings of the learner according to the frequent mistakes of this learner and those of many students. Information on these errors is maintained in the learner model. Students' knowledge can be accessed from a conversation between the system and the learner. This diagnostic dialogue can be planned according to the learner's beliefs. From the results of the diagnosis, the explanations of the errors are adapted to each student according to his. In some cases, when there are ambiguities about the explanations, the learner's error history can be consulted to determine the appropriate explanations.

The other functionalities are also important and interesting even if they are present in few systems, for example: the monitoring of the progress of the learner, the automatic construction of exercises, etc. The presentation and comparison of the student's progress encourages the student to become more active. The automatic (or semi-automatic) construction of exercises allows tutors to increase their effectiveness. Peer research is very useful in collaborative models.

The majority of systems have two or more features at the same time, especially the two essential features of personalization of learning and assessment of learner knowledge, for example, *AHM, AHA!, ANATOM-TUTOR*, etc. Some systems focus on a single feature, which presents a mechanism for representing and maintaining the learner's actions by noting temporal aspects, in order to provide the learner with an overview of his or

her model (long-term and short-term). This feature is important for getting relevant learner information and can be useful for other features, including learning adaptation and ambiguities resolution in diagnosing learner errors or misunderstandings.

The Composition of a Learner Model in Existing AHES

Based on the survey we have presented in our previous work (Anouar Tadlaoui et al., 2016), we could resume the composition of learner models in different AHES into four major categories: characteristics of the learner, learning state, Learner Knowledge and Interactions between the system and the learner (Kay, 2000)

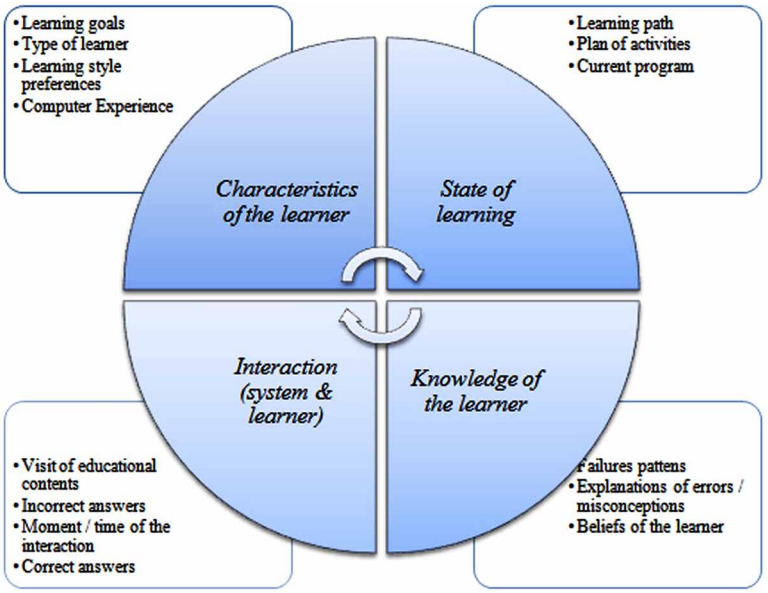
- ***Characteristics of the Learner:*** This category includes the learner's general or psychological characteristics, such as his or her learning purpose, type of learning, learning style preferences, computer experiences, level of learning concentration, the desired level of detail, availability, etc. The level of concentration could be inferred according to its interactions with the system, for example the time it is no longer active in the system. From this information, we can specify the anticipated needs of the learner.
- ***Learning State:*** Current or past states are classified in this category. More specifically, this type of model contains the learning plan, the program followed, the learning history, etc. This information is then used to analyze and maintain the learner's situation.
- ***Interactions Between the System and the Learner:*** This is one of the key categories of learner information. Interactions between the system and the learner are recorded and updated. At the appropriate time, the system infers the learner's knowledge or learning status according to the recorded data. These interactions can be divided into two sub-categories: system visits and answers to questions. Visits include visits to educational content, such as the number of visits to the same unit, the duration of the same visit, the type of content, etc. The number of examples or aids requested is also recorded. Then the answers include the correct answers and the wrong answers. In fact, the system does not keep the answers; instead it records the corresponding parameters, for example the number of errors, the frequency of a particular error, the more frequent errors, the number of tests, etc.

- ***Learner Knowledge:*** This is another important category. The data or information in the previous categories is used to infer the learner's knowledge to provide a personalized learning. In this category, there may be the learner's level of knowledge, exam or test scores, chess patterns, learner's beliefs and degrees of correction, explanations of errors/misunderstandings, knowledge of prerequisite concepts, knowledge of sub-domains, knowledge to be validated, knowledge acquired, etc.

Figure 2 shows the proportion of the use of each category in AHES. It is impossible and not necessary to build a complete learner model with all the elements mentioned, because it requires too many resources. Most of the proposed learner models contain only a few parts of these four categories, especially the last two. Although researchers place less emphasis on learning status, it is useful for personalizing learning by considering the learner's learning path and progress.

We can also classify this information, as we presented in previous work (Anouar Tadlaoui et al., 2016) into two groups according to their relationship to the domain: domain-independent or domain-specific. The personal data and the characteristics of the learner are information independent of the field. They

Figure 2. The composition of a learner model in AHES



are relatively static. Normally the data is provided by the students themselves by completing the forms or questionnaires. The learner could change some elements if necessary during the learning process. Few modifications are necessary to reuse them in different systems, in different domains. Most of the other three categories are domain specific. Some parameters are obtained directly by observing the actions of the learner. Some others are inferred from the first data. They are dynamic and automatically updated by the system.

DEVELOPMENT OF A LEARNER MODEL IN ADAPTIVE HYPERMEDIA EDUCATIONAL SYSTEMS

After presenting the functionalities of the learner model in different AHES. We will present in this section of the chapter, the three phases of learner model's development in AHES. We will begin by explaining the process of learner model development and then we will present a comparative study concerning the three phases of the development process according to 10 AHES.

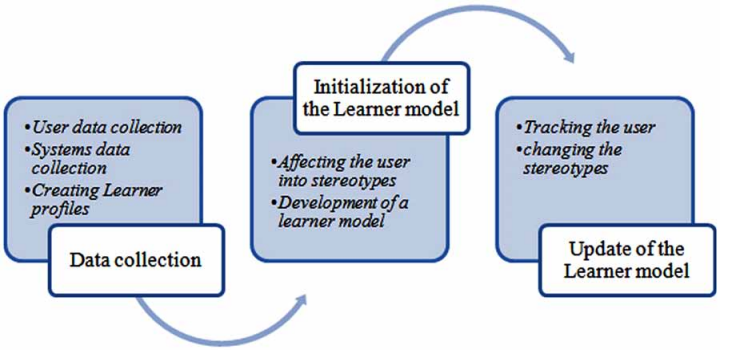
The Process of Developing a Learner Model in AHES

Despite these various attempts to model the learning that is characterized by a dynamic aspect, we always find it difficult to achieve this goal. The proposed approaches give us just a static view of the learner model, but in practice this model is in full development (the learner knowledge is evolving in the same module) to a dynamic view. In order to monitor the behavior of the learner in real time during training, we must adopt a model for dynamic management of the learning model.

All actions of the learner in a learning situation are not limited to valid or invalid actions (true and false), but these actions are characterized according to the learner learning path during his training. From this observation, we cannot represent the information from the system of each learner as a relative data. This demands putting our work in a probabilistic context due to the changes in the learner model during training (Koch, 2000)

Figure 3 represents the stages of development of a model of the learner. In the data collection phase, they are three major steps: the collection of data about the user, the collection of data about the system and creating a learner profile based on this initial data collected.

Figure 3. The process of developing a learner model in AHES



In the initialization stage of a learner model, the collected data undertakes a transformation process towards the model of the learner. This initialization process is realized through the implementation of several methods. The system affects the user to a specific stereotype according to the data collected. Then continue to collect data about the user all along his learning path using several methods like Bayesian networks or machine learning.

The information that is used to update the learner model can be retrieved, implicitly or explicitly from various sources of information. Among the sources of information, we find the information currently stored in the learner model. This information can be used as a source for which we derive new information or make changes to the alleged information. Furthermore, the information currently stored in the other system components may be useful.

The Construction of a Learner Model in Existing AHES

Table 2 represents a comparative between these different aspects of the construction of a learner model in AHES. We could notice that mainly all the AHES dispose of a system for data composition and representation. The main difference between this AHES is the methods used to collect data; we could notice that the old AHES based its data collection in general construction methods, and the specific AHES used more individual methods to extract precise data about the user.

The construction of an MA concerns the determination of the composition and structure of a learner model. For example, what categories of information should be included in the learner model? What concrete elements are needed? And what are the links of these elements between them? We must also

Table 2. Comparative table between the different aspect of the constraction of a learner model in existing AHES

Construction of the learner model (data collection)	**AHA**	**ADAPTWEB**	**AVANTI**	**ANATOMTUTOR**	**AHM**	**INSPIRE**	**HYPADAPTER**	**ELM-ART**	**HYNECOS**	**METADOC**
Data Composition / structure	-	X	X	X	X	X	X	-	-	X
Data representation	X	X	X	X	X	X	-	-	X	X
Data collection general construction methods	X	-	X	-	X	X	-	X	-	X
Long-term / short-term model of data collection	-	-	-	-	X	-	X	-	-	-
Group / individual model of data collection	-	-	-	X	-	-	-	X	X	-
Empirical studies	-	X	-	-	-	-	-	-	X	-

consider how to effectively represent this structure and these elements. Some authors concretely present the use of certain formalisms of representation. The process or method of construction indicates how to organize and acquire this information and knowledge. For example, how to extract knowledge from empirical studies.

The Inisialisation of a Learner Model in Existing AHES

The initialization of a learner model is a fairly important step in the development process. Researchers have exploited four ways to initialize a learner model: through questionnaires or pre-tests, by stereotypes, by the previous cases and by the default values. Among them, stereotypes are most often used. Stereotypes represent the knowledge and characteristics of typical user classes. So each student is assigned to one of the predefined classes (ie stereotypes). The major task of initialization is to select the appropriate stereotype for a learner. The questionnaires are practical and relatively easy to implement. Therefore, they are used in several systems.

Table 3 represents a comparative between these different aspects of the initialization of a learner model in AHES.

Sometimes, to know the initial level of knowledge of the learner, the learner is asked to do a simple test before starting his apprenticeship. The result of the test could be used to initialize some learner model values, or to show the progress of learning. Using previous cases to initialize the model is an interesting method. Previous experiences (models) of individual students or groups are used as stereotypes for future learners. Default values are used frequently in traditional systems. The initial values are assigned and then adjusted as appropriate in the treatment process.

The Update and Management of a Learner Model in Existing AHES

The methods and steps of a learner model management are related to the appropriate times to update the data or knowledge stored in the models. The learner model maintenance mechanism is specific to everyone because it has a close relationship with many aspects of the model, such as its structure, mode of representation, use, and so on.

Table 4 represents a comparative between these different aspects of the update and management of a learner model in AHES.

Table 3. Comparative table between the different aspect of the initialization of a learner model in existing AHES

The initialization of the learner model	**AHA**	**ADAPTWEB**	**AVANTI**	**ANATOMTUTOR**	**AHM**	**INSPIRE**	**HYPADAPTER**	**ELM-ART**	**HYNECOS**	**METADOC**
Pre-tests / questionnaires	-	X	X	-	-	-	-	X	-	-
Previous cases	X	-	-	-	-	-	X	-	-	-
Stereotypes	-	-	X	X	-	X	-	-	X	X
By default	-	-	-	-	-	-	-	-	-	X
Machine learning	-	X	-	-	-	X	-	X	-	-

Table 4. Comparative table between the different aspect of the update and use of a learner model in existing AHES

The update and management of the learner model	**AHA**	**ADAPTWEB**	**AVANTI**	**ANATOMTUTOR**	**AHM**	**INSPIRE**	**HYPADAPTER**	**ELM-ART**	**HYNECOS**	**METADOC**
Learner identification	X	X	X	-	X	X	X	X	X	-
Initialization of the model	X	X	-	X	-	-	X	-	-	X
Retention of learning states	X	X	-	-	X	-	X	-	X	-
Update of the model	-	-	-	-	X	-	X	-	-	-
Inference of other parameters	-	-	X	-	-	-	-	X	-	-
knowledge modeling	-	-	-	X	-	-	X	-	-	-

Some parameters in the category of personal data are used to identify the learner, for example the name, the user name or login name, the email, etc. Some personal data (eg age, experiences, gender, training, etc.) and some characteristics of the learner (learning purpose, type / style of learning, computer experiences, level concentration, preferences, etc.) are used to initialize the model, especially to select the appropriate stereotype for the learner. A stereotype represents the common characteristics of the learning style. Learning paths or activity plans could also be exploited to preserve the present or past states of the learner

The statistical parameters concerning the interaction between the learner and the system (the frequency of a specific error, the units visited more frequently, etc.) are the results of the calculation or reasoning based on certain visible parameters on the actions of the learner. the learner. They could also change some characteristics of the learner, including the level of concentration. Interaction parameters and characteristics are used to evaluate the learner's knowledge. Conversely, the level of knowledge assessed could also influence / modify certain characteristics of the learner.

The Modeling Approches Used for Learner Modelling in Existing AHES

A learner model is a combination of all relevant data on the learner in relation to a learning environment. There are common types of information among learners' models such as object domain information, goals, motivation, training and experience, cognitive skills, preferences and demographic training data.

To develop and manage the learner model, several methods/techniques have been used. Table 5 represents a comparative between these different modeling techniques and models used in modelling the learner in AHES.

DISCUSSION

Learner models can be used in very different ways, depending on the actions and characteristics of the learner in the system. Since there are different types of adaptive e-Learning systems, the applied learner models are different.

In many systems, the learner model may not be explicitly described as a simple functional module. It can be spread over several elements of the system. Thus, it is clearly visible what is connected to the model of the learner.

Table 5. Comparative table between the different methodes/approches used in learner modelling in existing AHES

Learner model modeling techniques/ methods	**AHA**	**ADAPTWEB**	**AVANTI**	**ANATOMTUTOR**	**AHM**	**INSPIRE**	**HYPADAPTER**	**ELM-ART**	**HYNECOS**	**METADOC**
Stereotypes	-	-	X	X	-	X	-	-	X	X
Overlay Model	X	-	X	-	X	-	X	X	-	-
Perturbation model	-	-	-	-	X	-	-	-	-	-
Differential model	X	-	-	-	-	-	-	-	-	-
Machine Learning	-	X	-	-	-	X	-	X	-	-
Bayesian Networks	-	-	-	-	X	-	X	X	-	-

Therefore, a learner model may not be available as an additional component but properties, which are related to a user model and are assigned to the long-term model user.

We could say, based on this study, that the learner model is an essential element in adaptive e-Learning systems. The adaptation of an e-Learning system primarily involves the selection and presentation of each successive teaching activity based on the full scope of the learner's knowledge of the subject taught and other relevant characteristics of the subject. As a result, the learner model is used to change the interaction between the system and the student to meet the individual needs of the students.

A learner model must be built, initialized and updated. Initializing a learner model is an important topic, where an appropriate way to gather the requested information has to be found. In particular, the effort for the user during initialization should be considered as this process affects the accuracy and usability of the learner model and the entire system. To keep the information stored on the learner updated, the modification of learner information must be included in the learner template. After the information within a learner's model is changed, the new information must be delivered. Delivery affects systems that use the learner model and should keep information consistent across all places where it is used.

CONCLUSION

An adaptive system needs information about the target to which it adapts. Since this target is most often adaptive to the learner of the adaptive system, a learner model is required. By using a learner model, an adaptive system can use this learner model in three different types of system actions. The system can interpret the actions of the learner differently regarding the features stored in the learner's model. For example, users with dyslexia may have a particular problem with a few words. The system recognizes these typos and automatically corrects the entry. In the other direction, the actions of the machine or the output of the system can be adapted to meet the needs of the user, and finally, internal actions can be influenced by the information stored in the user's model.

The information stored in a learner model varies between different models and depends on the adaptive e-learning system surrounded or often used. To provide as much interoperability for a learner modeling system to be used by multiple systems, it is necessary to agree on the information contained

in a learner model. These agreements are represented by standards. There are several standards in the field of user modeling that we will describe in the next chapter.

As a conclusion, it is safe to say that the learner model plays an important role in most hypermedia system and adaptive educational hypermedia systems in particular. We have presented in previous work, a probabilistic approach to manage dynamically the learner model in AHES (Anouar Tadlaoui et al., 2014; Anouar Tadlaoui et al., 2015) with an approach that can manage two types of independent and specific information of the domain of the learner, and that can be relevant to the three stages of the construction of the learner model. And we have also presented a process to combine the stereotypes method and Bayesian networks to initialize the learner model in AHES (Anouar Tadlaoui et al., 2017; Anouar Tadlaoui et al., 2018) in a probabilistic work frame to respond to the problematic of uncertainty in the learner model.

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Development of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Beaumont, I. (1994). User modelling in the interactive anatomy tutoring system Anatom-Tutor. *User Modeling and User-Adapted Interaction*, *4*(1), 21–45. doi:10.1007/BF01142356

Boyle, C., & Encarnacion, A. O. (1998). MetaDoc: an adaptive hypertext reading system. In *Adaptive Hypertext and Hypermedia* (pp. 71–89). Dordrecht: Springer. doi:10.1007/978-94-017-0617-9_3

Brusilovsky, P. (2001). *User Modeling and User-Adapted Interaction*. Academic Press.

De Bra, P., Aerts, A., Berden, B., De Lange, B., Rousseau, B., Santic, T., ... Stash, N. (2003, August). AHA! The adaptive hypermedia architecture. In *Proceedings of the fourteenth ACM conference on Hypertext and hypermedia* (pp. 81-84). ACM. 10.1145/900051.900068

De Koch, N. P. (2001). *Software engineering for adaptive hypermedia systems (PhD thesis)*. Munich: Verlag Uni-Druck.

Han, B. (2001). *Student modelling and adaptivity in web-based learning systems*. Massey University New Zealand.

Hardman, L., & Bulterman, D. C. A. (1997). Document Model Issues for Hypermedia. In W. I. Grosky, R. Jain, & R. Mehrotra (Eds.), *The Handbook of Multimedia Information Management*. Prentice Hall.

Kay, J. (2001). User modeling for adaptation. *User Interfaces for All, Human Factors Series*, 271-294.

Kobsa, A. (1993). User modeling: Recent work, prospects and hazards. *Human Factors in Information Technology*, *10*, 111–111.

Niederhausen, M., Karol, S. U., Aßmann, & Meißner, K. (2009). HyperAdapt: Enabling Aspects for XML. In *Web Engineering, 9th International Conference, ICWE 2009, ser. Lecture Notes in Computer Science*. Springer.

Papanikolaou, K. A., Grigoriadou, M., Kornilakis, H., & Magoulas, G. D. (2003). Personalizing the Interaction in a Web-based Educational Hypermedia System: The case of INSPIRE. *User Modeling and User-Adapted Interaction*, *13*(3), 213–267. doi:10.1023/A:1024746731130

Schwabe, D., Feijó, B., & Krause, W. (1990). Intelligent Hypertext for Normative Knowledge in Engineering. In A. Rizk, N. Streitz, & J. André (Eds.), *Hypertext: Concepts, Systems and Applications*. Cambridge, UK: Cambridge University Press.

Warpechowski, M., De Oliveira, J. P. M., Souto, M. A. M., Musa, D. L., Brunetto, M. A. C., de Freitas, V., & Proença, M. L., Jr. (2004). Adaptive hypermedia in the adaptweb environment. In *First International Workshop on Engineering the Adaptive Web (EAW)* (*Vol. 1*, pp. 68-73). Academic Press.

Weber, G., & Brusilovsky, P. (2001). ELM-ART: An adaptive versatile system for Web-based instruction. *International Journal of Artificial Intelligence in Education*, *12*, 351–384.

Zhou, Y., & Evens, M. W. (1999). A practical student model in an intelligent tutoring system. In *Tools with Artificial Intelligence, 1999. Proceedings. 11th IEEE International Conference on* (pp. 13-18). IEEE.

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learning Path: A collection of learning situations that the learner takes in a certain period of time; it could be composed of a pretest, a learning activity, or an evaluation.

Learning Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

Chapter 2
A Comparative Study of the Modeling Techniques and Models of a Learner Model in Adaptive Hypermedia Educational Systems

ABSTRACT

The main objective of the learner model is to modify the interaction between the system and the learner in a dynamic way to address the needs of each learner on an individual basis. To obtain a complete learner model, we need the proper techniques and methods to initialize it and update it. This chapter present a comparative study of different adaptive hypermedia systems and the methods and techniques used in with them. This study lies within the range of modeling the learner in adaptive educational system as a conceptual modeling of the learner. Although there are several methods that deal with the learner model, like stereotypes methods or learner profile, they are likely unable to handle the uncertainty embedded in the dynamic modeling of the learner. The chapter aims studies different models and approaches to model the learner in an adaptive educational system and comes up with the most appropriate method based on the dynamic aspect of this model.

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INTRODUCTION

The user module is an essential component for Adaptive e-Learning systems. The term adaptation in e-Learning systems involves the selection and manner of presentation of each learning activity as a function that examines the entity of knowledge, skills and other information given by each subject taught.

The main objective of learner model is to modify the interaction between the system and the learner in a dynamic way to address the needs of each learner on an individual basis. Generally, the adaptation process involves three major steps: Data collection about the user, processing the information gathered about the user to initialize the model of the learner and to use the initialized Learner model to adapt the system to the needs of each learner.

Its must be noted that in the process of adaptation, we must differentiate between two types of the user that must be taken into account in the e-learning systems. In hypermedia systems, there are two types of users: The student who enters the system to learn or develop his skills, and the teacher whose role is the transmission of knowledge to learners.

THE USER MODEL IN ADAPTIVE HYEPERMEDIA

The Architecture of Adaptive Hyeprmedia Educational Systems

In general, the architecture of Adaptive Hypermedia Educational Systems (AEHS) comprises two layers: the storage and implementation layer.

The storage layer is the main engine that controls adaptive process whose main tasks are:

- Initialization and update of the learner model
- The choice of the domain model concepts, learning resources by applying specific rules.
- Storing the learning resources, domain ontologies, the model of the learner, etc.

The execution Layer is responsible for the presentation of the adaptive learning material to the user and the observation of the user's actions so as to update the learner model.

Figure 1 represents the architecture of AHES (Henze & Nejdl, 2004), the storage layer in this architecture has four models:

- **Domain model** structure of knowledge domain which is often referred to as a graph. Several researchers intend to build the domain model by using ontologies.
- **Media Model** contains learning resources and associated descriptive information (metadata).
- **Adaptation model** is the main component that gives effect to adaptation. It contains content and concepts selection rules. By applying these rules in content selection, it helps us choose the appropriate educational resources from the internal model. On the other hand, the concept selection rules are used to select the appropriate notions of the domain model. These rules must comply with a user model so that the selection becomes correct.
- **User Model** contains information and data about the user.

Figure 1. The architecture of Adaptive Hypermedia Educational systems

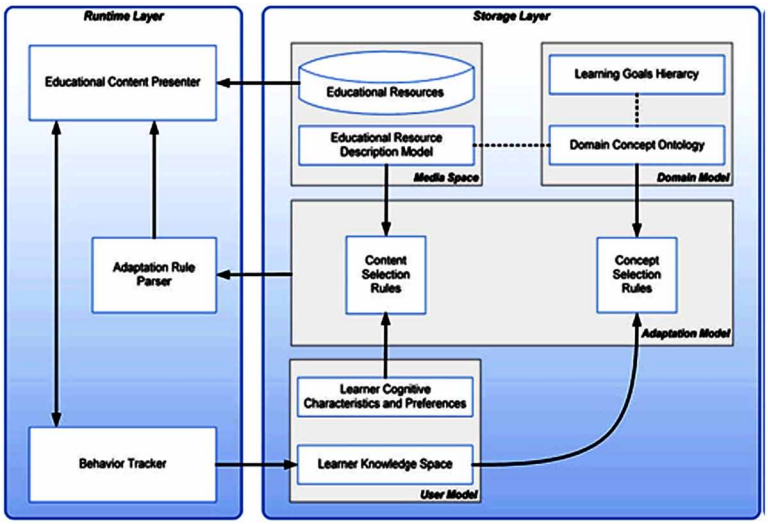
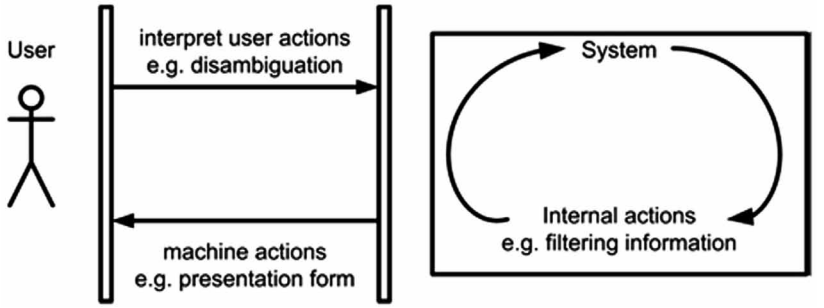


Figure 2. the role of the User Model in Adaptation



The Role of the User Model in Adaptation

According to Kay (2000), the user model can assist in the adaptation of the system in three major ways. Figure 2 indicates different uses of the user model during the interaction between the user and the system.

The first usage of the user model is represented by the user's arrow towards the system; the fact which reflects the possible actions of the user with the interface such as writing through the keyboard, selection by using the mouse and audio / video inputs. In this phase of interaction the role of the user model is to interpret the information in the system. The above figure illustrate the way the user model supports or allow the system to clarify the user input when it is put in an ambiguous form by identifing the applications in areas such as natural language understanding, interepting command line and misspellings by dyslexic users or typing problems by users with mobility problems.

The second type of interaction is represented by the arrow from the system toward the user. In this phase The user model is used to modify and control the system and adjust the shares according to the preferences of the user. This method is used to adapt the system according to the user's actions by adapting the content and its representation. For example, e-Learning systems can adapt their activities according to the knowledge's field of the user based on learners information, and assign learning activities according to the level of each learner in a specific field. Adaptive hypermedia systems focus on adapting the navigation and content preferences according to the domain knowledge stored in the user model.

The third usage of the user model is concerns with the internal system actions. The user model assist the system to filter the information received before saving.

The combination of these three types of action is used in adaptive systems. concidering an e-learning system that helps learners solve problems, the system first takes use of the user module to interpret the action of the user. Thus, the system performs a set of interiors actions that are interrelated to the user model, to select the most suitable learning situation for the learner's request. After these interiors actions, the system generates actions in the interface.

According to Koch (2000), there are seven key features of the user model. These features are user-centric:

- Assist the user during the learning of a specific subject.
- Provides information to adjust the user.
- Adapt the interface to the user.
- Help users to find information.
- Give immediate feedback to the user on his level of knowledge.
- Support collaborative work.
- Assist the user during use of the system.

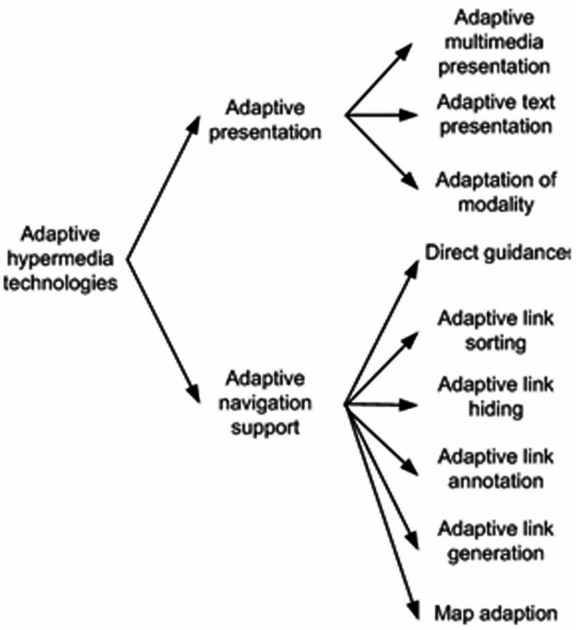
The User Model in Adaptive Hypermedia Educational systems

Before presenting the model users in adaptive educational hypermedia systems, we must first graspe the position of adaptation in educational hypermedia systems. According to Brusilovsky (2000), the adaptation of hypermedia can be applied mainly in the presentation and navigation between hyperspaces.

Figure 3 represents the breakdown of adaptation in several technologies used in adaptive hypermedia.

To adapt the presentation of the learning content and navigation with the needs of the user, the adaptive system needs a user model that includes goals or task, history and preferences to accumulate response to how and why adaptation. Other learner models according to Lee (Park & Lee, 2003) also include interest and personal traits such as personality factors, cognitive factors and learning styles; that contains constant characteristics on the user even if his interests changes over time.

Figure 3.The level of adaptation in hypermedia technologies



THE CARACTERISTIQUES OF A LEARNER MODEL

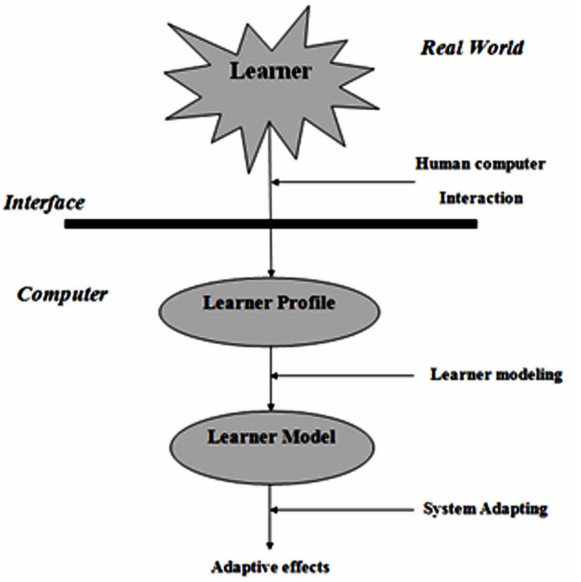
The Difference Between the Learner Profile and the Learner Model

Before defining user model, learner model and learner profile. It is interesting first to illustrate the difference between "learner profile" and "learner model."

The learner profile is a collection of personal information about the learner. This information is recorded without any description or interpretation. Learner profiles represents the essential information of the learner, such as cognitive skills, skills, intentions, learning styles, preferences and interaction of the learner with the system. The modeling of this stored information gives us the model of the learner.

Figure 4 represents the process of adaptation performed by the learner model in an adaptive system. The learner information can be modeled on the basis of the content and the amount of information about the user which is stored in the user profile that change within time. Thus, the user profile is used to retrieve the necessary information to formulate a learner model. Koch describes a model of the user that the representation of the beliefs of the

Figure 4. Learner's profile and learner model in adaptation



system on the user. The user of the "real world" is perceived by the system through the human-machine interface.

A profile contains personal information without deduction or interpretation. Unlike the learner model which is a higher level than the learner profile, learner profile is seen as an abstract view of the learner. Moreover, the learner model is able to deduct additional information about the learner. The learner model is based upon such information and is therefore only a small part of the actual learning. Nevertheless, the learner model must represent the necessary characteristics of the learner in the context of the education system.

The Components of a Learner Model

The components of a learner model are stored information that can be analyzed and grouped according to different levels of information. These components are connected to the application of the learner model. There are two types of components in the model of the learner:

- The performance model stores data sets related to assessments of learner skills. (Zhou & Evens, 1999).
- The model of learning history follows types of data presented to the learner during use of the system, and measures system knowledge level

based on the history of the interaction with the interface (Jeremić & Devedžić, 2004).

According to Zhou, it is necessary to put additional components to provide complete information about the learner. Such as: response history and balance the sheet of solutions. The learner's response history is attached to each unit of instruction; it stores information about the learning items and the learner responses during a learning situation. The number of errors and descriptions of these errors during the problem solving process are stored in the solution or the balance sheet. (Zhou & Evens, 1999)

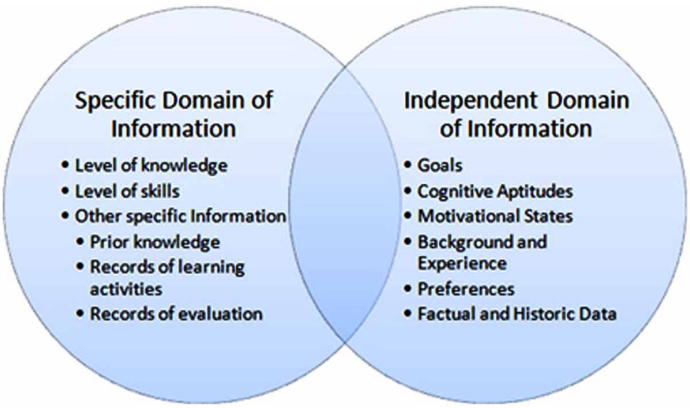
According to Castillo et al., (2003) the authors propose that the learner model must be divided into several components such as profile, model of cognitive overlay and an overlay model.

The Contents of a Learner Model

According to Self, a complete learner model must contain information about the domain knowledge of the learner, his preferences, key goals, interests, his progress and other information about the learner. All this information is essential for the use of the systems (Self, 1994)

Brusilovsky states that learners models can be classified according to the nature and form of the information contained in the models. Taking the example of a subject area, the information stored in the learner model is composed of two areas of information: the specific domain of information and independent domain of information. Figure 5 shows the components of

Figure 5. Learner domaines of informations



each information domain, the combination of these two areas of information provides a complete view of learners for adaptive systems (Brusilovsky, 2000)

Specific Domain of Information

The specific domain of information is a reflection of the level of knowledge and skills of a student in a learning situation.

Brusilovsky, names of the specific domain of information to the model of a specific area. The knowledge model can be based on the combination of two or more initialization method and models such as: scalar model, the overlay model, error model, genetic model ... in this chapter, we will not argue the initialization methods of the domain model, but we will discuss in the following sections some aspect of this methods to explain what we mean by the initialization of a learner model (Brusilovsky, 2000)

Furthermore, the specific domain of information stores other additional information, which is related to the learner in a specific area, in the learner model. Theses information can be stored as follows:

- The requirements in the area of learning to the learner.
- An archive of information on learning activities.
- An archive on the assessments and tests.

Independent Domain of Information

In addition to storing the level of current knowledge of a learner, independent domain of information facilitates the process of adaptability. According to Han, the independent area information on a learner includes (Han, 2003):

- ***Goals:*** It is important to know the goals of the learner and to determine the learning strategies. The goal can be divided into two different types: The first type is the learning goal which is relatively stable for a training unit. The second type is the problem-solving goal which can shift from one problem to another within the same learning situation.
- ***Cognitive Aptitudes:*** Cognitive aptitudes are the intellectual capacity for different kinds of cognitive performance. Such as, musical ability, mathematical ability ...
- ***Motivation States*****:** Measures the learner's motivational state in training, teaching… Motivation is measured using a number of long-term and

short-term parameters. These parameters are for example the effort, attention, interest, distraction and persistence, etc. These parameters are related to other factors such as the level of knowledge, preparation, the complexity of the subject and the learning outcomes.

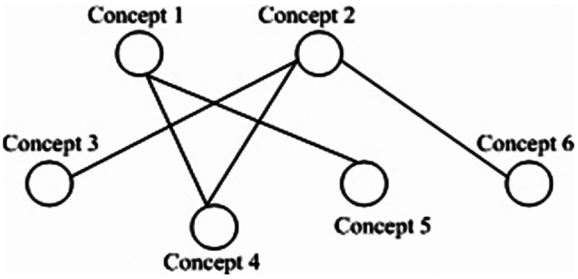
- ***Background and Experience:*** The background and experience of a learner are derived from the model parameters, information about the background and experience are used. General information includes skills that can influence the achievement of learning. Such information displays the occupation, work experience or perspectives of a learner
- ***Preferences:*** Learners may have different preferences related to aspects of the learning environment. These preferences are considered non-inducible system. Thus, the student must inform the system directly or indirectly of his or her preferences

LEARNER MODELLING, TECHNIQUES AND METHODS

A learner model is a combination of all relevant data on the learner in relation to a learning environment. There are common types of information among learners' models such as object domain information, goals, motivation, training and experience, cognitive skills, preferences and demographic training data.

The contents of a learner model are arranged in multiple components depending on the type of information. To put together the necessary information, it is necessary to make use of different methods that will be presented in this section, and will be investigated to show the impact of each one of them on adaptive systems and its field of intervention (Anouar Tadlaoui et al., 2016)

Figure 6. Exemple of the overlay model structure



The Overlay Model

The main idea of overlay model is that the learner model is a domain model subset. In other words, the learner overlay model is a shot of the full domain model. Figure 6 represents the relationships between the different concepts of a domain model.

A domain model consists of a set of knowledge elements representing the knowledge of expertise; each element represents a concept, a topic or a theme in a major field. Thus, the model structure of the learner "mimics" the domain model structure. However, each model element of the learner (corresponding to each domain model element) has a specific value measuring the knowledge of the user of this element. This value is considered the master of the domain element included a certain range. In other words, the domain is decomposed into a set of elements and the overlay model (learner model) which is a set of the more mastered elements. Suppose that mastery level of each element ranges from 0 (not mastered) to 1 (mastered). The expert model is the superposition with 1 for each element and the learner model is the superposition 1 at most for each item.

The overlay modeling approach was based on the domain models which are often constructed as a knowledge network or hierarchical tree of knowledge. Experts are the authors with the responsibility to create the domain model. Normally, each concept in the domain model is mapped to a learning object. Today there is a tendency to build the domain model using ontologies.

Stereotype Method

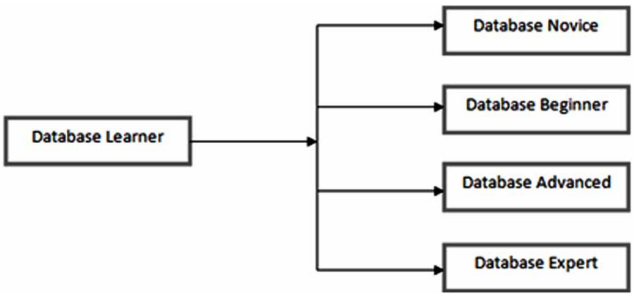
Generally, stereotypes represent a class or group of learners. There are two types of stereotypes: fixed and default.

In fixed stereotypes, the learner is assigned to a predefined stereotype on an abstract level. For example: in a data base module, learners are divided into four groups corresponding to four levels (novice, beginner, advanced and expert).

Figure 7 illustrates that each level is more difficult than the previous level: After getting individual information such as: knowledge, experience, skills ... the system assigns each student one of four levels, and it will never change in this type of stereotype.

In default stereotype, the system is more flexible. Therefore, the learner is assigned first to the initial stereotype. This means that the initial stereotype has

Figure 7. Example of the stereotype's method representation



a value "default". During the learning process the system will observe their learners and collect performance data, their actions, their test results ... Then, the system will modify the original stereotype again to a more appropriate stereotype, whereby the default stereotype setting is gradually replaced by a more accurate stereotype for the learner.

There are three important elements in every stereotype: triggers, inference and retraction:

- ***Trigger:*** Is used to activate a stereotype. In other words, it is a condition to assign a stereotype to the learner. For example: if the trigger "I have no knowledge of the database" is activated, the stereotype "Database-novice" will be assigned to the learner.
- ***Inference:*** Is an engine which is responsible for the deduction of information related to the learner. For illustration: if the learner is connected to stereotype "Database-expert" the inference engine should take both essential information and additional information such as, learner knows the design of databases, relational models SQL queries and ...
- ***Retraction:*** Provides the conditions to disable the stereotype of the learner. In the case of retraction, the learner is assigned with the stereotype "Database-novice" at the auto set of the course; but the learner then enriches the knowledge in database after the learning process, the fact that will make of the stereotype "Database- novice "an unsuitable stereotype. The event "the learner has passed the Database test with success" is the condition to retrace its stereotype "Database-novice" and it will be replaced with the stereotype "Database-Expert".

Machine Learning

For Webb, machine learning methods are used to model the cognitive processes underlying the actions of the learner like modeling differences between the learner's skills and the expert's skills, modeling behavioral preferences of the learner and his characteristics. Yet, it must be noticed that the two first objectives of this method are very often addressed, but modeling the behavior and characteristics of the leaner is rarely used by specialized scholars. (Webb et al., 2001)

Plan Recognition

Plan recognition is a sequence of actions of learners to achieve concrete goals. The plan recognition is based on the monitory of the performance of the user based on these entries (Kobsa, 1993).

User actions are adapted to a library of all possible plans. The plan most similar to the actions of the user actions will be chosen as a model of the learner. It is a plan recognition process. In this approach, it is very expensive to create a library and requires complex calculation and a large storage. And the implementation of this method requires a complex algorithm.

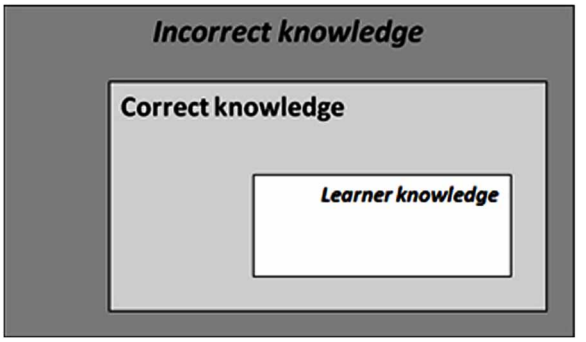
Deferential Model

The overlay model is based on domain knowledge of the expert, but it is necessary for the learner / teacher to transit the knowledge to the learner. This knowledge is called the expected knowledge. In other words, experts' knowledge is the domain knowledge that learners must master for some time.

Therefore, the differential model is essentially an overlay model on the knowledge provided, which in turn, is superimposed on the domain of expert knowledge. With the list of the top-down methodology, differential model is a variant of the overlay model.

However, the differential model is an instance of the class "default model", because knowledge should be considered as the knowledge that the user does not have.

Figure 8. Learner knowledge in the perturbation model



Perturbation Model

Both overlay model and differential model assume that the learner's knowledge is the subset of the misconceptions of expertise knowledge or lack of knowledge. These errors were considered false beliefs.

Figure 8 represents the hierarchy of the perturbation model in which the learner's knowledge is represented as a subset of expert's knowledge (as an overlay model) to add their false knowledge. Thus, the perturbation model is also an instance of the "fault pattern" class. This model, therefore, opens a new trend of modeling that can be supportive and suitable for adaptive system.

Bayesian Methods

Definition

Knowledge representation and reasoning from these representations has created many models. Probabilistic graphical models, specifically Bayesian networks initiated by Pearl (Pearl, 1998) in the 1980s, have proved to be useful tools for the representation of uncertain knowledge and reasoning from incomplete information.

A Bayesian network $\mathrm{B} = \left(\mathrm{G}, \mathrm{N}\right)$ is defined by $\mathrm{G} = \left(\mathrm{X}, \mathrm{E}\right)$ acyclic directed graph with vertices associated with a set of random variables:

$$\mathrm{X} = \left(\mathrm{X}, \ldots, \mathrm{Xn}\right)$$

$$N = \{P(Xi \mid Pa(Xi))\}$$

All the probabilities of each node Xi conditionally to the state of its parents $Pa(Xi)$ in G.

Thus, the graphical part of the Bayesian network indicates the dependency (or independence) between variables and provides a visual tool for knowledge representation that is easily comprehended by its users. In addition, the use of probability allows us to take into account the uncertainty in quantifying the dependencies between variables. Both properties have been the reason behind the first names of Bayesian networks, "probabilistic expert systems", where the graph is compared to the set of rules of conventional expert system, where the conditional probabilities presented as a quantification uncertainty about the rules.

Mayo has also shown that Bayesian networks allow representing compactly the joint probability distribution over the set of variables (Mayo & Mitrovic, 2001):

$$P(X1, X2, \cdots, Xn) = \prod_{i=1}^{n} P(Xi \mid Pa(Xi))$$

This decomposition of a global function, as a local product terms depending only of the node and its parents in the graph, is a fundamental property of Bayesian networks. It is the basis of the first work on the development of inference algorithms which calculate the probability of any variable of the model from the same partial observation of other variables. This has been proved NP-complete, but resulted in different algorithms that can be treated as information propagation methods in a graph. These methods obviously use the concept of conditional probability, i.e. what is the probability of Xi knowing that I have observed Xj but also the Bayes theorem that calculates, conversely, the probability of Xj knowing Xi when $P(Xi \mid Xj)$ is known.

Construction of a Bayesian Network

As we have seen in the definition, the complete specification of a Bayesian network requires specifying a share structure (directed acyclic graph that underlies) and other parameters (probability tables). To do this, two approaches

are possible and can be combined: the collection of expertise and machine learning, which is one of the contributions of Bayesian networks.

In the case of collection of expertise, the definition of the network structure begins with the identification of possible nodes and the distinction between (unobservable) informational variables (inputs) or hypothetical. The existence of an arc can be analyzed in terms of influence of one variable on another, but its orientation is more difficult. Traditionally, an arc is directed from A to B if A is a cause of B, but we will see that this interpretation is not so simple as in the case of the learner modeling. The parameters are in turn attached in an approximate manner by using frequentists or qualitative information.

Since Bayesian network is a probability distribution, we can use maximum likelihood as statistical learning parameters criterion. The result is as a Bayesian network whose structure is fixed and E which is a comprehensive basis of example, the maximum likelihood is achieved if the parameters of the Bayesian network are equal to the frequencies of the same features observed in E. statistical learning structure requires for its development test to determine whether or not the random variables are conditionally independent.

Using Bayesian Networks for Learner Modeling

In general, Bayesian methods are related to other modeling methods of the learner model like the overlay model, methods of stereotypes or the machine learning methods. Bayesian methods use probabilistic inference to update and improve the belief values of a learner during a learning situation. The main objective of Bayesian networks is the probabilistic inference. Bayesian network models explicitly the uncertainty between the requirements represented by use case and collaboration diagrams elements that's represents the user actions in an adaptive system.

We believe that Bayesian networks will provide a solution that will allow us to understand and measure dynamically all the actions of the learner in a learning situation. The networks obtained will provide us with a capacity to monitor and evaluate the performance of every learner at a real time, the learner's actions, the reason for these choices, and identification of each of the paths that will be followed during a learning situation.

LEARNER MODELLING METHODES: COMPARATIVE STUDY

Based on the conducted research on modeling the learner model in adaptive educational hypermedia, this section will try to present a comparative analysis of all the methods of learner modeling and management, and to work out an appropriate method that will gives us satisfying results.

Learner Modeling in the Existing AHES

In order to present a comprehensive comparative study on learner modeling in adaptive educational systems. It seems necessary compare the modeling of the learner model in ten different adaptive educational hypermedia systems.

Table 1 represents 10 different adaptive educational hypermedia systems. Reflecting for each AHES the methods or approaches used to model the learner model.

AVANTI is a system designed for a range of users with different needs. This system combines in the stages of data collection and initialization of the learner model stereotypes and superposition method to create initial assumptions, and to maintain the knowledge of the user.

The ***AHM*** system, in which the adaptation depends on the level of expertise on the concepts of the field know the system is a subset of all the user's domain concepts.

The ***ELM-ART*** system is an Adaptive distance Tutor system, which support learning Lisp programming language. It uses different techniques for initializing and updating its learning model: overlay model, the complex machine learning methods and Bayesian networks to represent episodic learning model.

The Modeling Methods' Area of Intervention

Table 2 represents a comparison between the different methods of learner modeling in adaptive system from previous research like Castillo et al., (2003), to Brusilovsky, (2000), and Zhou and Evens, (1999).

The machine learning method operates in the initialization and the update steps of the learner model, which enables the ability to manage accurately and dynamically the cotenants of a specific area of the information from a learner model. By using this method, we can represent the learner's knowledge

Table1. Learner modeling methods and techniques in AHES

AHES	Learner model modeling techniques/ methods					
	Stereotypes	**Overlay Model**	**Perturbation model**	**Differential model**	**Machine Learning**	**Bayesian Networks**
AHA	-	X	-	X	-	-
ADAPTWEB	-	-	-	-	X	-
AVANTI	X	X	-	-	-	-
ANATOMTUTOR	X	-	-	-	-	-
AHM	-	X	X	-	-	X
INSPIRE	X	-	-	-	X	
HYPADAPTER	-	X	-	-	-	X
ELM-ART	-	X	-	-	X	X
HYNECOS	X	-	-	-	-	-
METADOC	X	-	-	-	-	-

Table2. Comparative table between the learner modeling methods

Learner modeling methods	Learner modeling			Learner model cotenants	
	Data collection	**Learner model initialization**	**Learner model update**	**Domain specific information**	**Domain Independent information**
Machine Learning	-	X	-	X	-
Overlay model	-	X	X	X	-
Defferential model	-	X	X	X	-
Stereotypes	X	X	-		X
Plan recognition	-	X	X	-	X
Perturbation model	-	X	X	X	-
Bayesian networks	X	X	X	X	X

and skills and trace its evolution in a learning situation. However, there is a representation deficiency of independent information in the field of information in the learner model and in the data collection phase of a learner model.

The overlay model, the differential model and perturbation model are concerned with the representation of the specific domain of information of the knowledge domain as it is emphasized in previous sections. The representation of other aspects of the learner such as preferences, history, and learning

styles ... requires a combination of these methods with other methods that are concerned to manage the actions and preferences of the learner.

The method of stereotypes is the most useful method used during the stages of data collection and initialization of the learner in adaptive systems. But the update of the learner model requires the combination of this method with other more flexible methods such as machine learning or Bayesian networks. The stereotypes method does not give the system the ability to track and adapt dynamically to each share of the learner, it is limited to affect the learner to a well-defined stereotype after termination of the situation of learning.

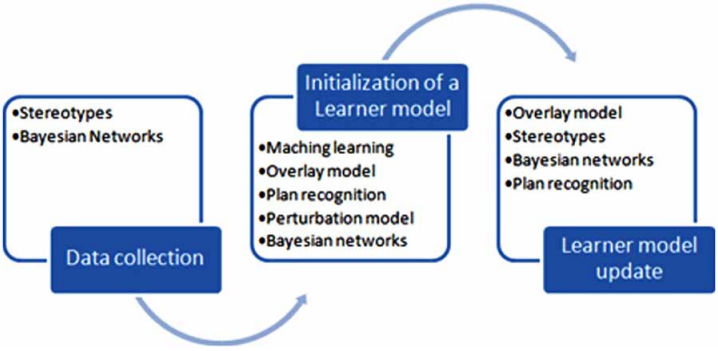
Bayesian networks appear to be formalism that enables us to ensure the inclusion of uncertainty in modeling the learner, such as implementations of different systems have shown. However the level of learner expertise should not be translated only by changes of probability but also by structural changes.

Learner Model Development

Despite these various attempts to model the learning that is characterized by a dynamic aspect, we always find it difficult to achieve this goal. The proposed approaches give us just a static view of the learner model, but in practice this model is in full development (the learner knowledge is evolving in the same module) to a dynamic view. In order to monitor the behavior of the learner in real time during training, we must adopt a model for dynamic management of the learning model.

All actions of the learner in a learning situation are not limited to valid or invalid actions (true and false), but these actions are characterized according to the learner learning path during his training. From this observation, we

Figure 9. Learner model's construction methods



cannot represent the information from the system of each learner as a relative data. This demands putting our work in a probabilistic context due to the changes in the learner model during training.

Figure 9 represents the stages of development of a model of the learner, and the intervention of each management method learner model. In the data collection phase, we find the method of stereotypes and Bayesian networks are the most used. The first method focuses on the learner's responses to the personal information stored for the formulation of the learner profile, where as for the Bayesian networks method represent the learner's information as a direct acyclic graph and constructs one or more network that contain this information.

In the initialization stage of a learner model, the collected data undertakes a transformation process towards the model of the learner. This initialization process is realized through the implementation of several methods. The overlay model is the most useful method that initializes then information of the domain of this model, but it neglects independent domain information. The same remark can be made about the perturbation and differential method. On the other hand, the plan recognition method sets up independent domain of information based on monitoring the performance of the user in adaptive systems. Yet, this method can be defined as a constant or a static method, since it is based on a predefined plan that the learner follows; a plan that is stored in the library of actions, and that generates initialization of the independent domain of information's problems.

The information that is used to update the learner model can be retrieved, implicitly or explicitly from various sources of information. Among the sources of information, we find the information currently stored in the learner model. This information can be used as a source for which we derive new information or make changes to the alleged information. Furthermore, the information currently stored in the other system components may be useful.

CONCLUSION

As a conclusion, it is safe to say that the learner model plays an important role in most hypermedia system and adaptive educational hypermedia systems in particular. However, it seems difficult to classify the models and choose the appropriate and relevant modeling methods. Each of these methods can be considered as a relative method since it emphasizes on one information side of the learner's model and ignore other sides of information in educational

hypermedia. Even if a method is applied in two types of domains information, it cannot be applicable in the three stages of construction of the learner model.

Based on our previous works (Anouar Tadlaoui et al. 2015;Anouar Tadlaoui et al. 2017, 2018), the use of Bayesian networks for initialization and updating the learner model seems to be more satisfying method at the level of tracking and evaluating the learner's performances during a learning situation. The contention of our work is to articulate a new approach that will help us in managing and modeling the learner model through an integration/ combination of several modeling methods mentioned in this work. Moreover, our work shivers to introduce an approach that can manage two types of independent and specific information of the domain of the learner, and that can be relevant to the three stages of the construction of the learner model.

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Brusilovsky, P. (2001). *User Modeling and User-Adapted Interaction*. Academic Press.

Castillo, G., Gama, J., & Breda, A. M. (2003, June). Adaptive Bayes for a student modeling prediction task based on learning styles. In *International Conference on User Modeling* (pp. 328-332). Springer. 10.1007/3-540-44963-9_44

De Koch, N. P. (2001). *Software engineering for adaptive hypermedia systems. Ph. DThesis*. Munich: Verlag Uni-Druck.

Han, B. (2001). *Student modelling and adaptivity in web-based learning systems*. Massey University New Zealand.

Henze, N., & Nejdl, W. (2004). A logical characterization of adaptive educational hypermedia. *New Review of Hypermedia and Multimedia*, *10*(1), 77–113. doi:10.1080/13614560410001728128

Jeremic, Z., & Devedzic, V. (2004, August). Design pattern its: Student model implementation. In *Advanced Learning Technologies, 2004. Proceedings. IEEE International Conference on* (pp. 864-865). IEEE.

Kay, J. (2001). User modeling for adaptation. *User Interfaces for All, Human Factors Series*, 271-294.

Kobsa, A. (1993). User modeling: Recent work, prospects and hazards. *Human Factors in Information Technology*, *10*, 111–111.

Mayo, M., & Mitrovic, A. (2001). *Optimising ITS behaviour with Bayesian networks and decision theory*. Academic Press.

Park, O. C., & Lee, J. (2003). Adaptive instructional systems. *Educational Technology Research and Development*, *25*, 651–684.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann.

Self, J. A. (1994). Formal approaches to student modelling. In *Student modelling: The key to individualized knowledge-based instruction* (pp. 295–352). Berlin: Springer. doi:10.1007/978-3-662-03037-0_12

Webb, G. I., Pazzani, M. J., & Billsus, D. (2001). Machine learning for user modeling. *User Modeling and User-Adapted Interaction*, *11*(1-2), 19–29. doi:10.1023/A:1011117102175

Zhou, Y., & Evens, M. W. (1999). A practical student model in an intelligent tutoring system. In *Tools with Artificial Intelligence, 1999. Proceedings. 11th IEEE International Conference on* (pp. 13-18). IEEE.

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). *Learner model in adaptive learning*. World Academy of Science.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

E-Learning: A concept that describes the cognitive science principles of effective multimedia.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learning Path: A collection of learning situations that the learner takes in a certain period of time; it could be composed of a pretest, a learning activity, or an evaluation.

Learning Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

Chapter 3
Development of Bayesian Networks From Use Case Diagrams for Managing the Learner Model

ABSTRACT

First of all, and to clarify the purpose, it seems important to say that the work presented in this chapter lies within the framework of learner modeling in an adaptive system understood as computational modeling of the learner. One must also state that Bayesian networks are effective tools for learner modeling under uncertainty. They have been successfully used in many systems, with different objectives, from the assessment of knowledge of the learner to the recognition of the plan followed in problem solving. The main objective of this chapter is to develop a Bayesian networks for modeling the learner from the use case diagram of the unified modeling language. The prototypes and diagrams presented in this chapter are arguments in favor of the objective. The network obtained also promotes reusing learner modeling through similar systems.

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INTRODUCTION

The problem of this chapter can be summarized as follows: Why and how can we represent a Learner model using Bayesian networks? How can we go from a dynamic representation of the Unified modeling language (UML) model to a probabilistic representation with Bayesian networks? Is this consideration experimentally justified?

The learner model is a data structure that represents the state of knowledge of a learner in a given field. This model identifies the learner's current level of understanding of the domain knowledge. It includes data on individual variables of a learner that allow updating of the learner profiles from information obtained during the interactions.

All existing approaches to model the learner are based generally on using the Unified Modeling Language, that quickly became a standard for the analysis and design in software development. Since it provides a schematic approach to describing the needs of the user, which begins with the use cases diagrams, and leads to a more formal specification, using stereotyped classes in the analysis model. The components of this modeling language form the basis of an architectural view in the system while providing the foundation for the design, implementation and validation and verification (Booch et al., 1999)

We have attempted in previous works, to model the learner using Bayesian networks and multi networks as a formalism to manage uncertainty in the management of learner model. In this chapter, we will try to offer a combination of these two approaches, starting with specifying the transformation rules on which we have based our work. We will then demonstrate how to transform the use case diagrams into a Bayesian network based on these rules. Finally we will present the formal structure for this consideration. (Anouar Tadlaoui et al., 2014; Anouar Tadlaoui et al., 2015)

USE CASE DIAGRAM: UML POINT OF VIEW

Concept and Definition

Use cases describe the form of actions, reactions and the behavior of a system from a user perspective. They allow defining the limits of the system and the relationship between the system and the environment.

Use cases are filling a lack of raw object methods, such as Rumbaugh (Rumbaugh et al., 1991) and Jacobson (Booch et al., 1999), which did not offer techniques, for the identification of needs. In this sense, the use cases associated with technical objects allow a comprehensive approach to the entire life cycle, from the specification to implementation.

A use case is a specific way of using a system. It is the image of system functionality, triggered in response to the stimulation of an external actor.

Use Case Diagram's Relationships

Use case diagrams represent actors and relationships between actions and actors. We will define in this section the main relationships in the use case diagram that we will use in our work, they are three types of relationships between actors and use cases:

Generalization Relationship

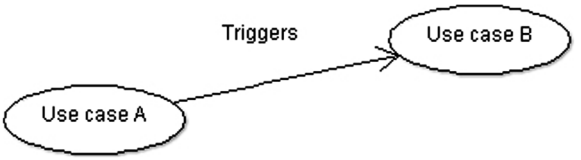
A case A is a generalization of a case B if B is a particular case of A. For example, the consultation of an account via the Internet is a particular case of the consultation. This relationship of generalization / specialization is present in most of the UML diagrams and results in the concept of inheritance in object-oriented languages.

In Figure 1, we observe that use case A initiates a use case B; this action is represented by an arrow from the initiator of the action to the triggered action.

Inclusion Relationship

A case A includes a case B if the behavior described by the case A includes the conduct of the case B: Where A depends on B. When A is applied, B also must be applied as a part of A.

Figure 1. Generalization relationship in use case diagram



This dependence is symbolized by the "include" stereotype. For example, accessing information from a bank account necessarily includes an authentication phase with a username and password.

The inclusions essentially allow factorizing a part of the description of a use case that would be common to other use cases like Figure.2 shows. The inclusions are also used to decompose a complex case into simpler sub-cases.

Extension Relationship

It is said that use case A extends a use case B when the use case A can be called during the execution of the use case B. Running B may possibly lead to the execution of A: unlike the inclusion, the extension is optional. This dependence is symbolized by the stereotype "extend"

LEARNER MODEL IN ADAPTIVE HYPERMEDIA EDUCATIONAL SYSTEMS

Concepts and Definition

A learner model allows keeping the learner information, for example his level of knowledge on a given topic (performance), his frequent mistakes/ misunderstandings, psychological characteristics, etc.

Figure 2. Inclusion relationship in a use case diagram

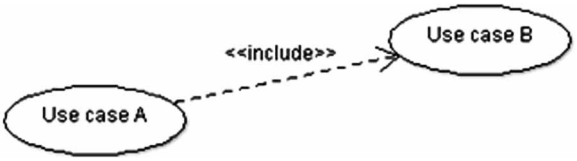


Figure 3. extension relationship in use case diagram



A learner model can be defined as a set of structured information about the learning process, and this structure contains values on the characteristics of the learner (Zaitseva et Boule, 2005) It provides the necessary data to the other modules to achieve the adaptation of teaching to the learner (Beck et al., 1996)

Many studies emphasize the uncertainty of the information contained in the student model and the importance of the intention behind the creation of this model. Thus, a student model represents the belief system about learners' beliefs (the system's beliefs about the learner's beliefs) accumulated during the diagnostic process.

Typologies of Learner Model

The learner model is a data structure in the computer sense that characterizes for the learning environment, the state of a subset of the learner's knowledge from the system point of view.

It will be defined by the difference between the learner knowledge and target knowledge, issue of learning, as represented in the system. The approach to represent this difference leads to distinguish two major classes of models:

- The models of partial or overlay expertise, in which the knowledge of the learner is only a subset of the target knowledge. The idea behind this type of model is that the learner present deficiencies or the poorly insured knowledge, or somehow weaknesses, it is identified to allow it to grow. The aim of the learning system is then to complete the knowledge of the learner in order to acquire all the knowledge outlined in the model (Carr & Goldstein, 1977)
- Differential models, which incorporate "false knowledge", corresponding to perturbations of the expert knowledge or erroneous preconceptions. In fact, studies show that many errors are not due to erratic behavior of learners, but the correct application of false procedures. To develop a model of learners' knowledge, one must take into account these types of systematic errors, that researchers will be designated by the term "bug" (bug). (Wenger, 1987)

While a partial model invites expertise in teaching strategies centered on the fact to fill the gaps of the learner, the incremental models will lead to strategies based on remediation.

BAYESIAN NETWORKS

Concept and Definition

Knowledge representation and reasoning from these representations has created many models. Probabilistic graphical models, specifically Bayesian networks initiated by Pearl in the 1980s, have proven to be useful tools for representing uncertain knowledge and reasoning from incomplete information (Pearl, 1988)

A Bayesian network $B = \left(G, N\right)$ is defined by

- $G = \left(X, E\right)$ acyclic directed graph with vertices associated with a set of random variables $X = \left(X, \ldots, Xn\right)$ and $\mathrm{N} = \{\mathrm{P}(\mathrm{Xi} \mid \ \mathrm{Pa}\left(\mathrm{Xi}\right))\}$
- All the probabilities of each node Xi .conditionally to the state of its parents $\mathrm{Pa}\left(\mathrm{Xi}\right)$ in G.

Thus, the graphical part of the Bayesian network indicates the dependencies (or independence) between variables and provides a visual tool for knowledge representation, more easily comprehensible by its users. In addition, the use of probability allows taking into account uncertainty in quantifying the dependencies between variables. Both properties have been the cause of the first names of Bayesian networks, "probabilistic expert systems", where the graph was compared to the set of rules of conventional expert system, and the conditional probabilities presented as a quantification uncertainty about the rules.

Heckerman Also have shown that Bayesian networks allow representing compactly the joint probability distribution over the set of variables (Geiger & Heckerman, 1996):

$$\mathrm{P}\left(\mathrm{X1}, \mathrm{X2}, \cdots, \mathrm{Xn}\right) = \prod_{i=1}^{n} \mathrm{P}(\mathrm{Xi} \mid \ \mathrm{Pa}\left(\mathrm{Xi}\right))$$

This decomposition of a global function as a local product terms depending only of the node and its parents in the graph, is a fundamental property of Bayesian networks. It is the basis of the first work on the development of inference algorithms which calculate the probability of any variable of the model from the same partial observation of other variables. This has been

proven NP-complete, but resulted in different algorithms that can be treated as information propagation methods in a graph. These methods obviously use the concept of conditional probability, i.e. what is the probability of Xi knowing that I have observed Xj but also the Bayes theorem, that calculates, conversely, the probability of Xj knowing Xi when $\mathrm{P(Xi \mid Xj)}$ is known.

Construction of a Bayesian Network

As we have seen in the definition, the complete specification of a Bayesian network requires specifying a share structure (directed acyclic graph that underlies) and other parameters (probability tables). To do this, two approaches are possible and can be combined: the collection of expertise and machine learning, which is one of the attractions of Bayesian networks.

In the case of collection of expertise, the definition of the network structure begins with the identification of possible nodes and the distinction between (unobservable) informational variables (inputs) or hypothetical. The existence of an arc can be analyzed in terms of influence of one variable on another, but its orientation is more difficult. Traditionally, an arc is directed from A to B if A is a cause of B, but we will see that this interpretation is not as simple in the case of the learner modeling. The parameters are in turn attached in an approximate manner by using frequentists or qualitative information.

Since Bayesian network is a probability distribution, we can use maximum likelihood as statistical learning parameters criterion. The result is as a Bayesian network whose structure is fixed and E which is a comprehensive basis of example, the maximum likelihood is achieved if the parameters of the Bayesian network are equal to the frequencies of the same features observed in E. statistical learning structure requires for its development test to determine whether or not the random variables are conditionally independent. (Becker & Naïm, 1999)

DEVELOPMENT OF BAYESIAN NETWORK FROM A USE CASE DIAGRAMME

The Choice of Bayesian Networks

As we previously presented, the diagrams of use cases is a top view of system features, it allows us to present all user actions (learner in our case). These

actions may require elements of uncertainty, this uncertainty will clearly present when poised to collaboration diagrams. Representing this uncertainty becomes very important when there are a large number of interdependent and potentially conflicting requirements that overwhelm the capacity of spontaneous human spirit.

Bayesian network models explicitly the uncertainty between the requirements represented by use case and collaboration diagrams elements. During the presentation of the functional evidence such as the importance of a particular learner, a quantitative assessment can be performed to the way we strongly believe the requirement is indicated. We therefore see the ability to transform the use case diagrams of Bayesian networks as a significant potential lead in the modeling of the learner.

We believe that Bayesian networks will provide a solution that will allow us to understand and measure a dynamic way all the actions of the learner in a learning situation. Networks obtained, we will give a capacity to monitor and represent at real time, all the actions of the learner, the rationale for these choices, and identification of each of the paths that will be followed during a learning situation.

Bayesian Network Development's Rules

Generalization Relationship

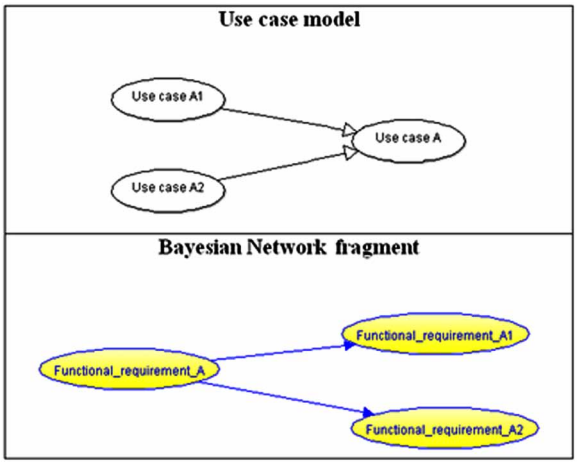
A generalized use case diagram contains a common functionality that is available for all the specialized use cases. The transformation of the generalization relationship to nodes of a Bayesian network is simple:

Consider Figure 4 in the use case A is a generalization of the use case A1 and the use case A2, we represent the functional requirement A1 and A2 being a descendant of the functional requirement of A.

This results in a Bayesian network with a similar structure. The direction of the arc flow from A to A1 and A2 reflecting a top-down decomposition. The information represented in the arrows of the use case will be included in the functional requirements. This indicates that it is more likely to encounter the general case of the specific functional requirement. Thus:

$$P\left(A\right) = prior$$

Figure 4. Bayesian fragment developed from the generalization relationship



$$P(\mathrm{A1} \mid \mathrm{A}) = \mathrm{P}(\mathrm{A} \mid \mathrm{A1})\mathrm{P}\left(\mathrm{A1}\right) \;/\; \mathrm{P}\left(\mathrm{A}\right)$$

$$P(\mathrm{A2} \mid \mathrm{A}) = \mathrm{P}(\mathrm{A} \mid \mathrm{A21})\mathrm{P}\left(\mathrm{A2}\right) \;/\; \mathrm{P}\left(\mathrm{A}\right)$$

Inclusion Relationship

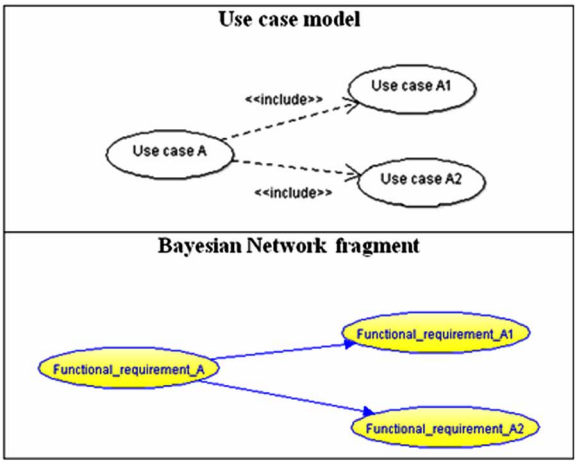
The inclusion relation in a use case diagram models the situation in which a use case is composed of a desired number of use cases. For inclusion, the high level of use cases cannot run without the implementation of sub use cases.

To see how this can be translated to fragments of the Bayesian network, consider Figure 5 use case A is linked to use cases A1 and A2 by an inclusion relation:

This results in a Bayesian network with a similar structure as the generalization relationship. The direction of the arc flow from A to A1 and A2 reflecting a composition from bottom to top in the information represented in the arrows of the use case will be included in the functional requirements. This indicates that it is more likely to encounter the general case of the specific functional requirement. Thus:

$$P\left(A\right) = prior$$

Figure 5. Bayesian fragment developed from the inclusion relationship



$$P(\mathrm{A1} \mid \mathrm{A}) = \mathrm{P}(\mathrm{A} \mid \mathrm{A1})\mathrm{P}\left(\mathrm{A1}\right) \;/\; \mathrm{P}\left(\mathrm{A}\right)$$

$$P(\mathrm{A2} \mid \mathrm{A}) = \mathrm{P}(\mathrm{A} \mid \mathrm{A21})\mathrm{P}\left(\mathrm{A2}\right) \;/\; \mathrm{P}\left(\mathrm{A}\right)$$

Extension Relationship

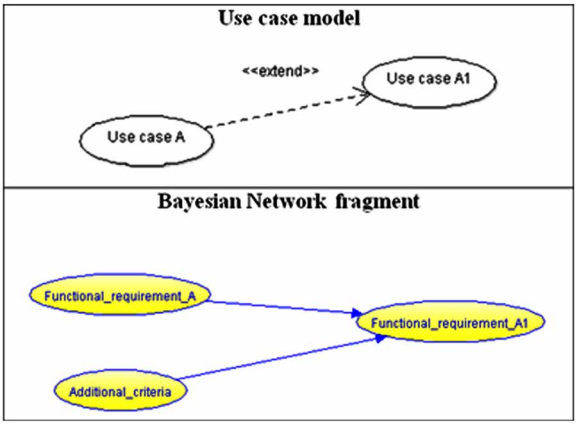
The extension relationship in a use case diagram represents a particular use case branched additional behavior given the satisfaction of certain conditions. In case of extension, the first use case does not need any more use case to run. The second use case is an exceptional behavior if the conditions are fulfilled.

Consider the general case schematized on Figure 6. A use case is extended by the case of A1 use. This models the situation in which an additional criterion triggers the case of using A1 after executing use case A.

The additional criterion is described in the flow of events from textual description. This situation is modeled as functional requirement A1 implied by the functional requirement A. The additional criterion is modeled as another functional requirement node. The direction of the implication is the additional criterion (AC) to the functional requirement A1. Thus:

$$\mathrm{P}(\mathrm{A1} \mid \mathrm{A},\ \mathrm{AC}) = \frac{\mathrm{P}(\mathrm{A} \mid \mathrm{A1},\ \mathrm{AC})\mathrm{P}(\mathrm{A1} \mid \mathrm{AC})}{\mathrm{P}(\mathrm{A} \mid \mathrm{AC})}$$

Figure 6. Bayesian fragment developed from the extension relationship



Learner Modelling Using Bayesian Networks

Our work lies in the framework of learner modeling in an adaptive educational system, to illustrate the ideas discussed in the previous sections; we will take an example of the actions of a learner in an adaptive system. We defined the Table 1 several actions of a learner in a learning situation.

Learner Use Case Diagram

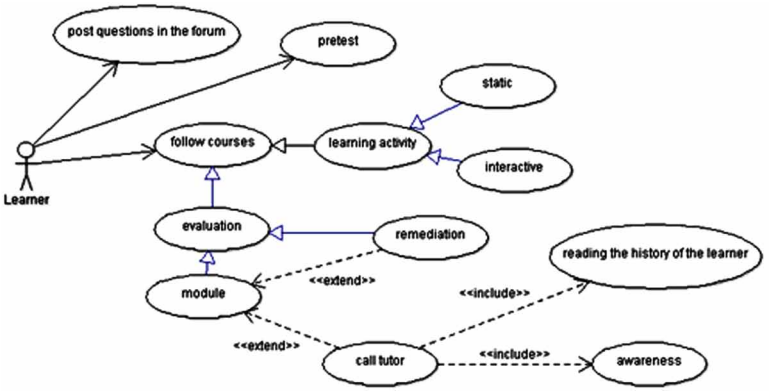
Considering Figure 7 a main actor is identified, named the learner. The figure shows the generalization relationships between use cases and the learner, and generalization relationships, inclusion and extension between use cases.

In particular, the functional requirement "follow courses" is represented with a generalization relationship between the functional requirements "learning activity" and "evaluation". The functional requirements "post in the forum issues" and "pretest" are represented with a generalization relationship with actor "Learner". There are also extensions relationships in the functional requirement "module" and its relationship to functional

Table 1. Learner's main actions in a Hypermedia system

Learner's actions
• Follow courses • Take pretest • Take evaluation

Figure 7. use case diagram of learner's action in a learning situation

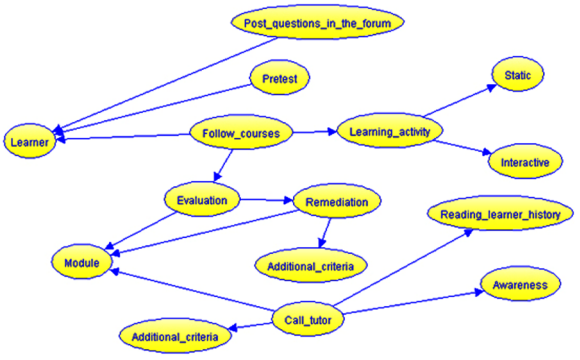


requirements "remediation" and "call tutor." Inclusion relations are presented in the representation of the relationships between functional requirements "call tutor", "reading the history of the learner" and "system awareness."

Bayesian Network Obtained

Once the use case diagrams have been created, it is easy to create the structure of the Bayesian network using the rules described in the previous sections. Figure 8 represents the Bayesian network representation of the main actions of the learner in a Learning situation, constructed from the use case diagram shown in Figure 7. Note how the conditional independence was directly modeled by applying the rules as shown.

Figure 8. Bayesian network developed of a learner's actions in a learning situation



CONCLUSION

We have shown in this work, how we can develop with well defined rules; Bayesian networks from use case diagrams of Unified Modeling Language

This work is a major step in our research in modeling the learner in an adaptive educational system, the transition from the use case diagrams towards Bayesian networks; give us the opportunity to reach our goal to use the Bayesian networks as a formalism to manage uncertainty in the modeling of the learner.

We see two main directions in which we can continue this work. On the one hand by applying our ideas to more advanced conceptual models as used so far. And on the other hand is transforming the Bayesian networks obtained a machine readable language, or one using probabilistic ontology as we proposed in previous work (Anouar Tadlaoui et al., 2016), or perform a combination of Bayesian networks with ontologies. (Anouar Tadlaoui et al., 2017 ; Anouar Tadlaoui et al., 2018)

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Beck, J., Stern, M., & Haugsjaa, E. (1996). Applications of AI in Education. *Crossroads*, *3*(1), 11–15. doi:10.1145/332148.332153

Becker, A., & Naïm, P. (1999). *Les réseaux bayésiens: modèles graphiques de connaissance*. Eyrolles.

Booch, G., Jacobson, I., & Rumbaugh, J. (1999). *The unified software development process*. Reading, MA: Addison Wesley.

Carr, B., & Goldstein, I. P. (1977). *Overlays: A theory of modelling for computer aided instruction (No. AI-M-406)*. Massachusetts Inst of Tech Cambridge Artificial Intelligence Lab.

Geiger, D., & Heckerman, D. (1996). Knowledge representation and inference in similarity networks and Bayesian multinets. *Artificial Intelligence*, *82*(1-2), 45–74. doi:10.1016/0004-3702(95)00014-3

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann.

Rumbaugh, J., Blaha, M., Premerlani, W., Eddy, F., & Lorensen, W. E. (1991). Object-oriented modeling and design: Vol. 199. *No. 1*. Englewood Cliffs, NJ: Prentice-hall.

Wenger, E. (1987). Artificial intelligence and tutoring system: Computational and Cognitive Approaches to the Communication of Knowledge. Morgan Kaufmann Publishers.

Zaitseva, L., & Boule, C. (2005). Learning systems in professional training. In Workshop "Industry meets research" within the conference. Interactive Computer Aided Learning (ICL).

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

Bayesian Networks: Probabilistic graphical model or a type of statistical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph.

Diagrams: Is a symbolic representation of information according to some visualization technique.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Unified Modeling Language: A modeling language used in the field of software engineering that aims to provide a standard way to visualize the design of a system.

Use Case Diagrams: Use case diagrams are UML diagrams describing units of useful functionality (use cases) performed by a system in collaboration with external users (actors).

User Model: Is the subdivision of human-computer interaction that describes the process of building up and modifying a conceptual understanding of the user.

Section 2

Chapter 4
A Learner Model Based on Bayesian Networks in Adaptive Educational Hypermedia Systems

ABSTRACT

The work presented in this chapter lies within learner modeling in an adaptive educational system construed as a computational modeling of the learner. All actions of the learner in a learning situation on an adaptive hypermedia system are not limited to valid or invalid actions (true and false), but they are a set of actions that characterize the learning path of formation. Thus, one cannot represent the information from the system of each learner using relative data. It requires putting the work in a probabilistic context due to the changes in the learner model information during formation. In this chapter, the authors propose to use Bayesian networks as a probabilistic framework to resolve the issue of dynamic management and update of the learner model. The experiments and results presented in this work are arguments in favor of the hypothesis and can also promote reusing the modeling obtained through different systems and similar modeling situations.

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INTRODUCTION

First of all, to clarify our purpose it seems important to note that the work presented in this chapter lies within Learner modeling in an adaptive educational system construed as a computational modeling of the learner. That is to say, the representation and specification of knowledge (broadly defined) on the learner. Different approaches were made to manage the model of the learner with multiple objectives, from the learner's knowledge evaluation, to the recognition of the plan followed in problem solving.

Despite these various attempts for modeling the learner which is characterized by a dynamic aspect, we always find difficulties in achieving this goal. The proposed approaches give us just a static view of the learner model, but this model is always in development (the learner knowledge is evolving in the same module), that is why a dynamic view is essential. In order to monitor the behavior of the learner in real time during formation, we must adopt a dynamic modeling approach to the learning model management.

All actions of the learner in a learning situation is not limited to valid or invalid actions (true and false), but it is the actions that characterize his learning path of his formation. From this observation, we cannot represent the information from the system of each learner using relative data. It requires locating our work in a probabilistic context due to changes in the learner model during formation.

The problem of this chapter can be summarized as follows: how to represent the different functions of a model of the learner? What approaches can be used to perform the update of the different characteristics of the learner model?

We propose in this work to use Bayesian networks as a probabilistic formalism to resolve the issue of management and dynamic update of the learner model. To resolve this issue, we must first ask: Why and how we can represent a learning model with Bayesian networks? How can we go from a dynamic representation of the UML model to a probabilistic representation with Bayesian networks? Is this consideration experimentally justified?

THE LEARNER MODE IN ADAPTIVE HYPERMEDIA EDUCATIONAL SYSTEMS

The purpose of this section is to bring to the readers the knowledge required in the fields of Learner modeling. We will come back to in this section on definitions and terminology of each of the main key words in our chapter.

Concepts and Definition

The learner modeling is the modeling of all the important features that affect the learner (knowledge, preferences, goals, etc.). It comes to identify relevant information, to structure, to initialize them, update them and exploit them. By replacing the word "learning" with the term "user" this definition is also applicable to the model of the user. In the case of an application other than the learner's educational model is called the user model.

A learner model allows keeping the learner information, for example his level of knowledge on a given topic (performance), his frequent mistakes/ misunderstandings, psychological characteristics, etc.

A learner model can be defined as a set of structured information about the learning process, and this structure contains values on the characteristics of the learner. It provides the necessary data to the other modules to achieve the adaptation of teaching to the learner (Zaitseva et al., 2005)

Many studies emphasize the uncertainty of the information contained in the student model and the importance of the intention behind the creation of this model. Thus, a student model represents the belief system about learners' beliefs (the system's beliefs about the learner's beliefs) accumulated during the diagnostic process (Beck et al., 1996)

The learner model can be an integral part of Hypermedia Systems Aadaptatif as it can be shared with multiple systems. In this last case we talk about user modeling servers. This type of server is used in environments or more distributed adaptive systems access this server to query or update user information. Cumulate is one of the most known and used systems for user modeling servers (Brusilovsky et al., 2007)

The Foundations of the Learner Model

Self (Self, 1991) defined a formalization of the learner model that is based on the beliefs and knowledge of the system and the learner. Beliefs are represented by formulas in the propositional calculus. The objects of belief are called propositions. Beliefs are related to the behavior of an agent (A), a user (U) or system (S). BA = {p/BAP} is the set of beliefs of the agent A. BAP are the proposals themselves.

BSU = {p / BSBUp} is the set of proposals that the S system believes they are believed by a user U as shown in Figure 1.

The learner model can be defined by a set of proposals that the system S thinks about U learner: UM = BS (U) = {p / BSp (U)}

Belief can be replaced by knowledge, therefore KAP = BAp.

To distinguish between the different aspects of the learner model, Self distinguishes the following proposals:

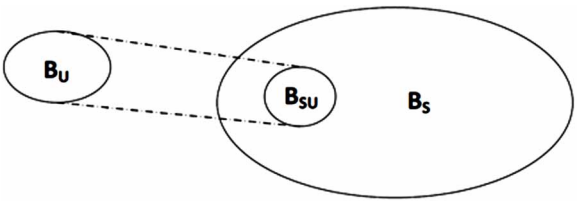
- Dependent proposals to a field that a learner acquires in a system;
- Independent clauses of the system domain. They are also called the background;

The proposals that describe the cognitive and personal characteristics of the learner, also known as behavioral skills such as preferences, tasks, goals and experience.

The Representation of the Learner Model

The learner model is used primarily to provide a structure for the representation of domain knowledge of the learner. According to Koch (2002), the data concerning the learner can be represented in different ways.

Figure 1. The representation of the system and users beliefs



Overlay Models

In the recovery model the knowledge of the learner is represented as a subset of the knowledge of the system. The latest is created from the expert's knowledge, the domain knowledge or knowledge expected of the learner. It is represented as a hierarchical or semantic network. A Boolean or discrete value is used to estimate the knowledge of the learner.

User Profiles

They are used to represent the cognitive skills, intellectual abilities, intentions, learning or preferences of a user styles. Each ability is associated with a value, that value belongs to a range of values.

Stereotyped Models

In this type; the model knowledge of the learner and the properties are also represented with a pair of values. The stereotypical model is different from the other models in that it models different pairs of values that are assigned to a user category (Stereotype) as novice, intermediate or expert. So a user inherits from each property to its stereotype. Stereotyped models can be combined with the recovery models when a stereotype is assigned to a user model for initialization. Stereotyped models are useful for modeling the learner but not enough when the individual adaptation requires a more precise description of the learner.

BAYESIAN NETWORKS

Before describing our interrogations about the use of Bayesian networks in Learner modeling, we return quickly on their definition and the meaning of inference in this context.

In the rest of this section, we take a typology of nodes inspired from, which is found in different terms in the literature. The field layer is the set of nodes modeling epistemic knowledge of the learner, and the task layer nodes modeling the actions of the learner (Conati et al., 2002)

Definition

Knowledge representation and reasoning from these representations has created many models. Probabilistic graphical models, specifically Bayesian networks initiated by Pearl (Pearl, 1988) in the 1980s, have proven to be useful tools for representing uncertain knowledge and reasoning from incomplete information.

A Bayesian network $B = \left(G, N\right)$ is defined by $G = \left(X, E\right)$ acyclic directed graph with vertices associated with a set of random variables:

$$X = \left(X, \ldots, Xn\right)$$

$$\mathrm{N} = \{\mathrm{P}(\mathrm{Xi} \mid \ \mathrm{Pa}\left(\mathrm{Xi}\right))\}$$

All the probabilities of each node Xi conditionally to the state of its parents $\mathrm{Pa}\left(\mathrm{Xi}\right)$ in G.

Thus, the graphical part of the Bayesian network indicates the dependencies (or independence) between variables and provides a visual tool for knowledge representation, more easily comprehensible by its users. In addition, the use of probability allows taking into account uncertainty in quantifying the dependencies between variables. Both properties have been the cause of the first names of Bayesian networks, "probabilistic expert systems", where the graph was compared to the set of rules of conventional expert system, and the conditional probabilities presented as a quantification uncertainty about the rules.

Mayo (Mayo & Mitrovic, 2001) also has shown that Bayesian networks allow representing compactly the joint probability distribution over the set of variables:

$$\mathrm{P}\left(\mathrm{X1}, \mathrm{X2}, \cdots, \mathrm{Xn}\right) = \prod_{i=1}^{n} \mathrm{P}(\mathrm{Xi} \mid \ \mathrm{Pa}\left(\mathrm{Xi}\right))$$

This decomposition of a global function as a local product terms depending only of the node and its parents in the graph, is a fundamental property of Bayesian networks. It is the basis of the first work on the development of inference algorithms which calculate the probability of any variable of the

model from the same partial observation of other variables. This has been proven NP-complete, but resulted in different algorithms that can be treated as information propagation methods in a graph. These methods obviously use the concept of conditional probability, i.e. what is the probability of Xi knowing that I have observed Xj but also the Bayes theorem, that calculates, conversely, the probability of Xj knowing Xi when $\mathrm{P(Xi \mid Xj)}$ is known.

Construction of a Bayesian Network

As we have seen in the definition, the complete specification of a Bayesian network requires specifying a share structure (directed acyclic graph that underlies) and other parameters (probability tables). To do this, two approaches are possible and can be combined: the collection of expertise and machine learning, which is one of the attractions of Bayesian networks.

In the case of collection of expertise, the definition of the network structure begins with the identification of possible nodes and the distinction between (unobservable) informational variables (inputs) or hypothetical. The existence of an arc can be analyzed in terms of influence of one variable on another, but its orientation is more difficult. Traditionally, an arc is directed from A to B if A is a cause of B, but we will see that this interpretation is not as simple in the case of the learner modeling. The parameters are in turn attached in an approximate manner by using frequentists or qualitative information.

Since Bayesian network is a probability distribution, we can use maximum likelihood as statistical learning parameters criterion. The result is as a Bayesian network whose structure is fixed and E which is a comprehensive basis of example, the maximum likelihood is achieved if the parameters of the Bayesian network are equal to the frequencies of the same features observed in E. statistical learning structure requires for its development test to determine whether or not the random variables are conditionally independent.

Arcs Orientation

The definition of the structure of a student model based on Bayesian network from expert knowledge (Anouar Tadlaoui et al., 2016), is often done from a representation of domain knowledge, we do not discuss here the validity of the skeleton (graph undirected) resulting in the type of links that are taken into account (mainly partitive or generic). Therefore, obtaining the model structure from the skeleton of the orientation requires arcs. These

guidelines determine the diagnosis obtained, since as they play a key role in the relationship dependency between variables.

The Influence of the Orientation of the Arcs on the Diagnosis

We point out an example of the influence on the arcs orientation of the diagnosis obtained. Figure 2 shows a simplified version of the model Hydrive, where the performances of the electronics learner can be observed. The set of variables representing the different skills of the learner is affected by this observation. Thus, if the student is found to be competent in electronics, for example because of their initial training, the diagnostic model is the same in all other disciplines.

Consider Figure 3, A graph having the same skeleton but with other orientations of the arcs. The spread of the information here is much more limited.

The diagnosis we got depends not only on arcs orientation's choices, but also it seems that the orientation depends on the expertise level of the learner. Indeed, it seems reasonable to consider the network of Figure 2 for a subject having followed all the training (for which we can assume a homogeneity especially in some skill levels), the network 3 seems more appropriate for a about the beginning of training, which can be very proficient in a particular area because of its course without the need to master all the skills.

Which Choice for the Orientation of Arcs?

In literature, the choice is massively in favor of a focus node of the domain layer to those of the task layer.

Figure 2. The flow of information in the learner model of Hydrive

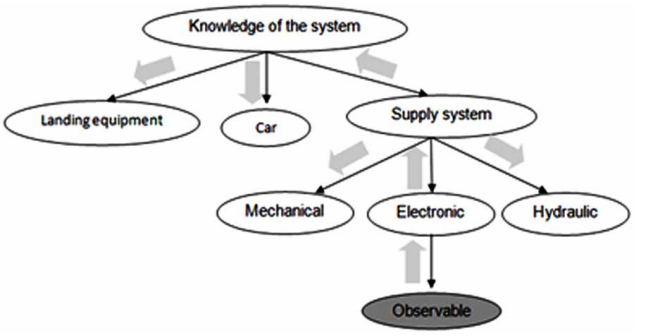
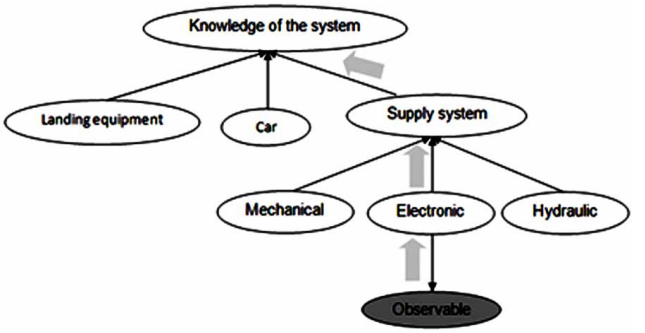


Figure 3. Flow of information in the modified leraner model of Hydrive



The question remains open regarding the arcs linking the nodes in the domain layer. It is common to present this choice as an alternative choice between a general orientation to the individual or it opposite. We find in literature examples of these two choices (Dimitrova et al., 1999; Mislevy et al., 1996), even if the justification given for this choice is not always totally convincing, even if sometimes it doesn't exist. This dichotomy itself is to our knowledge never has been partly explained the concept of equivalent Bayesian networks under Markov. (Zapata-Rivera et al., 2000)

The orientation of the arcs from the general to the particular is suitable when the skills of the learner have certain homogeneity because of dependencies of this orientation. The orientation on the other side is most appropriate for learners with diverse skills. Moreover, if we take the findings on the relationship between network structure and level of expertise of the learner, we conclude that the model must allow this structural change.

LEARNER MODELING IN ADAPTIVE HYPERMEDIA EDUCATIONAL SYSTEMS

In this section we will present the steps to follow when modeling the learner in an adaptive educational system using UML, beginning from the user meta model and into the use case diagram regrouping all the actions of the learner in adaptive system

The Learner's Meta-Model

We will present in this section a specific user meta-model for e-learning presented by Aammou (2013). This model features a combination of models for e-learning and adaptive hypermedia. It takes into account elements such as the history of actions, which are rarely taken into account in formal models. The construction of this model allowed us to understand the user's creative process model for adaptive hypermedia, helping us to build our hypernym model. (Anouar Tadlaoui et al., 2015)

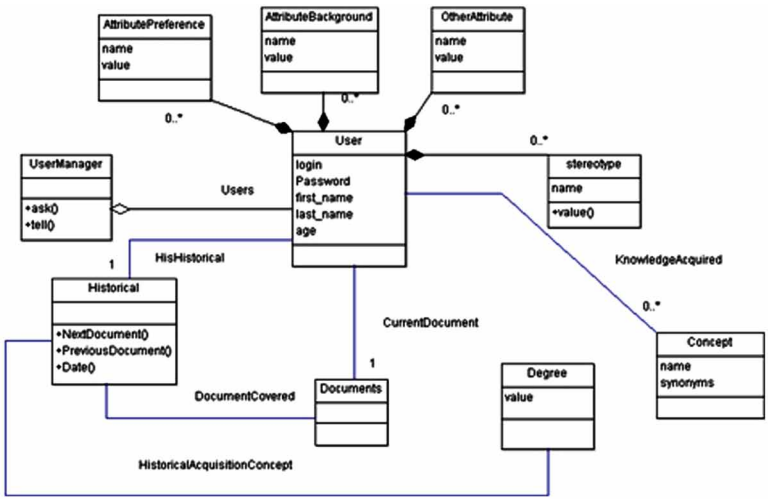
In our user model for e-learning, we want to be able to:

- Define the characteristics attributes, essential and common to all users: name, username, password and age;
- Define attribute categories to separate the user's preferences, their school / career and other attributes. This distinction will facilitate importing data, system maintenance, as well as communication with external systems; the attributes are differentiated according to their nature.
- Retain the documents covered by the user in two ways: first, by involving them in a whole course on the other hand, specifically related to the concept that they have investigated. The aim of this historical duplicate is to present the same documents to the user, when he wishes to come back on a concept already brought to its attention, that during his first learning this concept.

The UML class diagram representation of our user model is given in Figure 4.

- **The User Manager:** Class is responsible for interfacing with the other components of adaptive hypermedia system. For this purpose, it is provided of the Ask and Tell methods to ask questions and provide answers to the external components (domain model, adaptation model). It is connected to all the users; it is responsible for managing, by an aggregation relationship.
- **The User:** Class is responsible for representing information about a particular user. It is composed of predefined attributes: name, username, password and age.

Figure 4. UML class diagram representing the user's meta-model



- **Attribute Preference:** Class is responsible for representing the preferences of the user. These are view preferences: font size, color problems, contrast, etc., and his presentation preferences. He may prefer textual or graphic elements. He may not want audio element, for example.
- **The Attribute Background:** Class is responsible for representing the user attributes related to their academic / professional background.
- **The Stereotype:** Class is responsible for representing the various categories of stereotypes to which the user belongs. By definition, a stereotype is an image or a fixed design and schematic of an aspect of reality. In our model, a stereotype consists of a name and a value. The name sets the stereotype (eg "learning rate") and the value used to characterize the user (eg quick for the stereotype "learning rate"). The number of possible values is often reduced to a given stereotype. Values are often based on other attributes. Stereotypes are different from other attributes by their schematic characterization of the user, where they can represent much more granularity elements.
- **Other attribute:** Class is responsible for representing the user attributes which are not related to his career and which are not preferences, for example, a data encryption key. The existence of this class is to ensure compatibility of the model with standard models like IMS or PAPI

Learner. Because some attributes do not fit into other categories of attributes defined above.

- **Degree:** Is an association class which is responsible for giving a value to the knowledge of a concept by a user. The possible values are: very low, low, average, good, excellent. This scale is a range of values, it allows to have a good precision with respect to a binary classification, and avoids a too high degree of accuracy and therefore very useful for adaptation.
- **Historical:** Class is in charge of representing a historical document covered in the learner path, allowing to give the date of the course of a document, browsing history in order in a historical path (it contain two methods NextDocument() and PreviousDocument()). The historic class can be used to represent all the documents covered by a user's history, or to represent the historical documents covered to reach a certain degree of knowledge for a given concept.

Both class Document and class Concept are detailed in the model domain.

The Learner Model Use Case Diagram

Based on the meta-model, we were able to map out the functionality of the learner using the use case diagram Figure 5 to reflect a part of the student's actions in an adaptive system. We will explain in this part each of these actions beholding the relationships of these actions with each other and within the system operation process.

Based upon the meta-model presented in the previous section, we have illustrated in the following table "Table 1" learner's actions in a learning situation in an adaptive educational system:

Table 1. Learner's main actions in a Hypermedia system

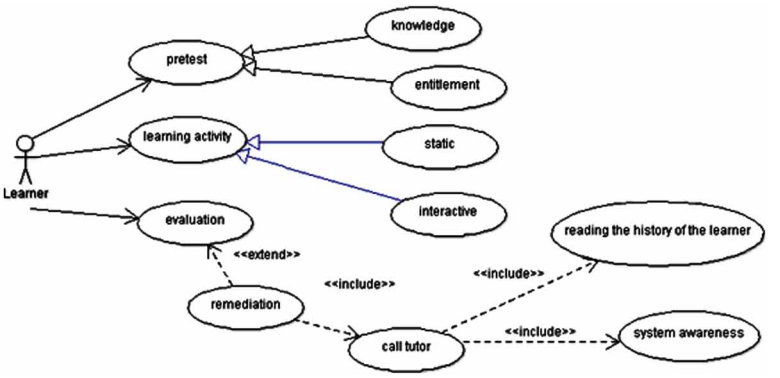
Learner's actions
• Follow courses • Take pretest • Take evaluation

In Figure 5 a main actor is identified, named the learner. The figure shows the generalization relationships between use cases and the learner, and generalization relationships, inclusion and extension between use cases.

In particular, the functional requirement "*learner*" represents all information about the learner in the hypermedia system (his knowledge, his skills, personal information ...), this functional requirement is shown with a generalization relationship with three functional requirements:

- "***Pretest***" Which represents the information about the pretest that the learner has to take before entering the learning situation, the pretest is composed of two types of evaluation components: tests of knowledge depicted with the functional requirement "*knowledge*" and a functional requirement "*skills*", which represents the test through which we will evaluate the learner's skills.
- "***Learning Activity***", This functional requirement represents the information about the learning activities, each learning activity in adaptive educational hypermedia system is of two types, static activities represented by the functional requirement "*Static*" and interactive activities represented by the functional requirement "*Interactive*"
- "***Evaluation***", Which represents the information on the evaluation that the learner is to take lead after the completion of each learning activity. In case of failure of the learner in the evaluation. The learner must pass to a remediation; the remediation is represented through a functional requirement "*remediation*" which is connected with the functional requirement "*evaluation*" through an extension of relationship.

Figure 5. Use case diagram UML representing the learner actions



In case of remediation, the functional requirement "*remediation*" involves the activation of the functional requirement "*call tutor*" through inclusion relation. This requirement represents the activation of the tutor to help the student to return to its shortcomings in the learning activity.

Another inclusion relation is represented in our figure which represents the actions of the learner in an adaptive system, appearing in the relationship between the functional requirement "*call tutor*" and requirements "*reading the history of the learner*" that activates the return of the system to the profile an the course information of the learner. And a requirement "*system awareness*", that enables the system to follow the course of the learner after remediation.

THE BAYESIAN NETWORK OF A LEARNER MODEL

In this section we will present the transformation formation of our use case diagram representing the learner model into a Bayesian network.

The Model Structure

The development of Bayesian network based on the use case diagram for modeling the learner in an adaptive educational system passes through two essential steps:

The Specification of the Model Structure

Taking the case of the node "*Learner*" to illustrate the stages of development of our Bayesian network representing the model of the learner, notes that this node has three parent nodes (Pretest, Learning Activity and Evaluation), each of these nodes is composed of child nodes, links to these nodes are prerequisites relationships:

- **Learning Activity:** In this node, all students following the course must pass through activities, activities in the adaptive system is of two types: static and interactive.
- **Pretest:** All learner, and before taking the learning activities of each course must pass a pre-test, it consists of two types of evaluation:

  - **Knowledge:** The student must answer more than 10 questions to measure how his wealth of knowledge. This evaluation reflects the evaluation part of the knowledge of the learner.
  - **Skills:** This is a written proof that responds if the student can apply the knowledge gained in the module. This type of evaluation reflects the part of skills of the learner.
- **Evaluation:** After the student follows the learning activity, it is carried to conduct an evaluation to determine their level of knowledge and skill within the module, the evaluation is essential to guide the course of the learner.

The value that measures the relative importance of each condition varies from 0 to 1, the values of each evaluation element is defined by the teacher.

In other words, it is the weight of the arc from the parent node to the child node. All weights for the child variable will build its CPT. the sum of the weights of all arcs to / from each child node / parent in case of hidden variables / evidence should be 1. This means that each weight is normalized.

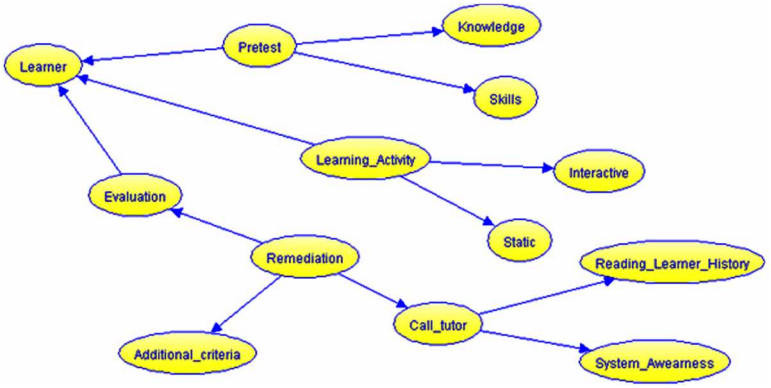
The relationship between the target variable (T) and the evidence variable (E) is to be from T to E because the process that calculates the posterior probability of target variable is the proof of knowledge of the diagnosis. So if variable evidence has no children, his parents must be the target variables. There are two types of relationships:

- Prerequisites Relations between target variables.
- Diagnostic Relations of target variables to evidence variables. The control of concepts (targets) effects on confidence of evidence. However, if the learner has failed a test, it is not sure of his lack of knowledge or ability because it can make an unexpected error.

The Specification of Variable Values

Once the use case diagrams were created, it is easy to create the structure of the Bayesian network using the rules described in the previous sections. Figure 6 represents the Bayesian network built from the use case diagram shown in the previous section. Note how the conditional independence was directly modeled by applying the rules as shown.

Figure 6. The Bayesian network developed of the learner model



In the Bayesian network developed, we observe that the node Learner (L) has three parents: Learning Activity (A), Evaluation (E) and Pretest (T) which in turn are corresponding to three weights of prerequisite relationship: w1=0.1, w2=0.5, w3=0.4. Conditional probability of (L) is computed as follows:

$$P\left(L|A,E,T\right) = w1 * h1 + w2 * h2 + w3 * h3$$

where:

$$h1 = \begin{cases} 1 if A = L \\ 0 otherwise \end{cases}$$

$$h2 = \begin{cases} 1 if E = L \\ 0 otherwise \end{cases}$$

$$h3 = \begin{cases} 1 if T = L \\ 0 otherwise \end{cases}$$

We should state that {L, A, E, T} is complete set of mutually exclusive variables, wich each also variable is random and binary.

Generalizing about formula below, it is that:

$$P\left(X = 1 | Y1, Y2 \ldots Yn\right) = \sum_{i=1}^{n} wi * hi$$

where $h1 = \begin{cases} 1 if Yi = X \\ 0 otherwise \end{cases}$ with given random binary variables X, Yi. Obviously,

$P\left(not\, X | Y1, Y2, \ldots, Yn\right) = 1 - P(X \mid Y1, Y2, \ldots, Yn)$,

- **The conditional probability table of the node "Learner"**

"Table 2" represent the CPT of each child node of the parent node Learner:

Because concepts A, E, T has no prerequisite knowledge for understanding, their CPTs are specified as prior probabilities obeying uniform distribution as stated in "Table 3" (assigned medium value 0.5 in most cases)

- **The conditional probability table of the node "Pretest"**

Table 2. The conditional probability table of "Learner" node.

A	E	T	P(J=1)	P(J=0) 1-p(J=1)
1	1	1	1.0 (0.1*1 + 0.5*1+ 0.4*1)	0.0
1	1	0	0.6 (0.1*1 + 0.5*1+ 0.4*0)	0.4
1	0	1	0.5 (0.1*1 + 0.5*0+ 0.4*0)	0.5
1	0	0	0.1 (0.1*1 + 0.5*0+ 0.4*0)	0.9
0	1	1	0.9 (0.1*0 + 0.5*1+ 0.4*1)	0.1
0	1	0	0.5 (0.1*0 + 0.5*1+ 0.4*0)	0.5
0	0	1	0.4 (0.1*0 + 0.5*0+ 0.4*1)	0.4
0	0	0	0.0 (0.1*0 + 0.5*0+ 0.4*0)	1.0

Table 3. The conditional probability table of "Learner" parents

P(A=1)	P(A=0)	P(T=1)	P(T=1)	P(E=1)	P(E=1)
0.5	0.5	0.5	0.5	0.5	0.5

"Table 4" represent the CPT of each child node of the parent node Pretest:

- **The conditional probability table of the node "Learning activity"**

"Table 5" represent the CPT of each child node of the parent node Learning activity:

EXPERIMENTATIONS

Lately, we will present in this section the validation tests of the Bayesian network derived from our model of the learner.

UnBBayes Software

UnBBayes (Costa et al., 2008) is a probabilistic network framework written in Java. It has both a GUI and an API with inference, sampling, learning and evaluation. It supports BN, ID, MSBN, OOBN, HBN, MEBN/PR-OWL, PRM, structure, parameter and incremental learning.

The JAVA UnBBayes uses a technique to reason by odds in intelligent systems. Through a probabilistic network - graph where the nodes are likely to variables representing domain knowledge and the arcs represent relationships

Table 4. The conditional probability table of "Pretest" node

K	P(J=1)	P(J=0) 1-p(J=1)
1	0.8(0.8*1)	0.2
0	0.0(0.8*0)	1.0

S	P(J=1)	P(J=0) 1-p(J=1)
1	0.2(0.2*1)	0.8
0	0.0(0.8*0)	1.0

Table 5. The conditional probability table of "Learning activity" node

S	P(J=1)	P(J=0) 1-p(J=1)
1	0.6(0.6*1)	0.4
0	0.0(0.6*0)	1.0

D	P(J=1)	P(J=0) 1-p(J=1)
1	0.4(0.4*1)	0.6
0	0.0(0.6*0)	1.0

between them - from certain evidence, we can estimate probabilities conditioned to the evidence that assist us in decision making. This calculation is called probabilistic inference. With the addition of tree technique can be an inference in probabilistic networks with high efficiency.

To make this technique easy to use, we create the JAVA UnBBayes which is a visual system, interactive and platform independent, which makes it possible to edit, build networks, evidence of entry and probabilistic reasoning.

Metrics

In this section, and before presenting the results of our tests, we will introduce the metric through which we will measure the performance of Learner module modeled using Bayesian networks. The UnBBayes software gives us the possibility to evaluate the performance of each node in our network dynamically and in real time (Anouar Tadlaoui et al., 2017)

Here are the metrics we used to evaluate our Bayesian network:

- **The Global Confusion Matrix (GCM):** Computed for the selected target node and all the chosen evidence nodes.
- **Probability of Correct Classification (PCC):** The probability of correct classification computed from the GCM considering all evidence nodes.

- **Marginal PCC (MPCC):** The probability of correct classification computed from the GCM given all evidence nodes other than the one presented in the row (see "Node" column).
- **Marginal Improvement (MI):** The probability of correct classification gained by adding the node presented in the row to the rest of other nodes,
- **Individual PCC (IPCC):** The probability of correct classification computed from the LCM considering only the evidence presented in the row.
- **Cost Rate:** The individual probability of correct classification over the cost ratio.

The Combined Bayesian Network

Before presenting the evaluation results of each node of our Bayesian network that models the learner model in an adaptive system, we begin by presenting the combined Bayesian network through the UnBBayes software.

Figure 7 gives a mapping of the combined network, with marginal variables of each node of our network developed; we can observe the change in the marginal variables of each node in our network, simply by changing one or more marginal variable of one or multiple parent node of the selected node.

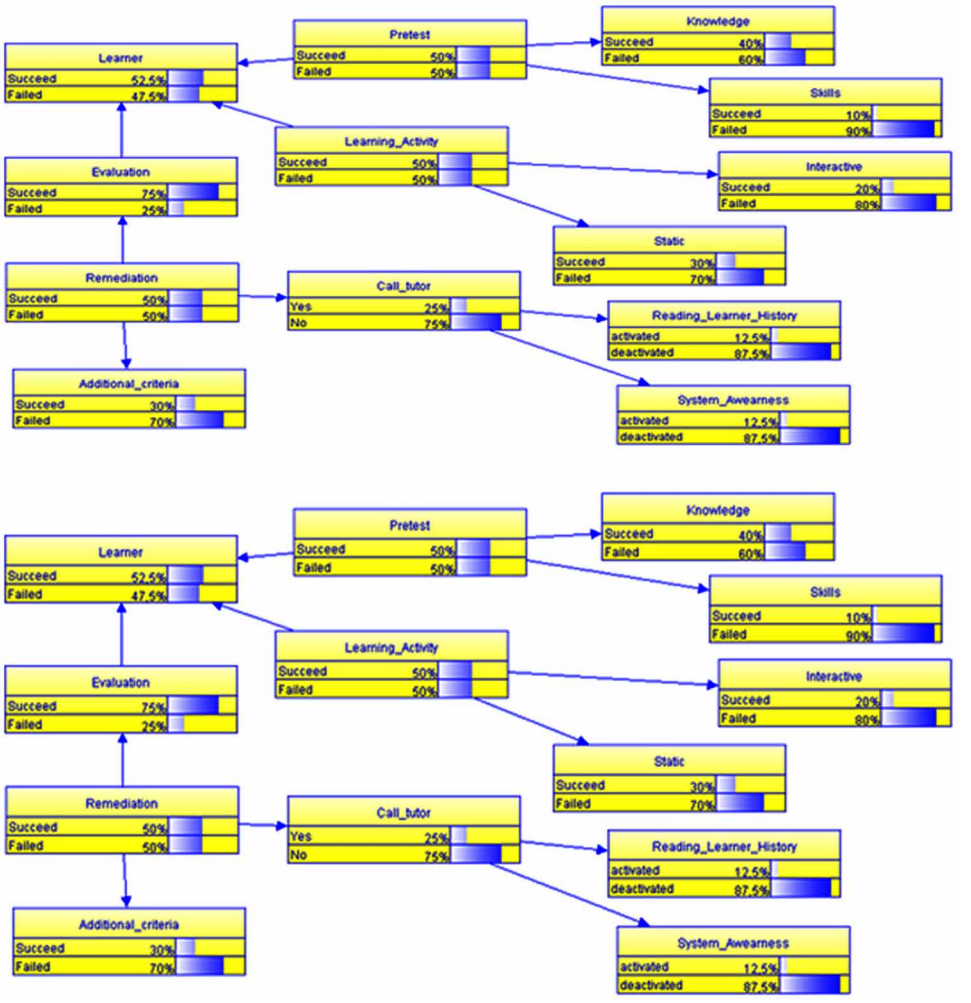
If we change the marginal variable "Succeed" of the node "konwledge" from 40% to 100%, and the marginal variable "Succeed" of the node "Skills" from 10% to 100%. We note that in Figure 7 the marginal variable "Succeed", of the parent node "Pretest" will change from the initial state 50% into a total from of 100% completion. We will also notice that marginal variables of the parent's node of the node "Pretest" which is the node "Learner" will also change from of 50% to 72.5%.

By changing the information of each node, and after compiling our network, all marginal variables will change automatically, which gives us the ability to track in a dynamic way the flow of the learners path and detect the causes of change during all stages of the situation of learning.

RESULTS

After compiling our Bayesian network, in this section will present all the results of our experiments on our Bayesian network.

Figure 7. the Bayesian network combined of the learner model



Nodes Evaluation

To evaluate the performance of each node of our network and its contribution value within a single node, or the entire network, we first begin with choosing the node we want to evaluate as an evidence node, and choose the parent of this nodes as target nodes, then we will define a sample size that represents how often the software will repeat the simulations.

The metrics presented in the previous section, we will evaluate the influence of each node within its parent node and within our entire Bayesian network built.

- **Evaluation of the node "Pretest"**

For the pretest node, there are two nodes Parent: Knowledge and Skills, we will choose the node pretest as a target node and its parents as evidences nodes, we will obtain the results shown in Figure 8.

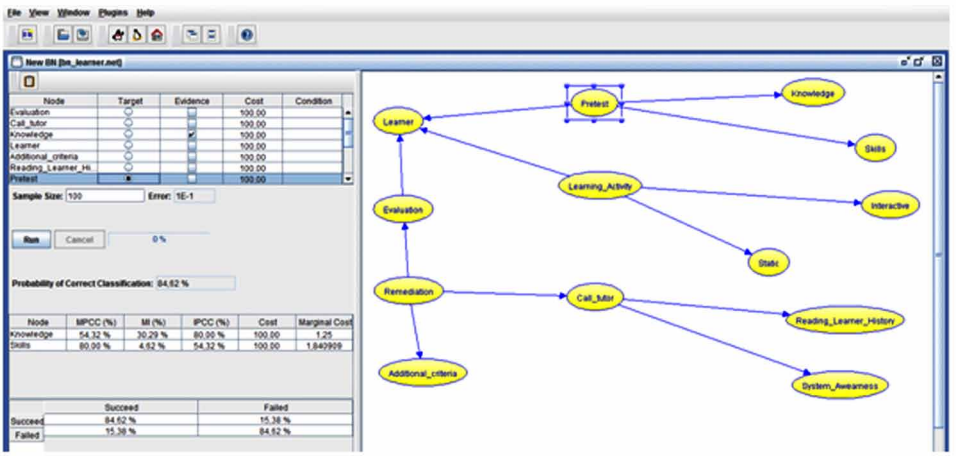
From after the results in the table of results, we find that:

By adding evidence nodes into our evaluation of the target node the percentage of the probability of correct classifications increases. And by measuring the probability of correct classification of each node, we see how each node contributes independently to classification. In this evaluation, we find that the node "Skills" is the node that contributes the most.

We find how each node contributes with respect to the set of nodes in front of them. In this evaluation, the marginal improvement of the node "Skills" mean that the influence of this node is larger compared to the target node. We also note that even if the cost is the same, the marginal cost of the two different sensors, the sensor which in the most evolution is the marginal cost of the variables of the node "Skills".

All of this reflects that the learner in this learning situation, to pass the pretest must rely more on skills than knowledge.

Figure 8. The evaluation results of the node pretest



- **Evaluation of the node "Learning activity"**

For the "Learning activity" node, there are two parents' nodes: Static and Interactive, we will choose Learning activity as a target node and its parents as evidence nodes; we obtain the results shown in Figure 9.

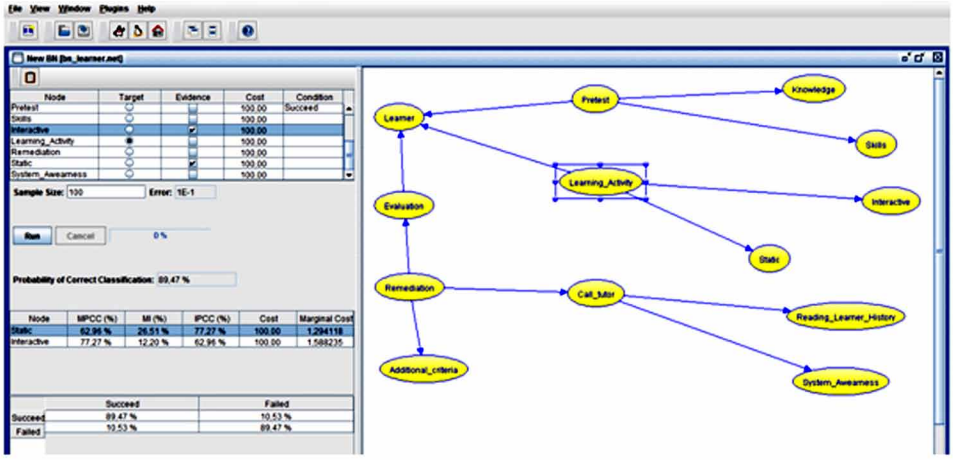
From after the results in the table of results, we find that:

By adding evidence nodes into our evaluation of the target node the percentage of the probability of correct classifications increases. And by measuring the probability of correct classification of each node, we see how each node contributes independently to classification. In this evaluation, we find that the node "Static" is the node that contributes the most.

We find how each node contributes with respect to the set of nodes in front of them. In this evaluation, the marginal improvement of the node "Static" mean that the influence of this node is larger compared to the target node. We also note that even if the cost is the same, the marginal cost of the two different sensors, the sensor which in the most evolution is the marginal cost of the variables of the node "Static".

All this reflects that the learner in the learning situation has follow a learning activity, the learner must focus on static activities grains more than the grains of interactive activities to increase the chances to him succeeding in this learning activity.

Figure 9. The evaluation results of the node learning activity



- **Evaluation of the node "Learner"**

For Learner node, there are three nodes Parent: pretest, Learning activity and Evaluation, by choosing Learner node as a target node and its parents as evidence nodes, we obtain the results shown in Figure 10.

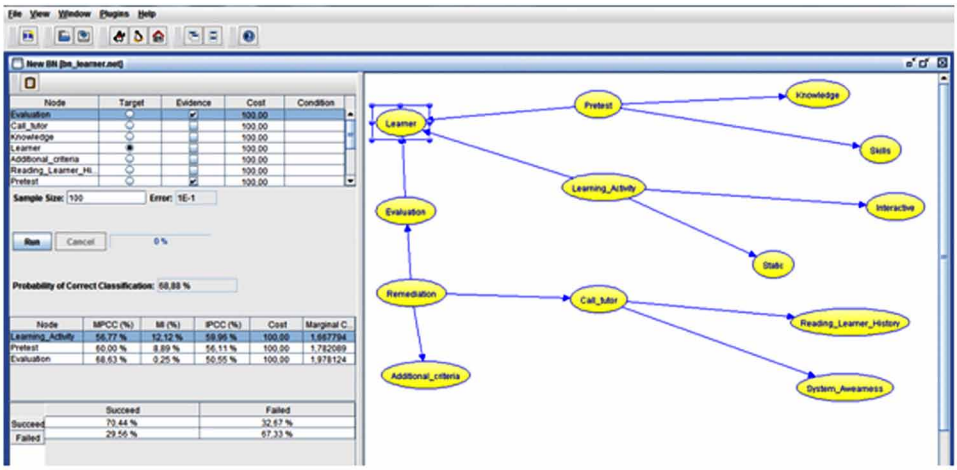
From after the results in the table of results, we find that:

By adding evidence nodes into our evaluation of the target node the percentage of the probability of correct classifications increases. And by measuring the probability of correct classification of each node, we see how each node contributes independently to classification. In this evaluation, we find that the node "Learning activity" is the node that contributes the most.

We find how each node contributes with respect to the set of nodes in front of them. In this evaluation, the marginal improvement of the node "Learning activity" mean that the influence of this node is larger compared to the target node. We also note that even if the cost is the same, the marginal cost of the two different sensors, the sensor which in the most evolution is the marginal cost of the variables of the node "Learning activity ".

All this reflects that the success of a learner in the learning situation, concerns his success in the learning activity more than the assessment or pretest.

Figure 10. The evaluation results of the node Learner



The Evaluation of the Bayesian Network

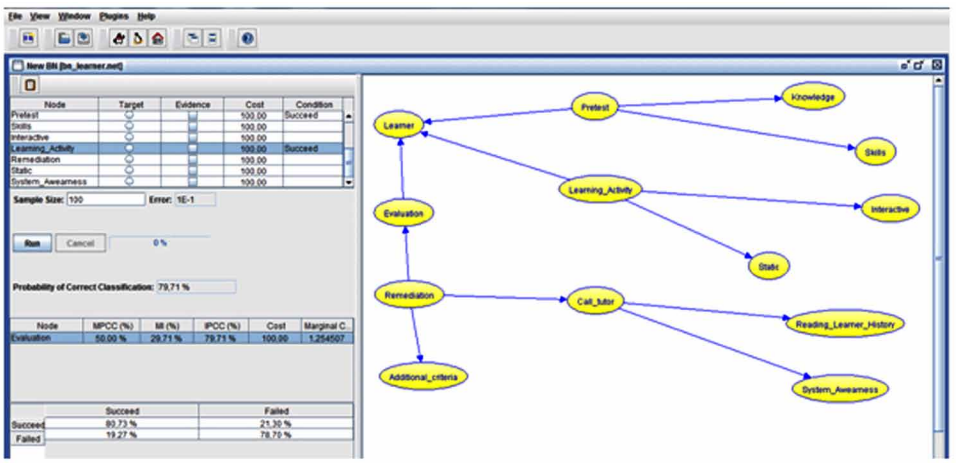
After validation of each node of our learner model Bayesian network. We will present in this section the validation results of the entire Bayesian network.

Figure 11 presents the Bayesian network validation results. In this evaluation of our network, we will consider that the learner has successfully passed the pretest and the learning situation. The marginal variable of the node evaluation in this case will be 79.71%. The change of one of these two nodes will affect in a probabilistically the marginal variables of our network.

Based on the results and validation of each node of the Bayesian network, we were able to manage the operation of the network in a comprehensive manner.

When a learner begins to take a course in an adaptive hypermedia system, he must first successfully pass the functional requirement "Pretest" which is composed of two functional requirements that measures its knowledge and skills in the chosen field. After validation of the pretest, he is automatically assigned to the functional requirement "learning activity", which is composed of two types, static and dynamic. During the end of the course, the learner is led to take an evaluation expressed in the functional requirement "Evaluation", the result of this test takes the learner in case of failure to the functional requirement "Remediation" to retake the learning activities in which the student could not succeed.

Figure 11. The evaluation of the entire learner model's Bayesian network



Failure in a learning situation requires a tutor calls by activating the functional requirement "Call tutor", which then activate two functional requirements "system awareness" and "Reading history learner". These two requirements are related to features of hypermedia system.

CONCLUSION

We have shown how a theoretical point of view and considering the analysis of the literature, it seems justified to select Bayesian networks as an effective tool to manage learner model, The use of Bayesian networks as a formalizing to manage the problem of uncertainty for learner model in an adaptive educational system, gives us satisfaction results to address the problem of probabilistic and real-time management of all learner's actions in a learning situation.

The experiments presented in this article are arguments in favor of our hypothesis on the modeling in a probabilistic way the learner model, using all the nodes as sensors to measure and evaluate the entire model.

The proposed rules for processing use case diagrams that schematizes the actions of a learner in an adaptive system can be applied to many use cases in different systems.

We see two main directions in which to continue this work. On the one hand by combining Bayesian networks with other modeling method of the learner, such as overlay models, on the other hand in transforming the Bayesian networks developed for the management of learner model into a machine-readable language, such as ontologies. Or, as we already proposed (Anouar Tadlaoui et al., 2014; Anouar Tadlaoui et al, 2018) ; by using probabilistic ontologies as a formalism that gives us the possibility to combine Bayesian networks with ontologies.

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Beck, J., Stern, M., & Haugsjaa, E. (1996). Applications of AI in Education. *Crossroads*, *3*(1), 11–15. doi:10.1145/332148.332153

Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In *The adaptive web* (pp. 3–53). Berlin: Springer. doi:10.1007/978-3-540-72079-9_1

Conati, C., Gertner, A., & Vanlehn, K. (2002). Using Bayesian networks to manage uncertainty in student modeling. *User Modeling and User-Adapted Interaction*, *12*(4), 371–417. doi:10.1023/A:1021258506583

Costa, P. C., Ladeira, M., Carvalho, R. N., Laskey, K. B., Santos, L. L., & Matsumoto, S. (2008, May). A first-order Bayesian tool for probabilistic ontologies. In *Proceedings of the Twenty-First International Florida Artificial Intelligence Research Society Conference* (pp. 631-636). Academic Press.

Dimitrova, V., Self, J., & Brna, P. (1999). The interactive maintenance of open learner models. In Artificial intelligence in education (Vol. 50, pp. 405-412). Academic Press.

Koch, N., & Wirsing, M. (2002, May). The Munich reference model for adaptive hypermedia applications. In *International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems* (pp. 213-222). Springer. 10.1007/3-540-47952-X_23

Mayo, M., & Mitrovic, A. (2001). Optimising ITS behaviour with Bayesian networks and decision theory. *International Journal of Artificial Intelligence in Education*, *12*, 124–153.

Mislevy, R. J., & Gitomer, D. H. (1995). The role of probability-based inference in an intelligent tutoring system. *ETS Research Report Series, 1995*(2).

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann.

Self, J. A. (1991). Formal approaches to student modelling. In *Student modelling: The key to individualized knowledge-based instruction* (pp. 295–352). Berlin: Springer.

Souhaib, A. (2013). *Conception de l'intéropérabilité sémantique des systèmes hypermédia adaptatifs éducatifs, basée sur les ontologies*. Academic Press.

Zaitseva, L., & Boule, C. (2005). Learning systems in professional training. In Workshop "Industry meets research" within the conference. Interactive Computer Aided Learning (ICL).

Zapata-Rivera, J. D., & Greer, J. E. (2000, June). Inspecting and visualizing distributed Bayesian student models. In *International Conference on Intelligent Tutoring Systems* (pp. 544-553). Springer. 10.1007/3-540-45108-0_58

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

Bayesian Networks: Probabilistic graphical model or a type of statistical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learning Path: A collection of learning situations that the learner takes in a certain period of time; it could be composed of a pretest, a learning activity or an evaluation.

Learning Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

User Model: Is the subdivision of human-computer interaction that describes the process of building up and modifying a conceptual understanding of the user.

Chapter 5
The Determination of Learning Styles in a Learner Model Using the Combination of Bayesian Network and the Overlay Model

ABSTRACT

This chapter aims to treat the problem of dynamic modeling in an adaptive educational system construed as computational modeling of the learner. Modeling the learner in adaptive systems involves different information such as knowledge of the domain, the performance of the learning goals, background, learning styles, etc. Although there are several methods to manage the learner model, like the stereotype model or learner profiles, they do not handle the uncertainty in the dynamic modeling of the learner. The main purpose of this chapter is to show the link between the structure of the learner model and the characteristics of a learning profile and the learning style of a learning situation. This chapter shows how the combination of these two approaches to learner modeling can address the dynamic aspect of the problem in the modeling of the learner. The experiments and results presented in this work are arguments in favor of the hypothesis and can also promote reusing the modeling obtained through different systems and similar modeling situations.

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INTRODUCTION

Despite the different attempts to model the learning that is characterized by a dynamic aspect, we always find it difficult to achieve this goal. The proposed approaches give us just a static view of the learner model, but on practice this model is in full development (the learner knowledge is evolving in the same module). Thus, a dynamic view is essential. Therefore, in order to monitor the behavior of the learner in real time during a learning situation; we must adopt a model for dynamic management of the learning model.

The overlay model responds to the problem of dynamic management of learner model by showing knowledge of the learner as a subset of the knowledge of the system. We also presented in a previous work (Anouar Tadlaoui et al., 2014) how Bayesian networks are considered an effective tool to manage the problem of uncertainty in the model of the learner.

Our work focuses on identifying learning styles in different learning situations. More generally, it focuses on the initialization of a learner model in an adaptive educational hypermedia system. The main objective of this article is modeling the learner by combining Bayesian networks, and the overlay model. We aim in this chapter to use the combination of these two methods, to determine the learning style of each learner in a probabilistic way during the learning situation. And to achieve the, a dynamic e-assessment of each learner based on the learning styles determined.

First, we present the concepts and definitions of the learner's model and the learning styles on which we will base our work. Second, we will define Bayesian networks and overlay model. Then, we will focus on the combination rules on which we based our work to incorporate Bayesian networks with the overlay model. Afterwards, we demonstrate with an example of a learning situation the validity of this combination. Finally, we describe a formal structure for the definition of each learning style for a learning situation. The experiments and results presented in this work are arguments in favor of our hypothesis. This combination can promote also reusing the modeling obtained through systems and similar situations.

LEARNER MODELLING IN ADAPTIVE EDUCATIONAL HYPERMEDIAS

The learner modeling is the modeling of all the important features that affect the learner (knowledge, preferences, goals, etc.). The purpose of modeling the learner is to identify relevant information, to structure, to initialize, to update, and to exploit them. By replacing the word "learning" with the term "user" this definition is also applicable to the model of the user. In the case of an application other than the learner's educational model, it is called the user model.

The learner model can be an integral part of Adaptive Hypermedia Systems as it can be shared with multiple systems. In the latter case we speak of user modeling servers (Yudelson et al., 2007). This type of server areused in distributed environments whereadaptive systems can access this server to query or update user information. Cumulate (Brusilovsky et al., 2005) is one of the most known and used systems for user modeling servers.

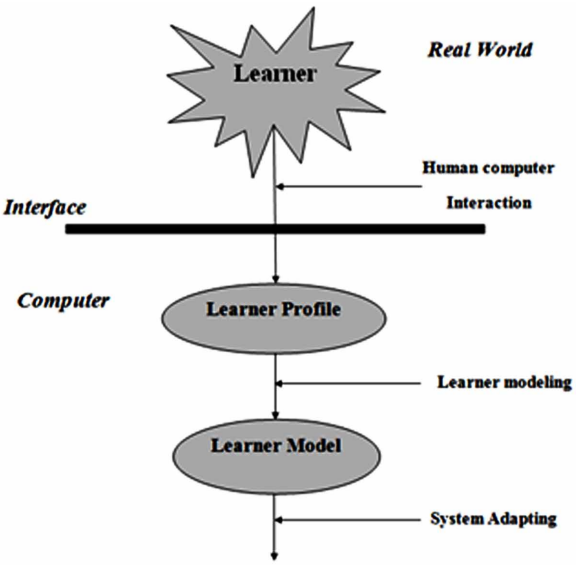
The Role of a Learner Model

We will describe in this section the difference between the term "learner profile" and the term "learner model."

The learner profile is a collection of personal information of the learner. This information is recorded without any description or interpretation. Learner profiles represent the essential information of the learner, such as cognitive skills, skills, intentions, learning styles, preferences, and interactions of the learner with the system. The modeling of this information stored gives us the model of the learner (Anouar Tadlaoui et al., 2016)

Figure 1 represents the process of adaptation a learner adaptive system goes through. The learner information changes over time, depending on the content and amount of information about the user, which is stored in the user profile. Besides, a user can be modeled. Thus, the user profile is used to retrieve the necessary information to build a model of the learner. Koch (2000), describes a user model as the representation of the beliefs of the system about the user. The user of the "real world" is perceived by the system through the human-machine interface.

Figure 1. Learner's profile and learner model in adaptation



A profile contains personal information without deduction or interpretation. The learner modelis considered as an abstract view of the learner, thus it is a higher level conceptualization of the learner. In addition, the learner model is able to deduct additional information about the learner. The learner model is based upon such information and is therefore only a small part of the actual learning. Nevertheless, the learner model must represent the necessary characteristics of the learner in the context of the education system.

The Components of a Learner Model

The components of a learner model are stored information that can be analyzed and grouped according to the different levels of information. These components are connected to the application of the learner model. There are two types of components in the model of the learner:

- **The Performance Model:** That stores data sets related to assessments of learner skills (Zhou et al., 1999).
- **The Model of Learning History:** That follows specific types of data presented to the learner during the use of the system, and measures system knowledge level based on the history of the interaction with the interface (Jeremi´c et al., 2004).

According to Zhou (1999), it is necessary to add additional components to provide complete information about the learner. Such as: the history of responses and a balance the sheet of solutions. The learner answers history is attached to each instruction's unit; it stores information about the learning items and the learner responses during a learning situation. The number of errors and descriptions of these errors during the problem solving process are stored in the solution or the balance sheet.

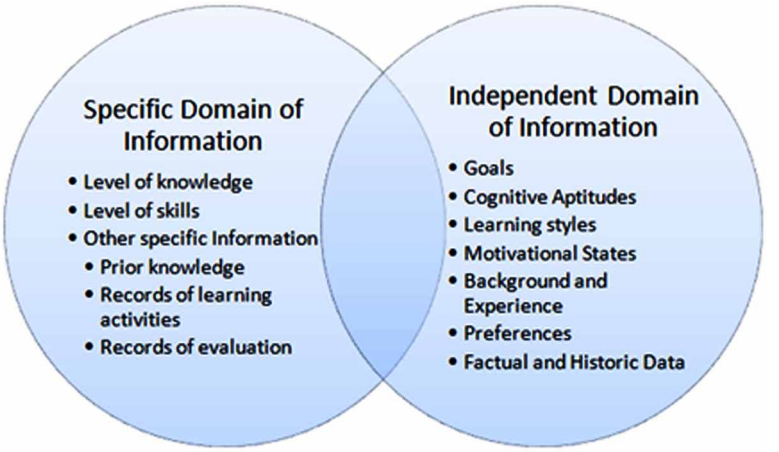
Another approach proposed by Castillo (2003) isto divide the learner model into several components. More specifically,in three components: a profile, a model of cognitive overlay, and a model of course overlay.

The Contents of a Learner Model

According to Self (1991), a complete learner model must contain information about the domain knowledge of the learner, his preferences, key goals, interests, his progress,amongother information. All this information is essential for the use of the systems.

Brusilovsky (2001) states that learners models can be classified according to the nature and form of the information contained in the models. Taking the example of a subject area, the information stored in the learner model is composed of two areas of information: the specific domain of information and independent domain of information. Figure 2 shows the components of each information domain, the combination of these two areas of information provides a complete view of learners for adaptive systems.

Figure 2. Learner domains of information



Specific Domain of Information

The specific domain of information is a reflection on the level of knowledge and skills of a learner in a learning situation.

Brusilovsky (2001) gives the name of the specific domain of information to the model of a specific area.The knowledge model can be based on the combination of two or more initialization methods and models such as: scalar model, the overlay model, error model, genetic model, etc.In this work we will not state explicitelyabout these initialization method of the domain model, but we will return in the following section into some of thesemethods to explain the initialization of a learner model.

It addition, the specific domain of information stores other information relatedto the learner in a specific area, the learner modelstores theseinformation, such as:

- The requirements in the area of learning to the learner.
- An archive of information on learning activities.
- An archive on the assessments and tests.

Independent Domain of Information

In addition to storing the level of current knowledge of a learner, independent domain of information deals with enabling adaptability. The independent area information on a learner includes:

- **Goals:** To specify the learning strategies, it is important to know the goals of the learner. The goal can be divided into two different types: first, the learning goal, which is relatively stable for a training unit;second, the problem-solving purpose, which can change from one problem to another even within the same learning situation.
- **Cognitive Apptitudes:** Cognitive skills are the intellectual capacity to different kinds of cognitive performance. For example, musical ability, mathematical ability, etc.
- **Motivational States:** To measure training in teaching the learner's motivational state is used. Motivation is measured using a number of long-term and short-term parameters. These parameters are for example the effort, attention, interest, distraction, persistence, etc. These parameters are related to other factors such as the level of knowledge, preparation, the complexity of the subject, and the learning outcomes.

- **Background and Experience:** To derive the model parameters of the learner, information about the background and experience are used. General information includes skills that can influence the achievement of learning. Such information is, for example, occupation, work experience or perspectives.
- **Preferences:** Learners may have different preferences related to aspects of the learning environment. These preferences are considered non-inducible system. Thus, the learner must inform the system directly or indirectly from his or her preferences

Learner's Learning Styles

In this section, we will present the learning styles of the learner, which are part of the domain of independent information. Based on the importance of learning styles in education area, and their influence on the learner's learning path. We see that it is the perfect ground to test our hypothesis to combine the overlay model and Bayesian networks to manage the domain of independent information of the learner model.

Research (Brusilovsky et al., 2001) in the field of education shows us that we tend to teach based on our own learning style. *I.e.*, if our learners have a different learning style than us, then there will be difficulties ahead. It would therefore be relevant to any guardian to become familiar with the different learning styles for the simple reason that it will help them become more effective guardians.

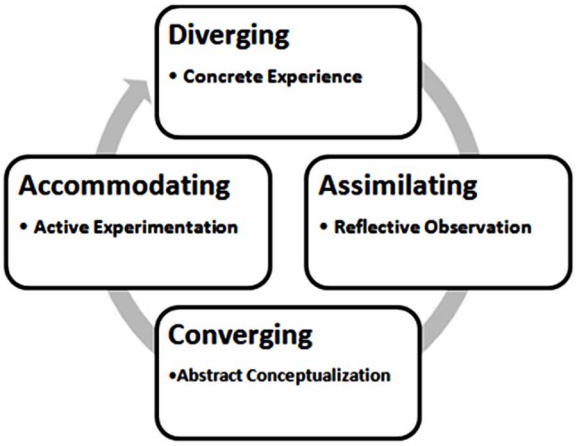
David Kolb (1984) is an educator who has contributed much to the study of learning styles. His researches on adult learning styles have shown that adults, although they are continually learning, tend to favor a learning mode.

This does not mean that they have only one way to learn, but that they learn better with a particular approach. Kolb (2005) identified, from the various modes of learning, four learning styles represented in Figure 3.

Accommodating Style

The learner in this category is mainly taught by "manipulation", *i.e.*, by performing tasks. Therefore he: likes to be involved in the planning and implementation of activities; tends to solve problems by trial / error rather than logic; tends to rely on the thoughts of others rather than on its own analysis; agrees to take risks.

Figure 3. Description of Kolb's learning styles



The types of activities that interest learners that prefer this style are:

- Games and role playing;
- Participation in activities and exercises in small groups;
- Exchange of comments.

Diverging Style

This type of learner has a strong sense of observation: he is clever to perceive an object or problem from different angles; he excels in innovative activities such as brainstorming sessions; he has a vivid imagination and varied interests; he is interested in people and attaches great importance to feelings.

The types of activities that interest this learner are:

- Learning from new experiences: role playing, games, etc.;
- Exchange and discuss with peers;
- Follow tutoring;
- Observe, synthesize and draw conclusions.

Assimilating Style

This learner is skilled at reorganizing logically disparate information. He tends to prefer to juggle ideas and theories rather than their practical application.

The types of activities that interest this leaner are:

- The theoretical courses;
- Objectives examinations;
- Reading about different theories.

Converging Style

This learner is eligible to apply ideas and theories, solve problems, and make decisions. He prefers, however, to solve problems that have a unique solution. Finally, it is easier for him to perform technical tasks than engaging in interpersonal or social controversies.

The types of activities that interest this learner are:

- Failure directed study time;
- Case studies;
- Projects and self-directed individual activities.

The Representation of the Learner Model

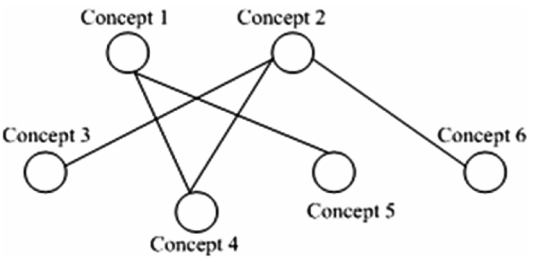
The learner model is used primarily to provide a structure for the representation of domain knowledge of the learner. According to Koch (2000), the data concerning the learner can be represented in different ways. Using different methods (steotypes, bayesian networks…) or differents models (overlay model, diffrentiel model, perturbation modeles …)

Overlay Models

The main idea of overlay models is that the learner model is a subset of the domain model. In other words, the learner overlay model is a partof the full domain model. Figure 4 represents the relationships between the different concepts of a domain model.

A domain model consists of a set of knowledge elements representing the knowledge of expertise; each element represents a concept, a topic, or a theme in a major field. Thus, the model structure of the learner "mimics" the domain model structure. However, each model element of the learner (corresponding to each domain model element) has a specific value measuring the knowledge of the user of this element. This value is considered the mastery of the domain element included in a certain range. Simply, the domain is decomposed into a set of elements and the overlay model (learner model) is a set of the more

Figure 4. Example of the overlay model representation



mastered elements. Suppose that mastery level of each element ranges from 0 (not mastered) to 1 (mastered). The expert model is the superposition with 1 for each element and the learner model is the superposition 1 at most for each element.

The overlay modeling approach was based on the domain models which are often constructed as a knowledge network or hierarchical tree of knowledge. Experts are the authors with the responsibility to create the domain model. Normally, each concept in the domain model is mapped to a learning object. Today there is a tendency to build the domain model using ontologies.(Anouar Tadlaoui et al., 2014).

User Profiles

They are used to represent the cognitive skills, intellectual abilities, intentions, learning, or preferences of a user's style. Each ability is associated with a value, that value belongs to a range of values.

Stereotyped Models

In this type; the model knowledge of the learner and the properties are also represented with a pair of values. The stereotypical model is different from the other models in that it models different pairs of values that are assigned to a user category (stereotype) as novice, intermediate, or expert. So a user inherits from each property to its stereotype. Stereotyped models can be combined with the recovery models when a stereotype is assigned to a user model for initialization. Stereotyped models are useful for modeling the learner but not enough when the individual adaptation requires a more precise description of the learner.

BAYESIAN NETWORKS

Knowledge representation and reasoning from these representations has created many models. Probabilistic graphical models, specifically Bayesian networks initiated by Pearl (1988) in the 1980s, have proven to be useful tools for representing uncertain knowledge and reasoning from incomplete information.

A Bayesian network $B = \left(G, N\right)$ is defined by $G = \left(X, E\right)$ acyclic directed graph with vertices associated where E is a set of directed edges with a set of random variables:

$$X = \left(X, \ldots, Xn\right)$$

$$N = \{P(Xi \mid Pa\left(Xi\right))\}$$

All the probabilities of each node Xi conditionally to the state of its parents $Pa\left(Xi\right)$ in *G*.

Thus, the graphical part of the Bayesian network indicates the dependencies (or independence) between variables and provides a visual tool for knowledge representation, more easily comprehensible by its users. In addition, the use of probability allows taking into account uncertainty in quantifying the dependencies between variables. Both properties have been the cause of the first names of Bayesian networks, "probabilistic expert systems", where the graph was compared to the set of rules of conventional expert system, and the conditional probabilities presented as a quantification uncertainty about the rules.

Mayo and Mitrovic (2001) also have shown that Bayesian networks allow representing compactly the joint probability distribution over the set of variables:

$$\mathrm{P}\left(\mathrm{X1}, \mathrm{X2}, \cdots, \mathrm{Xn}\right) = \prod_{i=1}^{n} \mathrm{P}(\mathrm{Xi} \mid \ \mathrm{Pa}\left(\mathrm{Xi}\right))$$

This decomposition of a global function as a local product terms depending only of the node and its parents in the graph is a fundamental property of Bayesian networks. It is the basis of the first work on the development of

inference algorithms, which calculate the probability of any variable of the model from the same partial observation of other variables. This has been proven NP-complete, but resulted in different algorithms that can be treated as information propagation methods in a graph. These methods obviously use the concept of conditional probability, *i.e.* what is the probability of Xi knowing that Xj has been observed, but also the Bayes theorem, that calculates, conversely, the probability of Xj knowing Xi when $P(Xi \mid Xj)$ is known.

Bayesian Networks Construction

As we have seen in the definition, the complete specification of a Bayesian network requires specifying a part of its structure (directed acyclic graph that underlies) and other parameters (probability tables). To do this, two approaches are possible and can be combined: the collection of expertise and machine learning, which is one of the attractions of Bayesian networks.

In the case of collection of expertise, the definition of the network structure begins with the identification of possible nodes and the distinction between (unobservable) informational variables (inputs) or hypothetical. The existence of an arc can be analyzed in terms of influence of one variable on another, but its orientation is more difficult. Traditionally, an arc is directed from A to B if A is a cause of B, but we will see that this interpretation is not as simple in the case of the learner modeling. The parameters are defined in an approximate manner by using frequentists or qualitative information.

Since Bayesian network is a probability distribution, we can use maximum likelihood as statistical learning parameters criterion.

The result obtained is then a Bayesian network whose structure is fixed and in which E is a complete example base, the maximum likelihood is achieved if the parameters of the Bayesian network are equal to the frequencies of the same configurations observed in E.

Statistical learning of the structure requires the development of a test to determine whether or not the random variables are conditionally independent

Applying Bayesian Networks Into the Overlay Model

The basic idea of the overlay model is that the user model is the domain model subset. The field is divided into a set of knowledge elements and the overlay model is simply a set of elements mastered by the user. Suppose that mastery of each element ranges from 0 (unchecked) to 1 (mastered) in the

overlay model. The relationship of A for B is often prior relationship, so we can deduce that the user must understand A before learning B.

Although the overlay model is a simple but powerful approach to represent a user model, it does not provide a way to deduce the knowledge of the user from the evidence collected in the learning process (Anouar Tadlaoui et al., 2015)

Bayesian Network's Combination Rules

The learner modeling based on the overlay model should be associated with other probabilistic approaches to solve this problem and Bayesian networks are the best fit So we tried to combine in this work the Bayesian network and the recovery model through the transformation of the overlay model's structure, the transformation of the prior relationships, and the transformation of the knowledge elements. The following sections describe these transformations.

The Transformation of the Overlay Model's Structure

The structure of the overlay model is a directed acyclic graph, same as a Bayesian network. We will consider this structure as a Bayesian network in our combination where the knowledge elements will become the nodes of the Bayesian network.

Instead of using the weight of each item, we will assign the probability for each estimation variable of mastery of knowledge. All variables are binary (0 means not mastered and 1means mastered).

Prior Relationships Transformation

The prior relationships between knowledge elements are known as conditional statements in dependence Bayesian network. Therefore, each node has a conditional probability table (CPT), which gives the probability of each value given every possible combination of values for its parents.

Knowledge Elements Transformation

All knowledge elements will be defined as target variables and all other learning objects that are used to evaluate the performance of the learner in the process of learning (tests, exams, exercises, and activities in the case studies) will be considered as variables of evidence.

Then we will add these variables into the Bayesian network after determining the conditional dependency relationships between target variables and all their evidence. We stated that the values of the target nodes will change if the evidence nodes changes.

THE DEVELOPMENT OF BAYESIAN NETWORK COMBINING THE OVERLAY MODEL

After completing the three steps described above, the development of Bayesian network for a learning situation goes through two key steps: the specification of the structure model and the specification of the variables' values, which are described in the following sections.

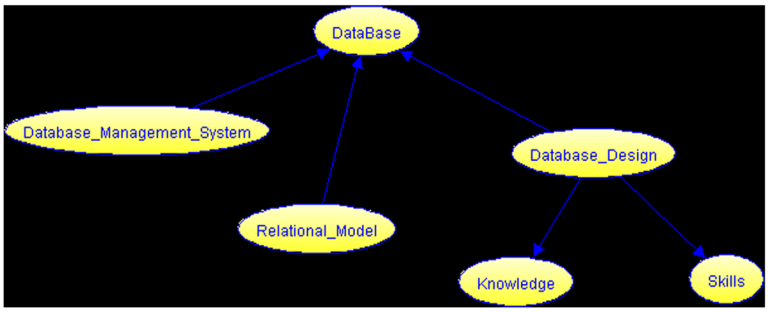
The Specification of the Structure Model

In this section, we will take an example of a learning situation to illustrate and test our hypothesis. To illustrate a learner model, imagine the "*Database*" module with three main concepts (*the Database Management System* - DBMS, *the relational model*, and *the database design*), in this chapter, we will focus especially on the module database design to evaluate the Bayesian network in a real contest based on the result of the students in this module. The relationships of these concepts are prerequisite relationships. In addition, the evaluation of the database design element is composed of two types:

- ***Knowledge:*** The learner must answer more than 10 questions to measure his knowledge on the concept. This assessment reflects the knowledge acquired about the theory of that concept.
- ***Skills:*** This is a written proof that assesses whether the learner can apply the knowledge gained in the module to achieve a design of a database. This type of evaluation reflects the part of knowledge of the learner. We're talking about the first step towards assessing learner's skills in this module.

Figure 5 represent the Bayesian network of our learning situation combined with the overlay model. The structure of overlay model is considered as Bayesian network. Thus, knowledge elements in domain become variables (or nodes) in Bayesian network.

Figure 5. Bayesian overlay model of a Learning situation



Instead of using the weight of each element as above, we assign the probability to each variable for estimating the mastery of knowledge. All variables are binary (0 – not mastered and 1 – mastered). Note, knowledge item, knowledge element and concept are synonymic terms. The prerequisite relationships between knowledge elements are known as the conditional dependence assertions in Bayesian network. Accordingly, each node has a CPT.

The value that measures the relative importance of each condition varies from 0 to 1, the values of each evaluation element are defined by an expert, and in this case we are considering the teacher as the expert.

In other words, it is the weight of the arc from the parent node to the child node. All weights for the child variable will build its CPT. the sum of the weights of all arcs to / from each child node / relative in case of hidden variables / evidence should be 1. This means that each weight is normalized.

The relationship between the target variable (T) and the evidence variable (E) must be from T to E because the process that calculates the posterior probability of target variable is the proof of knowledge of the diagnosis. So the evidence variable has no children and its parents must be target variables. There are two types of relationships:

- **Prior Relations:** Between target variables.
- **Diagnostic Relations:** Of target variables to the evidence variables. The control of concepts (targets) effects on confidence of evidence. However, if the learner has failed a test, it does not necessarily mean that he has no knowledge or ability on the subject.

The Specification of the Variables' Values

The example structured in Figure 5 represents the Bayesian network integrated into the overlay model of a learning situation. The network is developed according to the rules explained in the precedents sections. In this example, the node *Database* (D) has three parents: *Database Management System* (DMBS), *Relational model* (RM), and *Database design* (DD) which in turn are corresponding to three weights of prerequisite relationship: w1=0.1, w2=0.5, w3=0.4. Conditional probability of (D) is computed as follows:

$$P\left(D|DMBS,RM,DD\right) = w1 * hww2 * hww3 * h3$$

where:

$$h1 = \begin{cases} 1 if DS = D \\ 0 otherwise \end{cases}$$

$$h2 = \begin{cases} 1 if RM = D \\ 0 otherwise \end{cases}$$

$$h3 = \begin{cases} 1 if DD = D \\ 0 otherwise \end{cases}$$

We should state that {D, DMBS, RM, DD} is complete set of mutually exclusive variables, which each also variable is random and binary.

Generalizing about formula below, it is that:

$$P\left(X = 1|\, Y1, Y2 \ldots Yn\right) = \sum_{i=1}^{n} wi * hi$$

$$hi = \begin{cases} 1 if\, Yi = X \\ 0 otherwise \end{cases}$$

where

$$hi = \begin{cases} 1 if Yi = X \\ 0 otherwise \end{cases}$$

With given random binary variables X, Yi. Obviously,

$$P\left(not\, X | \, Y1, Y2, \ldots, Yn\right) = 1 - P(X \mid Y1, Y2, \ldots, Yn)$$

So the CPT of DS,RM, and DD are determined in Tables 1, 2, and 3.

Because concepts DS, RM, and DD have no prerequisite knowledge for understanding, their CPTs are specified as prior probabilities obeying uniform distribution.

Table 1. The conditional probability table of "Database" module.

DMBS	RM	DD	P(D=1)	P(J=0) 1-p(J=1)
1	1	1	1.0 (0.1*1 + 0.5*1+ 0.4*1)	0.0
1	1	0	0.6 (0.1*1 + 0.5*1+ 0.4*0)	0.4
1	0	1	0.5 (0.1*1 + 0.5*0+ 0.4*1)	0.5
1	0	0	0.1 (0.1*1 + 0.5*0+ 0.4*0)	0.9
0	1	1	0.9 (0.1*0 + 0.5*1+ 0.4*1)	0.1
0	1	0	0.5 (0.1*0 + 0.5*1+ 0.4*0)	0.5
0	0	1	0.4 (0.1*0 + 0.5*0+ 0.4*1)	0.4
0	0	0	0.0 (0.1*0 + 0.5*0+ 0.4*0)	1.0

Table 2. The conditional probability table of "Database design" evaluation items.

DD	P(K=1)	P(J=0) 1-P(J=1)
1	0.8(0.8*1)	0.2
0	0.0(0.8*0)	1.0

DD	P(S=1)	P(J=0) 1-P(J=1)
1	0.2(0.2*1)	0.8
0	0.0(0.2*0)	1.0

Table 3. The conditional probability table of "Database" parents.

P(DMBS=1)	P(DS=0)	P(RM=1)	P(RM=1)	P(DD=1)	P(DD=1)
0.5	0.5	0.5	0.5	0.5	0.5

EXPERIMENTATION

After building our Bayesian network combining the overlay model, we will try to validate and justify our approach by testing it in a real context. For that, we have chosen the class of second year of DUT (*Diplôme Universitaire de Technologie*, Technical University Degree in English), at the Ecole Normal Superieure of Abdelmalek Essaadi University. The students have taking the test to determine the values on which we have based our probabilistic inference to each module and the initial rate of success to each element of the module. All the tests have been presented by the teachers of the modules.

Before presenting our experimentation on the Bayesian network developed. We will start by presenting the framework in which we will evaluate our approach, and then we will present the metrics in which we will base the evaluation. And then, we will present the combined Bayesian network and its performance evaluation.

Software UnBBayes

UnBBayes (Costa et al., 2008; Matsumoto et al., 2008) is a probabilistic network framework written in Java. It has both a GUI and an API with inference, sampling, learning, and evaluation. It supports Bayesian network (BN), Influence Diagram (ID), Multiple-Sectioned Bayesian Network (MSBN), Hybrid Bayesian Network (HBN), Object-Oriented Bayesian Network (OOBN), Probabilistic Relational Model (PRM), Multi-Entity Bayesian Network (MEBN), Probabilistic Web Ontology Language (PR-OWL), structure, parameter and incremental learning.

UnBBayes uses a technique to reason by odds in intelligent systems. Through a probabilistic graphical model, where the nodes are variables representing domain knowledge and the arcs represent relationships between them, and some evidence, we can estimate probabilities conditioned to the evidence that assist us in decision making. This calculation is called probabilistic inference.

Metrics

In this section, and before presenting the results of our tests, we will present the metrics by which we will measure the performance of our learning situation modeled with the combination of Bayesian networks with the overlay model. The UnBBayes software gives us the opportunity to evaluate the performance of each node in our network dynamically and in real time.

This is the metrics (Costa et al., 2008) we used to evaluate our Bayesian network:

- **The Global Confusion Matrix (GCM):** Computed for the selected target node and all the chosen evidence nodes.
- **Probability of Correct Classification (PCC):** The probability of correct classification computed from the GCM considering all evidence nodes.
- **Marginal PCC (MPCC):** The probability of correct classification computed from the GCM given all evidence nodes other than the one presented in the row.
- **Marginal Improvement (MI):** The probability of correct classification gained by adding the node presented in the row to the rest of other nodes.
- **Individual PCC (IPCC):** The probability of correct classification computed from the global confusion matrix computed for the selected target node and considering only the evidence presented in the row.
- **Cost Rate:** The individual probability of correct classification over the cost ratio.

The Combined Bayesian Network

Before presenting the evaluation results of each node of our Bayesian network combining the overlay model to model the learner in an adaptive system, we begin by presenting the combined Bayesian network through the UnBBayes software.

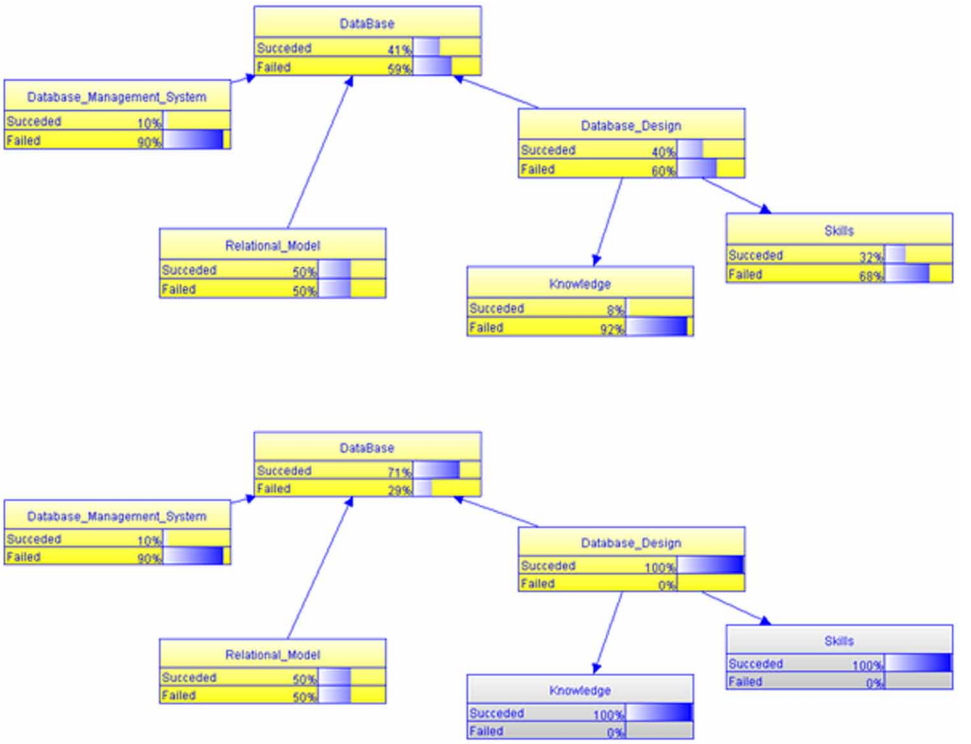
Figure 6 gives a mapping of the combined system with the marginal probabilities for each variable in the developed network. By entering evidence, we can update the posterior probabilities of all variables in the network, as shown in Figure 6.

In Figure 6, we present the Bayesian network obtained after the change of the marginal variables in both the parent nodes "*Knowledge*" and "*Skills*" of the "*Database_Design*" node.

By changing the marginal variables of both nodes from its initial percentage into 100%, we are telling the model that the learner has passed both of the evaluations successfully. With this evidence; we observe a change in the posterior probability of both "*Database_Design*" and "Database" variables. The posterior probability for the "*Succeded*" state has been updated to 100% and 71%, for the variables "*Database_Design*" and "Database", respectively.

Therefore, this means that the success of each learner in the given basic module is strongly related to the success he had in mastering the "*Database_Design*" module.

Figure 6 Combined Bayesian overlay model of a Learning situation



Performance Evaluation

Before evaluating the performance of our developed Bayesian network, we will first evaluate the performance of each node in our network. Using the UnBBayes software and evaluation metrics presented in the previous section.

Nodes Evaluation

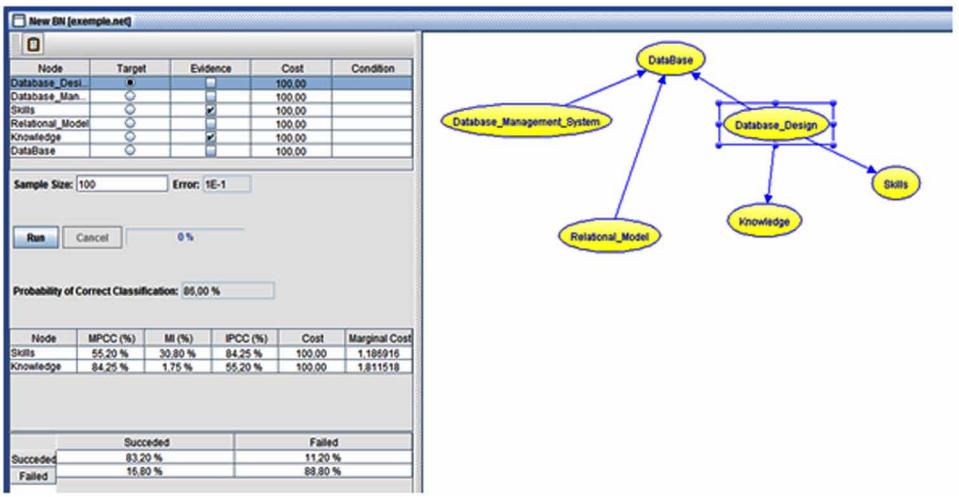
- **Evaluation of the node "*Database_Design*"**

For "*Database_Design*" node, there are two children nodes: "*Knowledge*" and "*Skills*" is selecting the "*Database_Design*" node as a target node and the children nodes as evidence, the results are presented in Figure 7.

Based on the evaluation of our Bayesian network fragment, we find:

By adding evidence nodes into our evaluation of the target node the percentage of the probability of correct classifications increases. Besides, by measuring the probability of correct classification for each node computed from the GCM given all evidence nodes other than the one presented in the row, we see how each node contributes independently to classification. In this evaluation, we find that the MPCC of the node "*Skills*" is 84.25% and the MPCC of the node "*Knowledge*" is 55.20%, which means that the node "*Skills*" is the node that contributes the most.

Figure 7. Evaluation of the node "Database_Design



Based on the probability of correct classification gained by adding the node presented in the row to the rest of other nodes. We find that the marginal improvement of the node "Skills" is 30.80% and for the node "*Knowledge*", the marginal improvement is of 1.75%. This means that the node "*Skills*" has the most influence compared to the target node. We also note that even if the cost is the same, based on the marginal cost of the two different sensors, the sensor which in the most influence on the evolution of the node is the node "*Skills*".

All this reflects the success of a learner in this module's element, is based more about his success in the type of evaluation that evaluates his skills more than the evaluation that concerns his knowledge.

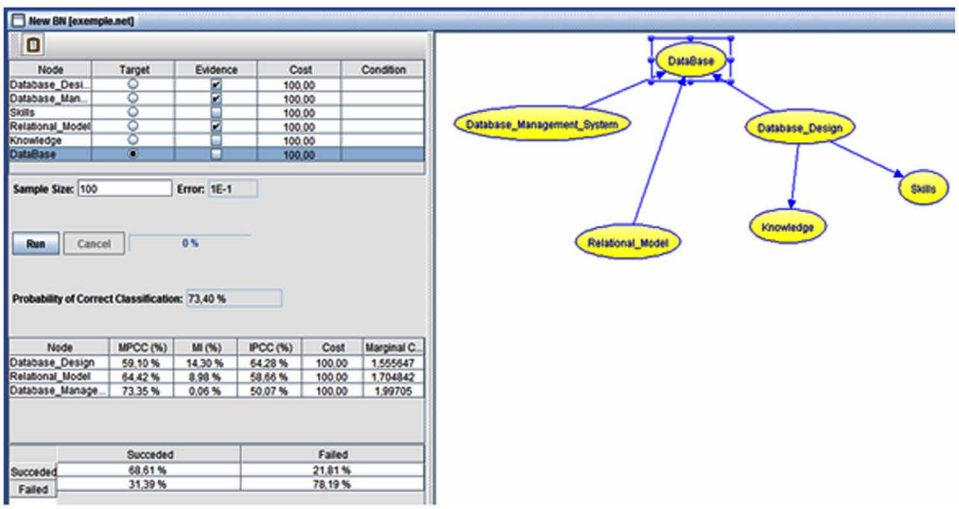
- **Evaluation of the node "*Database*"**

For the "*Database*" node, there are three children nodes: "*DBMS*", "*Relational_Model*" and "*Database_Design*". By choosing the "*Database*" node as a target node and its children as evidence, we obtain the results shown in Figure 8.

Based on the evaluation of our Bayesian network fragment, we find:

By adding evidence nodes into our evaluation of the target node the percentage of the probability of correct classifications increases. Besides, by measuring the probability of correct classification for each node computed

Figure 8. Evaluation of the node "Database"



from the GCM given all evidence nodes other than the one presented in the row, we see how each node contributes independently to classification. In this evaluation, we find that the MPCC of the node "*Database_design*" is 59.10%, the MPCC of the node "*Relational_Model*" is 64.42% and for the node "*DBMS*", the MPCC is 73.35% which means that the node "*DBMS*" is the node that contributes the most.

Based on the probability of correct classification gained by adding the node presented in the row to the rest of other nodes. We find that the marginal improvement of the node "*Database_design*" is 14.30% and for the node "*Relational_Model*", the marginal improvement is of 8.98%, and 0.06% for the marginal improvement of the node "*DBMS"*.. This means that the node "*Database_design*" has the most influence compared to the target node. We also note that even if the cost is the same, based on the marginal cost of the two different sensors, the sensor which in the most influence on the evolution of the node is the node "*Database_design*".

All this reflects the success of a learner in this module relates more success in the database design element more than the other elements of the module.

Bayesian Network Evaluation

After the validation of each node of the Bayesian network, we will present in this section the validation results of the entire Bayesian network.

Figure 9. Evaluation of the entire Bayesian network

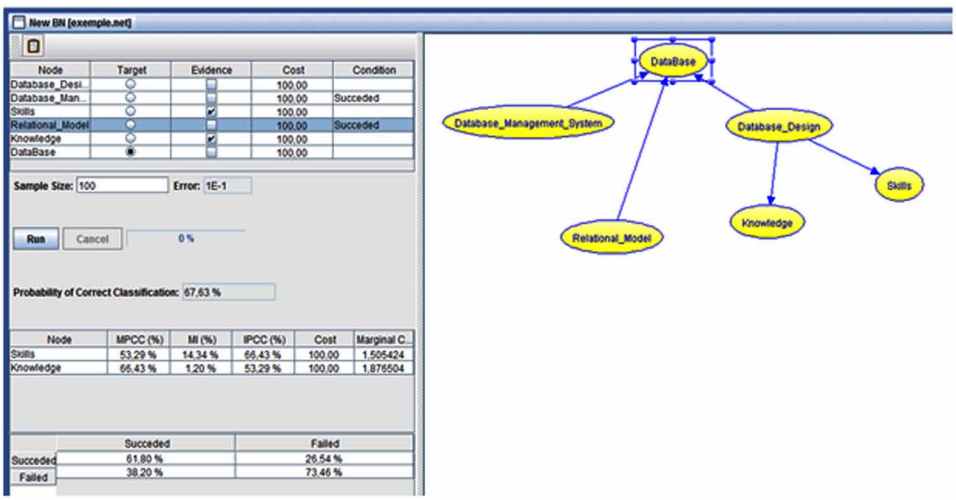


Figure 9 presents the entire Bayesian network validation results in a comprehensive manner. In this network evaluation, we assume that the learner has successfully passed both elements "*DBMS*" and "*Relational_Module*" by affecting both nodes the condition for success in the evaluation. The marginal variable nodes evaluation in this case will be 66.43%. The change of one of these two nodes affect a probabilistically marginal our network variables.

Based on the results and validation of each node of the Bayesian network, we were able to manage the operation of the network in a comprehensive manner. The success of a learner in this module relates more success in the database design element more than the other elements of the module. This means that the adequate learning style for this module is "*the converging style*".

DISCUSSION

In this learning situation, the success of the learner in the database management module relates to his success in the evaluation that tests his skills more than the evaluation that test his level of knowledge. This means that the success of the learner in the learning situation is related on his skills more than on his knowledge.

By returning to the learning styles of Kolb, described in the first section of this article, the learning style appropriate to the learner in the learning situation is the converging style. The learner is competent to practice ideas and theories, solve problems and make decisions. He prefers, however, to solve problems whose solution is unique.

The experiment presented in this work can be applied to any situation that learning in hypermedia systems or even in any e-learning system, starting first by determining the profile of the learner after the passage of a pre-test, and then perform the same test presented in this work to derive the learner profile suitable for each learning situation. Finally, to assign every learning situation to the learner based on the adequate profile.

By using Bayesian networks to determine dynamically the right profile of each learner before entering the learning situation, and assigning each learner to the right learning situation according to the learning style determined. The work presented in this chapter is the first step to achieve a well structured computer based assessment, in which we could track the evolution of each learner in the educational hypermedia, without limiting his actions to mainly Boolean actions (true/false).

CONCLUSION

The user model is an essential element in adaptive e-learning systems. The adaptation of an e-learning system mainly involves the selection and presentation of each successive teaching activity according to the full scope of the learner's knowledge of the subject taught and other relevant characteristics of the learner, which are also kept in the learner model. As a result, the learner model is used to change the interaction between the system and the student to meet the individual needs of the students.

We have shown how in a theoretical perspective, and by applying and testing our hypothesis in a specific case, that the combination of overlay model and Bayesian networks is an appropriate approach for the management of learning styles of learner in adaptive hypermedia systems. The experiments presented in this article are arguments in favor of our hypothesis on the modeling in a probabilistic way to design the learner model, using all the nodes as sensors to measure and evaluate the module of learner.

This approach may be difficult if a high number of data is stored in the system. That is why we proposed in previous works (Anouar Tadlaoui et al., 2017;Anouar Tadlaoui et al., 2015; Anouar Tadlaoui et al., 2018) the use of Multi-Entity Bayesian Networks (MEBN) to try to cover all the data even if the number of stored data is high and unknown.

This chapter contains a new probabilistic way to model the learner model in adaptive educational hypermedia, using a combination of methods and techniques to develop a complete learner model and updating it in real time. The results and models presented in this research insight would be considered as a frame work to a lot of upcoming works in adaptive web.

We see two main directions in which to continue this work. On the one hand this method includes formal analysis of learning styles in adaptive educational hypermedia system, that would lead us to a full e-assessment based on the action of the learner during the learning situation and not only his/her background knowledge when he enters the system. On the other hand in turns Bayesian networks developed for the management of learner model into a readable language by machines, such as ontologies, or as we already proposed before, using probabilistic ontologies as a formalism that gives us the possibility to combine Bayesian networks with ontologies.

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Brusilovsky, P. (2001). *User Modeling and User-Adapted Interaction*. Academic Press. doi:10.1023/A:1011143116306

Brusilovsky, P., Sosnovsky, S., & Shcherbinina, O. (2005, July). User modeling in a distributed e-learning architecture. In *International conference on user modeling* (pp. 387-391). Springer. 10.1007/11527886_50

Castillo, G., Gama, J., & Breda, A. M. (2003, June). Adaptive Bayes for a student modeling prediction task based on learning styles. In *International Conference on User Modeling* (pp. 328-332). Springer. 10.1007/3-540-44963-9_44

Costa, P. C., Ladeira, M., Carvalho, R. N., Laskey, K. B., Santos, L. L., & Matsumoto, S. (2008, May). A first-order Bayesian tool for probabilistic ontologies. In *Proceedings of the Twenty-First International Florida Artificial Intelligence Research Society Conference* (pp. 631-636). Academic Press.

de Koch, N. P. (2001). *Software Engineering for Adaptive Hypermedia Systems-Reference Model*. Modeling Techniques and Development Process.

Jeremic, Z., & Devedzic, V. (2004, August). Design pattern its: Student model implementation. In *Advanced Learning Technologies, 2004. Proceedings. IEEE International Conference on* (pp. 864-865). IEEE.

Kolb, A. Y. (2005). The Kolb learning style inventory–version 3.1 2005 technical specifications. Boston, MA. *Hay Resource Direct*, *200*, 72.

Kolb, D. (1984). *Experiential learning as the science of learning and development*. Prentice-Hall Inc.

Mayo, M., & Mitrovic, A. (2001). *Optimising ITS behaviour with Bayesian networks and decision theory*. Academic Press.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann.

Self, J. A. (1991). *Formal Approaches to Student Modeling*. Technical Report AI-59. Lancaster University.

Yudelson, M., Brusilovsky, P., & Zadorozhny, V. (2007, July). A user modeling server for contemporary adaptive hypermedia: An evaluation of the push approach to evidence propagation. In *International conference on user modeling* (pp. 27-36). Springer.

Zhou, Y., & Evens, M. W. (1999). A practical student model in an intelligent tutoring system. In *Tools with Artificial Intelligence, 1999. Proceedings. 11th IEEE International Conference on* (pp. 13-18). IEEE.

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

Bayesian Networks: Probabilistic graphical model or a type of statistical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learning Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

Learning Path: A collection of learning situations that the learner takes in a certain period of time; it could be composed of a pretest, a learning activity, or an evaluation.

Multi-Entity Bayesian Networks: A logic system that integrates first order logic (FOL) with Bayesian probability theory.

Chapter 6
The Combination of Bayesian Networks and Stereotypes to Initialize the Learner Model in Adaptive Educational Hypermedia Systems

ABSTRACT

This chapter aims to propose a new way to initialize a learner model in adaptive educational hypermedia systems. Learner modelling in adaptive systems contains several indicators. Even if there are several methods for initializing the learner model, they do not manage the side of uncertainty in the dynamic modeling of the learner. The main purpose of this chapter is the initialization of the learner model based on the combination of the Bayesian networks and the stereotypes method. In order to carry out a complete initialization of this model, the authors propose to use a combination of the stereotype method to process the content of the specific domain of information and the Bayesian networks to process the contents of the independent domain of information. The experiments and results presented in this work are arguments in favor of the hypothesis and can promote also reusing the modeling obtained through different systems and similar modeling situations.

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INTRODUCTION

The user module is an essential component for Adaptive e-Learning systems. The term adaptation in e-learning systems involves the selection and the manner of presentation of each learning activity as a function focused on the entity having of knowledge and skills and other information given by each subject taught (Yudelson et al., 2007)

Despite the different attempts to model the learning that is characterized by a dynamic aspect, we always find it difficult to achieve this goal (Anouar Tadlaoui et al., 2016). The proposed approaches give us just a static view of the learner model, but on practice this model is in full development (the learner knowledge is evolving in the same module). Thus, a dynamic view is essential. Therefore, in order to monitor the behavior of the learner in real time during a learning situation; we must adopt a model for dynamic management of the learning model (Brusilovsky et al., 2005; Zaitseva et al., 2005; Han, 2001)

The structure of this chapter consists on combining Bayesian networks with stereotypes method to initialize the learner model in AHES. To achieve that goal, we will firstly, return to the notions and definitions of the learner's model, the process of its development, its domains of information and their contents, and then we will concentrate on the Bayesian networks, their definitions and their rules of construction. Then, we will explain our approach for the initialization of the learner model based on a combination of the stereotype method and the Bayesian networks, precisely the field of intervention of each method and their expected results. Finally, and in order to disclose the validity of our hypothesis; we will present the experiments and the tests carried out. The results obtained from these experiments presented in this work are all arguments in favor of our hypothesis. This combination also promotes its reuse in the step of updating the learner model in different adaptive educational hypermedia systems.

THE INITIALIZATION OF THE LEARNER MODEL IN THE AHES

We will concern this part to the initialization of the model of the learner in the AHES, begin by describing the process of initialization of the model

that we will propose by combining the Bayesian networks as we presented in the preceding chapters and the stereotypes in order to achieve a complete initialization in all aspects are understood.

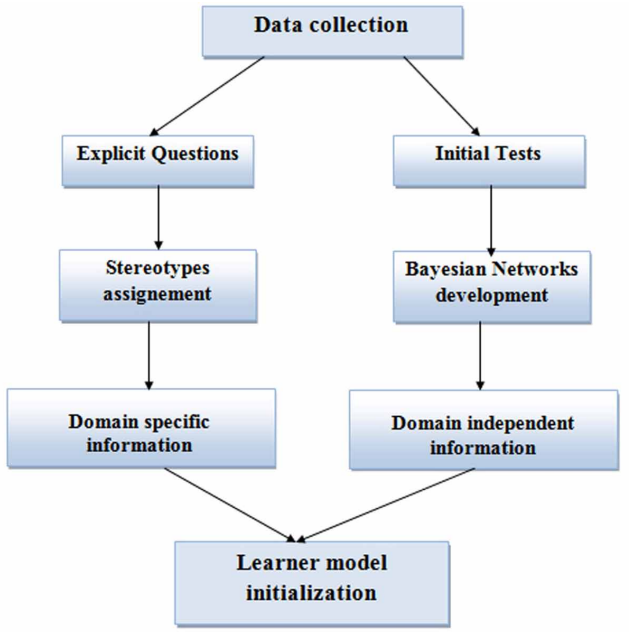
The Process of Initializing the Learner Model

The initialization of the learner model represents the process of gathering information about the learner and transferring this information to the model. This process of initialization represents a major problem for adaptive systems.

In this section, we will present our process of collecting data about the learner. According to Self (1991), the learner model can be initialized in three ways, using explicit questions, initial tests, or the method of stereotypes.

Figure 1 shows our proposed process for collecting learner data. We propose in this chapter the use of two methods simultaneously to gather all the information related to the learner, which will give us a more complete learner model, and this will be reflected on the adaptation of the system to the needs of the learner in a more precise way.

Figure 1. The process of initializing the learner model



To achieve this goal, we will use two methods for data collection: explicit questions, and initial tests.

In order to gather specific information about the learner that makes up the learner's profile, such as personal information, goals, cognitive skills, preferences ... we will base this process on explicit questions, which will guide us in assigning each learner to a well-defined stereotype.

And for independent learner information, which reflects its level of knowledge and skills for each module in the system, and which represent the key element for system adaptation. We base this process on initial tests, using Bayesian networks as a formalism to properly represent and manage this information in a probabilistic way.

Building the Learner Profile

Initial learner models are often constructed directly by direct questioning of the learner as soon as he or she enters the system and before he or she has been affected into a learning situation. This method is considered very effective for collecting general information about the learner, the problem encountered using this method, is to find a number of appropriate questions to collect consistent information about the learner taking into consideration that the increase of the number of questions can irritate the learner and increase the declination to the system, which can create a situation where the learner leaves the system and never returns. According to Tsiriga (Tsiriga & Virvou, 2003), the dependence on this method alone does not allow sufficient extraction of information for the initialization of a learner model.

In order to answer this problem of the numbers of questions for the extraction of the data on the learner, we propose to use the stereotypes method to group the learners in categories. Stereotypes would concede a very powerful method to provide considerable information based on initial observations.

Stereotypes: Definition and Characteristic

In general, stereotypes represent a category or group of learners. There are two types of stereotypes: Fixed and default.

In *fixed stereotypes*, the learner is assigned a predefined stereotype at an abstract level. For example: in a module, learners are divided into four groups, corresponding to four levels (novice, beginner, advanced and expert) each level is more difficult than the previous level: After obtaining individual information such as: knowledge, experience, skills ... the system attributes

each learner one of the four levels and it will never change in this type of stereotype.

In *default stereotype*s, the system is more flexible. Therefore, first, the learner is assigned to the initial stereotype. This means that the initial stereotype has a "default" value. The system will observe the learners and collect their performance data, test results ... during the learning process. Finally, the system will modify the initial stereotype to new stereotype more appropriate. Simply, the default stereotype setting is gradually replaced by a more accurate stereotype for the learner.

There are three important elements in a stereotype: triggering, inference and retraction:

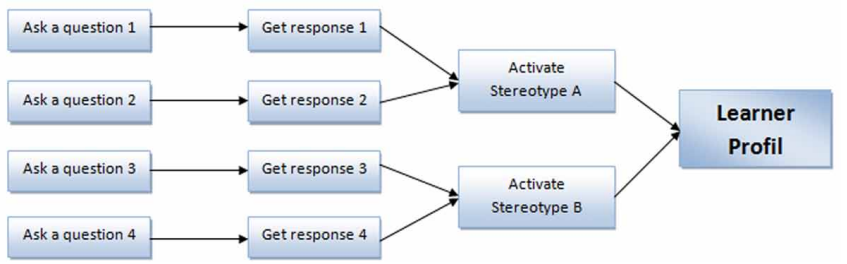
- **Trigger:** Is used to activate a stereotype. In other words, it is a condition for assigning a stereotype to the learner.
- **Inference:** Is an engine, responsible for inferring information related to the learner.
- **Retraction:** Are the conditions used to disable the stereotype of the learner. There is a circumstance.

The Process of Building a Learner Profile

Figure 2 shows an overall view of the process of building our profile of each learner. As soon as the learner enters the system, the system will ask the learner a set of questions about his personal information, and then he will receive answers on these questions. This responses will be then stored in the system.

After one or more of these responses (which represent triggers or stereotypes), one or more stereotypes will be activated. These stereotypes will

Figure 2. The process of building a learner profile



group a group of learners into specific categories according to well-defined characteristics. All of these stereotypes will build a profile of the learner.

The Development of Stereotypes

The use of stereotypes in learner modeling began with GRUNDY (Rich, 1979), which allows the learner to give himself a personal description. This description is used by the system to trigger a predefined trigger in the system. Depending on the trigger triggered, the system adapts to the needs of the learner.

Assuming an S-stereotype that aims to collect learner information to initialize part of a learner's model in an adaptive system, and learner responses to explicit system questions as components *{cj}* of the system, each of these components represent aspects of the learner during his or her time in the system.

1. Activation of Stereotypes

The activation of each stereotype is related to a set of triggers *{tSi},* where each trigger *{tSi}* is a Boolean expression based on a component *{cj}* or a function of a set of components *f({ck})* model of the learner.

The first action of a stereotype is related to the validity of the learner's response to an explicit question posed by the system. Thus:

$$if\,\exists i, tS_i = true \rightarrow active\left(S\right)$$

Meaning that when a trigger *{tSi}* has become true, stereotype *S* will be activated.

2. The Retraction of Stereotypes

There is also in the stereotype method a series of retractions *{rSi}* which is considered the basis on which an S stereotype is deactivated.

A stereotype S is deactivated if a retraction condition *{rSi}* has become true:

$$\exists\, j, rS_i = true \rightarrow desactive\left(S\right)$$

INITIAL TESTING WITH BAYESIAN NETWORKS

For a complete collection of learner information, we will use the initial test method, which will allow us to initialize the learner model in a complete way taking into account all aspects and components of this model. By asking the learner to pass tests, the initial parameters of the learner model can be obtained through the analysis of the results of these tests.

The problem encountered in using this method is the control of the length of the tests proposed to the learner. Length or redundancy in these tests may cause the learner to leave the system. To solve this problem we propose in this work to use the Bayesian networks as a method to construct these initial tests. On the one hand, we can benefit from the power of this method for managing the probabilistic aspect of the learner's information which will guide us towards the construction of a well-structured set of tests and, on the other hand, to realize a comprehensive analysis of the domain information of the learner model based on the results of each test and on the real-time monitoring of the learner during each proposed test.

- **The specification of the structure of the model**, in which we define the nodes and the orientation of the arcs for all the components of our network.
- **The specification of the values of variables**, in which we will calculate the value tables of the variables of each node of our network.

The Structure Specification of the Model

To illustrate the stages of development of Bayesian networks to model the initial tests for the collection of data on the learner, we will begin by defining the nodes of our network. Our network consists of an initial "*Initial Test*" node, which is composed of several parent nodes representing the modules taught in the Specialized Master "*Pedagogical Engineering Multimedia"* (*Ingénierie Pédagogique Multimédia*) at Abdelmalek Essaâdi University; in our work, we chose three modules with different criteria to test the validity of our hypothesis (*Project Management, Digital Image Processing, Human Machine Interaction*). Each of these nodes is also composed of the parent nodes, the links of these nodes are preliminary relations:

- **Initial Tests:** This node allows the collection of all the data from the tests of each module the learner chosen to take.
- **Project Management:** The learner, and before following the training of this module, he is led to take an initial test to measure his level of knowledge and competence, the latter consists of two types of evaluation
  - **Knowledge:** The learner must answer on more than 10 questions to measure how much of his knowledge. This part of the assessment reflects the evaluation of the learner's knowledge.
  - **Ability:** This is a written proof that responds if the learner can apply the knowledge acquired in the module. This type of evaluation reflects the part of the learner's know-how.
- **Digital Image Processing:** The learner, and before following the training of this module, he is led to take an initial test to measure his level of knowledge and skill, the latter consists of two types of evaluation:
  - **Knowledge:** The learner must answer on more than 10 questions to measure how much of his knowledge. This part of the assessment reflects the evaluation of the learner's knowledge.
  - **Ability:** This is a written proof that responds if the learner can apply the knowledge acquired in the module. This type of evaluation reflects the part of the learner's know-how.
- **Human Machine Interaction:** The learner, and before following the training of this module, he is led to take an initial test to measure his level of knowledge and skill, the latter consists of two types of evaluation:
  - **Knowledge:** The learner must answer on more than 10 questions to measure how much of his knowledge. This part of the assessment reflects the evaluation of the learner's knowledge.
  - **Ability:** This is a written proof that responds if the learner can apply the knowledge acquired in the module. This type of evaluation reflects the part of the learner's know-how.

The value that measures the relative importance of each condition varies from 0 to 1, the values of each evaluation element is defined by the teacher.

In other words, it is the weight of the arc from the parent node to the child node. All weights regarding the child variable will build its CPT. the sum of the weights of all arcs at / from each child / parent node in case of hidden variables / proofs should be 1. This means that each weight is standardized.

The relationship between the target variable (T) and the variable of the proof (E) must be from T to E because the process that calculates the posterior probability of the target variable is evidence of diagnostic knowledge. So, if variable of evidence has no child and its parents must be target variables. There are two types of relationships:

- Prerequisite relationships between the target variables.
- Diagnostic relationships of the target variables to the proof. The mastery of concepts (targets) effects on the confidence of evidence. However, if the learner has failed an exam, he is not sure of his lack of knowledge or ability because he can make an unexpected mistake.

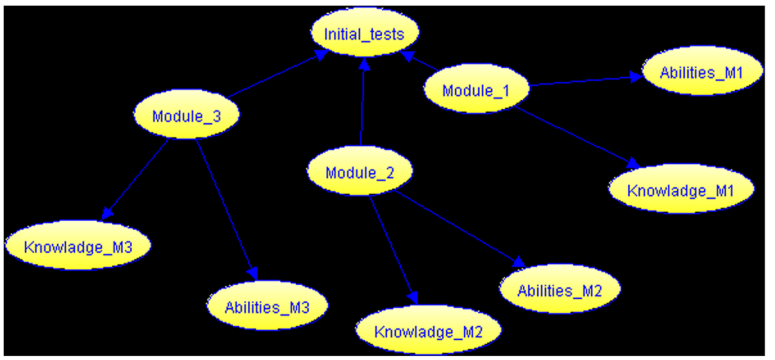
The Specification of the Values of the Variables

Once the network structure is presented, it is easy to define the values of the variables. Figure 3 shows the Bayesian network of initial tests for the initialization of the learner model in an educational hypermedia system.

In the developed Bayesian network we observe that the initial test of node (I) consists of three parents: Digital Image Processing (T), Project Management (G) and Human Machine Interaction (M) corresponding to three reports of preliminary weights: w1 = 0.1, w2 = 0.5, w3 = 0.4. The conditional probability of (I) is calculated as follows:

$$P\left(I|T,G,M\right) = w1 * h1 + w2 * h2 + w3 * h3$$

Figure 3. The Bayesian network of initial tests



Thus:

$$h1 = \begin{cases} 1 if T = I \\ 0 otherwise \end{cases}$$

$$h2 = \begin{cases} 1 if G = I \\ 0 otherwise \end{cases}$$

$$h3 = \begin{cases} 1 if M = I \\ 0 otherwise \end{cases}$$

We should indicate that {I, T, G, M} is a complete set of mutually exclusive variables, whose variable is also random and binary.

By generalizing on the formula below, it is that:

$$P\left(X = 1 | Y1, Y2 \ldots Yn\right) = \sum_{i=1}^{n} wi * hi$$

where

$$h1 = \begin{cases} 1 if Yi = X \\ 0 otherwise \end{cases}$$

With random binary variables X, Yi. Obviously,

$$P\left(not X | Y1, Y2, \ldots, Yn\right) = 1 - P(X \mid Y1, Y2, \ldots, Yn)$$

- **The conditional probability table of the node "Initial test"**

Table 1 shows the CPT of each child node of the initial test of the parent node.

Because the concepts T, G, M does not have prior knowledge for comprehension, their CPTs are specified as prior probabilities obeying a

Table 1. Conditional Probability Table of the "Initial Test" Node

T	G	M	P(J=1)	P(J=0) 1-p(J=1)
1	1	1	1.0 (0.1*1 + 0.5*1+ 0.4*1)	0.0
1	1	0	0.6 (0.1*1 + 0.5*1+ 0.4*0)	0.4
1	0	1	0.5 (0.1*1 + 0.5*0+ 0.4*0)	0.5
1	0	0	0.1 (0.1*1 + 0.5*0+ 0.4*0)	0.9
0	1	1	0.9 (0.1*0 + 0.5*1+ 0.4*1)	0.1
0	1	0	0.5 (0.1*0 + 0.5*1+ 0.4*0)	0.5
0	0	1	0.4 (0.1*0 + 0.5*0+ 0.4*1)	0.4
0	0	0	0.0 (0.1*0 + 0.5*0+ 0.4*0)	1.0

uniform distribution as shown in Table 2 (mean value assigned 0.5 in most cases).

- **The conditional probability table of the node "Digital image processing"**

Table 3 represents the CPT of each child node of the parent node *digital image processing/*

- **The conditional probability table of the "Project Management" node**

Table 4 shows the CPT of each child node of the parent node *Project management/*

- **The conditional probability table of the node "Man Machine Interaction"**

Table 2. Parent conditional probability table of the "Initial Test" node

P(T=1)	P(T=0)	P(G=1)	P(G=1)	P(M=1)	P(M=1)
0.5	0.5	0.5	0.5	0.5	0.5

Table 3. Conditional probability table of the "Digital image processing" node

C	P(J=1)	P(J=0) 1-p(J=1)
1	0.8(0.8*1)	0.2
0	0.0(0.8*0)	1.0

H	P(J=1)	P(J=0) 1-p(J=1)
1	0.2(0.2*1)	0.8

Table 4. The conditional probability table of the "Project Management" node

C	P(J=1)	P(J=0) 1-p(J=1)
1	0.6(0.6*1)	0.4
0	0.0(0.6*0)	1.0

H	P(J=1)	P(J=0) 1-p(J=1)
1	0.4(0.4*1)	0.6
0	0.0(0.6*0)	1.0

Table 5 shows the CPT of each child node of the parent node. *Man Machine Interaction*.

RESULTS

After developing our Bayesian network combining the superposition model, we will try to validate and justify our approach by testing it in a real context. To do this, we chose the first year class of IPM (Master's Degree in Engineering Pedagogy Multimedia)

Before presenting our experimentation results, using the developed Bayesian network. We will begin by presenting the framework in which we will evaluate our approach and then present the parameters on which we will base the evaluation. Next, we will present the combined Bayesian network and its performance evaluation.

Evaluation Metrics

In this section, and before presenting the results of our tests, we will present the metric by which we measure the performance of the Learner module

Table 5. The conditional probability table of the node "Man Machine Interaction"

C	**P(J=1)**	**P(J=0)** **1-p(J=1)**
1	0.7(0.7*1)	0.3
0	0.0(0.7*0)	1.0

H	**P(J=1)**	**P(J=0)** **1-p(J=1)**
1	0.3(0.3*1)	0.7
0	0.0(0.7*0)	1.0

modeled using Bayesian networks. The UnBBayes (Costa et al., 2008) software allows us to evaluate dynamically and in real time the performance of each node in our network. Here are the parameters we used to evaluate our Bayesian network:

Here are the metrics we used to evaluate our Bayesian network:

- ***The Global Confusion Matrix (GCM)*** calculated for the selected target node and all selected proof nodes.
- ***Probability of Correct Classification (PCC):*** the probability of a correct classification, it is calculated from the global confusion matrix taking into account all the control nodes of the Bayesian network.
- ***Marginal CPC (MPCC):*** the probability of a correct classification, it is calculated from the global confusion matrix, taking into account all the control nodes in the Bayesian network other than that presented in the row.
- ***Marginal Improvement (MI):*** the probability of a correct classification, it is calculated from the global confusion matrix, taking into account all the nodes of evidence in the Bayesian network and obtained by adding the node presented in the row to remains of other nodes.
- ***Individual PCC (IPCC):*** the probability of a correct classification calculated from the LCM by considering only the evidence presented in the row.
- ***Cost Rate:*** the individual probability of a correct classification on the cost ratio.

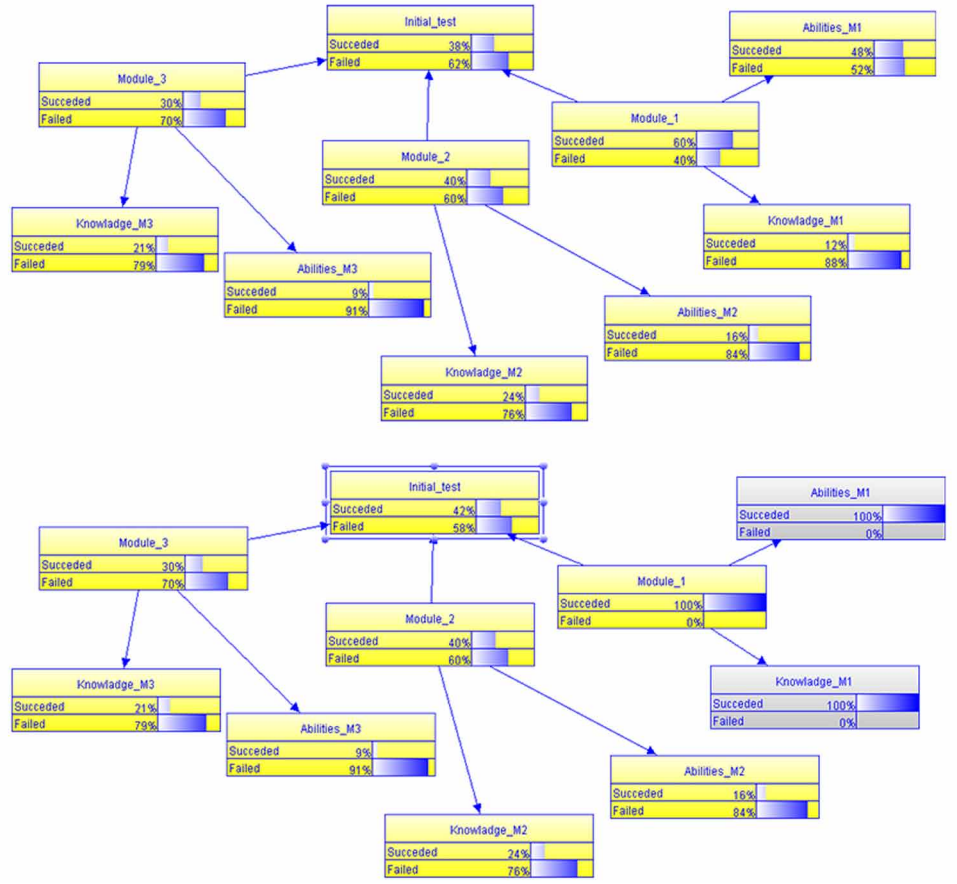
The Combined Bayesian Network

Before presenting the evaluation results of each node of our Bayesian network representing the initial tests to initialize the learner model in an adaptive system, we will begin by presenting the combined Bayesian network through the UnBBayes software.

Figure 4 gives us a diagram of the combined network, with the marginal variables of each node of our network developing; we can observe the change in the marginal variables of each node of our network, simply by changing one or more marginal variables of one or more parent nodes of the selected node.

In Figure 4, we present the Bayesian network obtained after the change of the marginal variables in the two parent nodes "*Knowledge*" and "*Skills*" of the node "*Project management*".

Figure 4. The Bayesian network compiled of the learning situation



The marginal variables of these two nodes are changed from the initial percentage to 100%, which means that the learner to pass both evaluations successfully. We note that the marginal variables of the nodes "*Project management*" and "*Initial test*" will also change. For the "*Project management*" node, the marginal success variable is high up to 100%, and for the "*Initial test*" node, the marginal success variable is raised to 68%.

All this means that the success of each learner in the initial set of tests is primarily related to his / her success in the tests of each module.

Evaluation of Node Performance

In order to evaluate the performance of our developed Bayesian networks, we will first evaluate the performance of each node in our network, using the UnBBayes software and the evaluation metrics presented in the previous section.

Evaluation of the Node "Digital Image Processing"

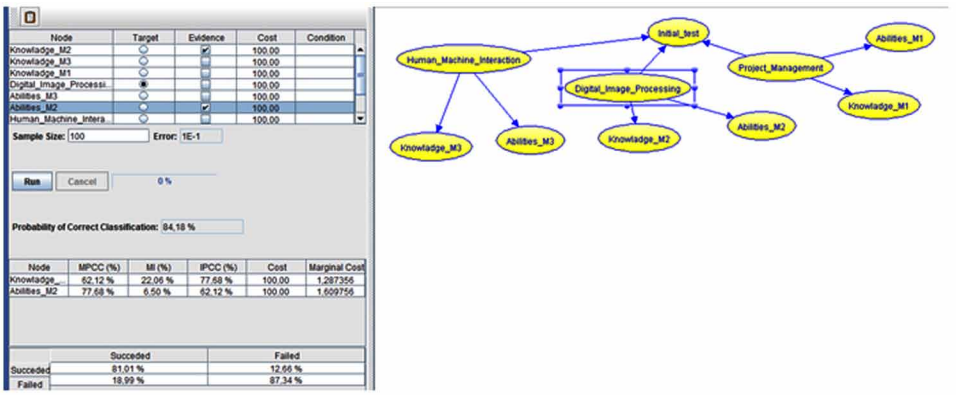
For the "*Digital image processing*" node, there are two parent nodes: "*Knowledge*" and "*Abilities*", choosing the "Digital image processing" node as a target node and the parents as nodes of results shown in Figure 5.

According to the results of the results table, we find that:

By adding nodes of evidence in our evaluation of the target node, the probability percentage of correct classifications increases. And by measuring the probability of a correct classification of each node, we see how each node contributes independently to the classification. In this evaluation, we find that the node "*Abilities*" is the node that contributes the most.

We find how each node contributes according to the set of nodes in front of them. In this evaluation, the marginal improvement of the node "*Abilities*" means that the influence of this node is greater with respect to the target node. We also note that, although the cost is the same, the marginal cost of the two different sensors, the sensor, which in most cases represents the marginal cost of the variables of the "*Abilities*" node.

Figure 5. Evaluation of the node "Digital image processing"



All this reflect that the success of a learner in this module of *Digital Image Processing* is based more on his success in the test that relates to these abilities, more than the test that relates to his knowledge. The system can therefore, on the basis of its results to define the level of knowledge of the learner (based on the result of the knowledge test), his level of skill (based on the result of the ability test), and also to deduce the learning style and preferences of the learner in this learning situation, in order to adapt according to the profile of each learner, we shift affect the appropriate module.

Evaluation of the Node "Project Management"

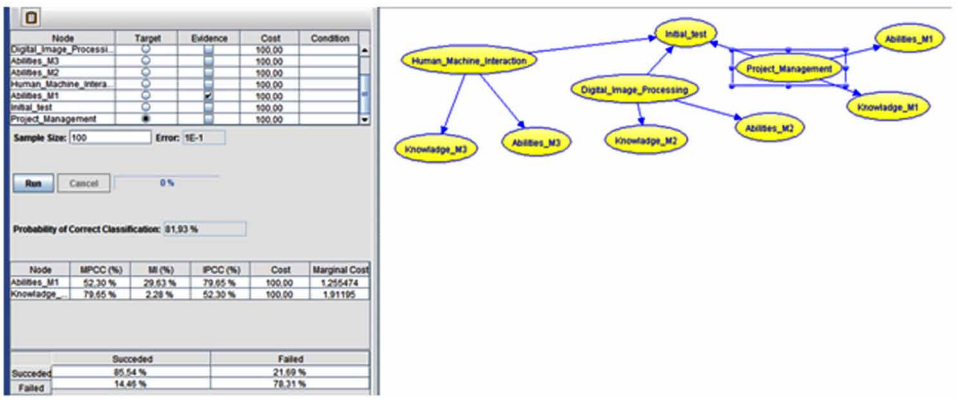
For the "*Project Management*" node, there are two parent nodes: "*Knowledge*" and "*Abilities*", choosing the "*Project Management*" node as a target node and the parents as nodes of evidence, in Figure 6.

According to the results of the results table, we find that:

By adding nodes of evidence in our evaluation of the target node, the probability percentage of correct classifications increases. And by measuring the probability of a correct classification of each node, we see how each node contributes independently to the classification. In this evaluation, we find that the node "*Knowledge*" is the node that contributes the most.

We find how each node contributes according to the set of nodes in front of them. In this evaluation, the marginal improvement of the "*Knowledge*" node means that the influence of this node is greater than the target node. We also note that, although the cost is the same, the marginal cost of the two

Figure 6. Evaluation of the node "Project management"



different sensors, the sensor, which in most cases represents the marginal cost of the variables of the Knowledge node.

All this reflect that the success of a learner in this module of *Project Management* is based more on his success in the test that concerns this knowledge, more what the test relates to his abilities. The system can therefore, on the basis of its results to define the level of knowledge of the learner (based on the result of the knowledge test), his level of skill (based on the result of the ability test), and also to deduce the learning style and preferences of the learner in this learning situation, in order to adapt according to the profile of each learner, we shift affect the appropriate module.

Evaluation of the Node "Interaction Man Machine"

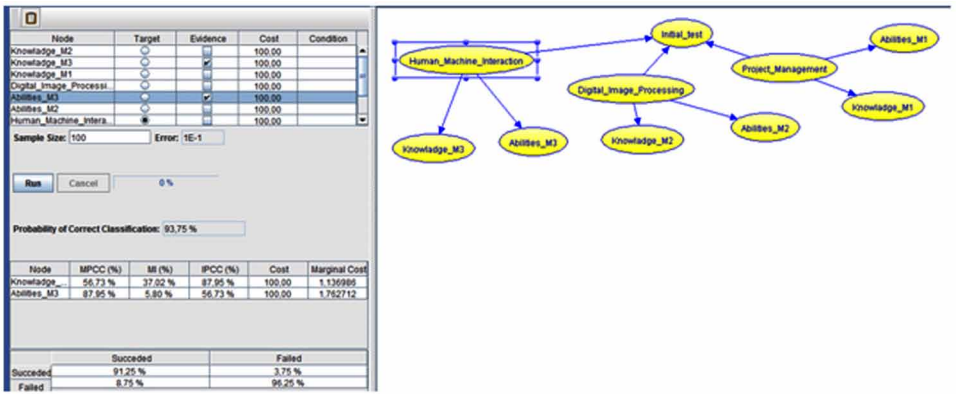
For the *Human machine interaction* node, there are two parent nodes: "*Knowledge*" and "*Abilities*", selecting the «*Human machine interaction*» node as a target node and the parents as nodes of evidences, in Figure 7.

According to the results of the results table, we find that:

By adding nodes of evidence in our evaluation of the target node, the probability percentage of correct classifications increases. And by measuring the probability of a correct classification of each node, we see how each node contributes independently to the classification. In this evaluation, we find that the node "*Abilities*" is the node that contributes the most.

We find how each node contributes according to the set of nodes in front of them. In this evaluation, the marginal improvement of the "*Abilities*" node means that the influence of this node is greater than the target node. We also

Figure 7. Evaluation of the node "Interaction man machine"



note that, although the cost is the same, the marginal cost of the two different sensors, the sensor, which in most cases represents the marginal cost of the variables of the *Abilities* node.

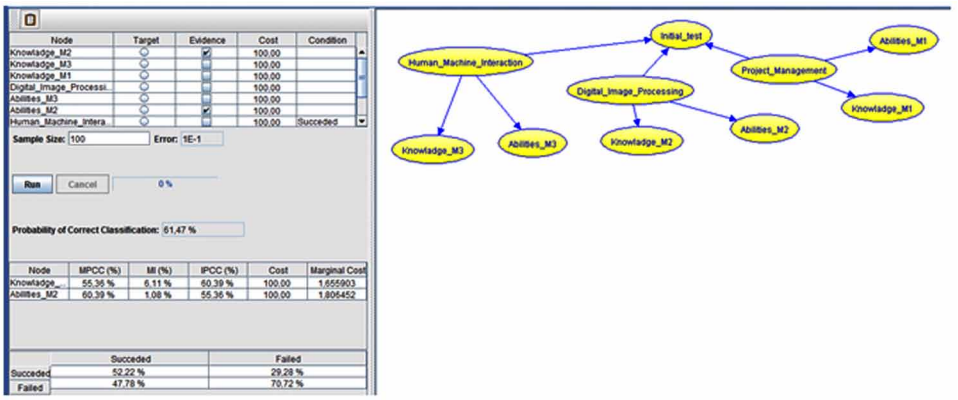
All this reflect that the success of a learner in this module Human machine interaction is based more on his success in the test that concerns this knowledge, more than the test that relates to his abilities. The system can therefore, on the basis of its results to define the level of knowledge of the learner (based on the result of the knowledge test), his level of skill (based on the result of the ability test), and also to deduce the learning style and preferences of the learner in this learning situation, in order to adapt according to the profile of each learner, we shift affect the appropriate module.

Evaluation of the Full Bayesian Network

After the validation of each node of the Bayesian network of our model of the learner. This section presents the validation results of the complete Bayesian network.

Figure 8 presents the validation results of the Bayesian network in a complete way. In this evaluation of the network, we will only ask the learner to successfully pass the two initial tests of the two modules "*Human Machine Interaction*" and "*Project Management*". The marginal variable of the initial node "*Initial test*" will in this case have a value of 61.47%. Changing one of these two nodes will affect the marginal variables of our network in a probabilistic way.

Figure 8. the evaluation results of the "initial test" node of the developed Bayesian network



Based on the results and the validation of each node of the Bayesian network, we were able to manage the network in a global way.

When the learner enters the system and before assigning the module to his / her needs and according to his / her level of knowledge and skills, the learner will be required to take a set of initial tests concerning all the modules available in adaptive educational hypermedia system. Each of these modules consists of two types of evaluation; an assessment based on the learner's knowledge, and an assessment based on these abilities.

The results from these two types of tests will enable us to define the level of knowledge, the level of competences, the learning styles and other information about each learner in our system; for example, if a learner passes the initial test of the "*Digital image processing"*, we will demonstrate his level of knowledge of the learner in this module based on the results of the "Knowledge" type tests and his skill level in this module based on the results of the "Skills" tests, and we can therefore deduce from the results of both types of tests the appropriate learning style of this learner in this module.

DISCUSSION

The approach presented in this chapter combines the method of stereotypes for the collection of contents of the specific information domain, based on the explicit questions posed to the learner after entering the system, using the Bayesian network method for the collection of contents of the independent information domain, based on the initial tests the learner is led to take before assignment in a specific learning situation.

Table 6 shows different contents of the learner model with their description and explanation, grouping each component according to the appropriate information model, and the methods used for the initialization of the set of these contents.

The results of tests and validation presented in the previous sections show that this combination for the collection of data on the learner in an adaptive educational hypermedia system will allow us to initiate the learner model in a clearer way and complete.

Table 6. Summary of methods used for the initialization of the learner model

Model	Cotenant	Description	Modeling technique used		
			Stereotypes	Bayesian networks	Other methods
Domain specific information	Personal information	Name; Email; Password	X	-	-
	Demographic data	Age; Sex; Nationality	X	-	-
	Academic background	Previous studies and courses taken	X	-	-
	Qualifications	Previous certificates taken	X	-	-
	Trace of personality	Psychological profile of the learner	X	-	-
	Deficiencies	Learner vision, using glasses or not.	X	-	-
	Learning styles	Determination of learning styles	-	X	X
	Cognitive capacities	Determination of the learner cognitive skills	X	-	-
Domain independent of information	Knowledge background	Learner previous knowledge on a learning situation	-	X	-
	Objectives	The objectives of the learning situation	-	X	-
	Navigation description	Kipping a register of each page completed	-	X	-
	Knowledge acquired	A collection of knowledge transformed on concepts for every learning situation.	-	X	-
	Evaluation results	Kipping a register for every test data or assessment result.	-	X	-
	Learner Aptitude and interest	Definition of the capacity and aptitude to use the system	-	X	X
	Deadline extend	Determination of the duration of every learning situation.	-	X	-

(Anouar tadlaoui et al., 2017)

As we have shown in the table above, some content of the learner model such as the learning styles, and learner skills, even if they can be represented using Bayesian networks, we will propose use a combination of Bayesian networks with other modeling methods of the learner model, and precisely the superposition model that addresses the problem of the dynamic management of the learner model by representing the learner's knowledge as a subset of knowledge of the system.

CONCLUSION AND FUTURE DIRECTIONS

We have shown how, from a theoretical point of view and by applying our hypothesis on a concrete case, that the combination of the stereotype method and the Bayesian networks is an appropriate approach for the initialization of the learner model in the adaptive educational hypermedia systems.

The experiments presented in this article are all arguments in favor of our hypothesis on the probabilistic initialization of the learner model, using all the nodes as sensors to measure and evaluate the modulus of the learner.

This approach may encounter difficulties in the case of a large number of data stored in the system, for which we have proposed in previous works the use of multi Bayesian networks to try to cover all the data even if the number of data stored is pupil (Anouar Tadlaoui et al., 2014)

We see mainly two directions in which to continue this work. On the one hand, they integrate this method in the step of updating the learner model in an adaptive educational hypermedia system and on the other hand transform the Bayesian networks developed for the management of the learner model to a machine-readable language, such as ontologies, or as we previously proposed, using probabilistic ontologies as a formalism that gives us the possibility of combining Bayesian networks with ontologies. (Anouar Tadlaoui et al., 2015 ; Anouar Tadlaoui et al., 2018)

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Brusilovsky, P., Sosnovsky, S., & Shcherbinina, O. (2005, July). User modeling in a distributed e-learning architecture. In *International conference on user modeling* (pp. 387-391). Springer. 10.1007/11527886_50

Costa, P. C., Ladeira, M., Carvalho, R. N., Laskey, K. B., Santos, L. L., & Matsumoto, S. (2008, May). A first-order Bayesian tool for probabilistic ontologies. In *Proceedings of the Twenty-First International Florida Artificial Intelligence Research Society Conference* (pp. 631-636). Academic Press.

Han, B. (2001). *Student modelling and adaptivity in web-based learning systems*. Massey University New Zealand.

Rich, E. (1979, August). Building and exploiting user models. In *Proceedings of the 6th international joint conference on Artificial intelligence* (vol. 2, pp. 720-722). Morgan Kaufmann Publishers Inc.

Self, J. (1991). *Formal Approaches to Student Modeling*. Technical Report AI-59. Lancaster University.

Tsiriga, V., & Virvou, M. (2003, July). Initializing student models in web-based ITSs: a generic approach. In *Advanced Learning Technologies, 2003. Proceedings. The 3rd IEEE International Conference on* (pp. 42-46). IEEE. 10.1109/ICALT.2003.1215023

Yudelson, M., Brusilovsky, P., & Zadorozhny, V. (2007, July). A user modeling server for contemporary adaptive hypermedia: An evaluation of the push approach to evidence propagation. In *International conference on user modeling* (pp. 27-36). Springer.

Zaitseva, L., & Boule, C. (2005). Learning systems in professional training. In Workshop "Industry meets research" within the conference. Interactive Computer Aided Learning (ICL).

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

Bayesian Networks: Probabilistic graphical model or a type of statistical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learner Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

Stereotypes: A widely held but fixed and oversimplified image or idea of a particular type of person or thing.

Chapter 7
A Learner Model Based on Multi-Entity Bayesian Networks in Adaptive Hypermedia Educational Systems

ABSTRACT

This chapter presents a probabilistic and dynamic learner model based on multi-entity Bayesian networks and artificial intelligence. There are several methods for modelling the learner in AHES, but they're based on the initial profile of the learner created in his entry into the learning situation. They do not handle the uncertainty in the dynamic modelling of the learner based on the actions of the learner. The main purpose of this chapter is the management of the learner model based on MEBN and artificial intelligence, taking into account the different actions that the learner could take during his/her whole learning path. The approach that the authors followed in this chapter is marked initially by modelling the learner model in three levels: they started with the conceptual level of modelling with the unified modelling language, followed by the model based on Bayesian networks to be able to achieve probabilistic modelling in the three phases of learner modelling.

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INTRODUCTION

We have shown in previous works (Anouar Tadlaoui et al., 2017), that the learner model in adaptive hypermedia is characterized by its complexity, large data size, dynamic evolution, and relativities. We have also presented a very precise approach to its management by using a combination of methods, models and techniques to try to treat dynamically and probabilistically its evolution (Anouar Tadlaoui et al., 2016)

We will focus in this chapter on modeling the learner model in a dynamic and probabilistic way, we will propose in this work the use of the notion of fragments and M-theory to lead to a Multi-Entity Bayesian networks. The use of this Bayesian method can handle the whole course of a learner as well as all of its shares in an adaptive educational hypermedia.

The main hypothesis of this chapter is the management of the learner model based on multi-entity Bayesian networks. To achieve this goal, one must first ask the following questions: Why and how can one model the learner model with a probabilistic method? What is the approach to go from a conceptual modeling of this model to dynamic modeling? Is this taking into account experimentally justified?

First, we will return to the learner model that we first modeled using the Unified Modeling Language Use Case Diagram, and then we will present the Bayesian network of the learner model that we have developed. Then, we will explain the approach followed in this chapter for modeling the learner model with multi-entity Bayesian networks, beginning with the presentation of MEBNs and their composition, then explaining the notions of fragments and theories. Finally, and in order to dismantle the validity of our hypothesis, we will present the fragments of each node of our network, its random variables, and then present our multi-entity Bayesian network in a complete way.

LEARNER MODELING IN ADAPTIVE HYPERMEDIA

In this section, we will come back to the steps to follow when modeling the learner in an adaptive education system using UML, from the user's Meta model and in the use case diagram. Gathering all the learner's actions in the adaptive system.

The Learner Meta-Model

In this section, we will present a user-specific meta-model for e-Learning presented by Aammou (2013). This model includes a combination of models for e-Learning and adaptive hypermarkets. It takes into account elements such as the history of actions, which are missing in the formal models. The construction of this model allowed us to understand the user's creative process model for adaptive hypermedia, helping us build our hyperonym model (Anouar Tadlaoui et al., 2015)

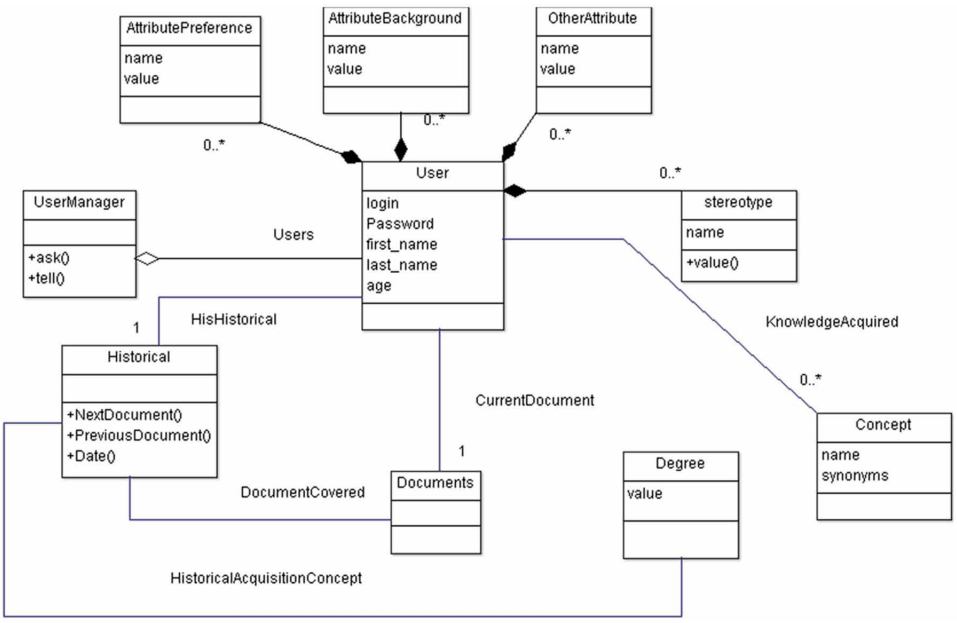
In our e-Learning user model, we want to be able to:

- Define characteristic attributes, essential and common to all users: name, username, password and age;
- Define the categories of attributes to separate the user's preferences, academic / professional characteristics and others. This distinction will make it easier to import data, maintain the system, and communicate with external systems; the attributes are differentiated according to their nature.
- Retain the documents covered by the user in two ways: first, by involving them in a complete course. On the other hand, specifically related to the notion they investigated. The purpose of this historical duplicate is to present the same documents to the user when he wishes to return to a concept already brought to his attention during his first learning of this concept.

The UML class diagram representation of our user model is given in Figure 1.

- **The User Manager** class is responsible for interfacing with the other components of adaptive hypermedia system. For this purpose, it is provided by the Ask and Tell methods to ask questions and provide answers to the external components (domain model, adaptation model). It is connected to all the users; and responsible for managing, by an aggregation relationship.
- **The User** class is responsible for representing information about a particular user. It is composed of predefined attributes: name, username, password and age.

Figure 1. The class diagram of the user Meta-model



- **Attribute Preference** class is responsible for representing the preferences of the user. These are view preferences: font size, color problems, contrast, etc., and his presentation preferences. He may prefer textual or graphic elements. And he may not want audio element, for example.
- **The Attribute Background** class is responsible for representing the user attributes related to their academic / professional background.
- **The Stereotype** class is responsible for representing the various categories of stereotypes to which the user belongs. By definition, a stereotype is an image or a fixed design and schematic of an aspect of reality. In our model, a stereotype consists of a name and a value. The name sets the stereotype (eg "learning rate") and the value is used to characterize the user (eg quick for the stereotype "learning rate"). The number of possible values is often reduced to a given stereotype. Values are often based on other attributes. Stereotypes are different from other attributes by their schematic characterization of the user, where they can represent much more granularity elements.

- **Other attribute** class is responsible for representing the user attributes not related to his career and which are not preferences, for example, a data encryption key. The purpose of this class is to ensure compatibility of the model with standard models like IMS or PAPI Learner, because some attributes do not fit into other categories of attributes defined above.
- **Degree** is an association class which is responsible for giving a value to the knowledge of a concept by the user. The possible values are: very low, low, average, good, excellent. This scale is a range of values that allows having a good precision with respect to a binary classification, and avoids a degree of accuracy too high and therefore it's very useful for adaptation.
- **Historical** class is in charge of representing a historical document covered in the learner path, allowing to give the date of the course of a document, browsing history in order in a historical path (it contains two methods NextDocument() and PreviousDocument()). The historic class can be used to represent all the documents covered by a user's history, or to represent the historical documents covered to reach a certain degree of knowledge for a given concept.

Both class Document and class Concept are detailed in the model domain

The Learner Model's Use Case Diagram

Based on the meta-model, we were able to map out the functionality of the learner using the use case diagram Figure 2 to reflect a part of the student's actions in an adaptive system. We will explain in this part each of these actions beholding the relationships of these actions with each other and within the system operation process.

Based upon the meta-model presented in the previous section, we have illustrated in the following table (Table 1).

Table 1. The main actions of a learner in a learning situation in an adaptive system

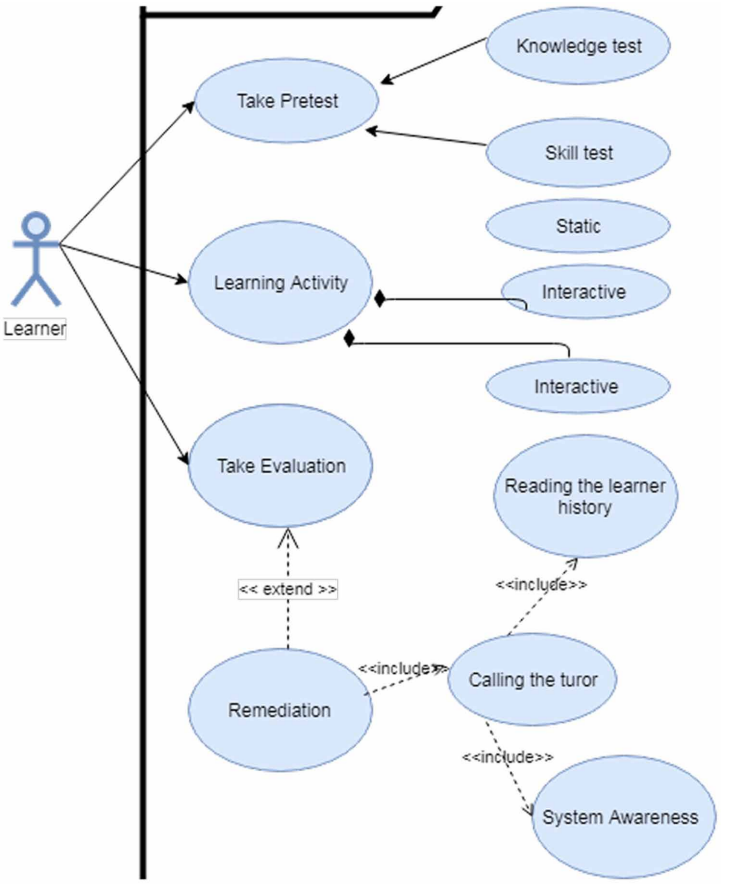
Learner's actions
• Follow courses • Take pretest • Take evaluation

In Figure 2 a main actor is identified, named "the learner". The figure shows the generalization relationships between use cases and the learner, and the generalization relationships: inclusion and extension between use cases.

In particular, the functional requirement "*learner*" represents all information about the learner in the hypermedia system (his knowledge, his skills, personal information ...). This functional requirement is shown with a generalization relationship with three functional requirements:

- "***Pretest***" which represents the information about the pretest that the learner has to take before entering the learning situation. The pretest is composed of two types of evaluation components: tests of knowledge depicted with the functional requirement "*knowledge*" and a functional

Figure 2. Use case diagram UML representing the learner actions



requirement "*skills*" which represents the test through which we will evaluate the learner's skills.

- "***Learning activity***": this functional requirement represents the information about the learning activities, each learning activity in adaptive educational hypermedia system is of two types, static activities represented by the functional requirement "*Static*" and interactive activities represented by the functional requirement "*Interactive*"
- "***Evaluation***", which represents the information about the evaluation tests that the learner has to take after the completion of each learning activity. In case of failure of the learner in the evaluation, the learner must pass to remediation; which is represented through a functional requirement "*remediation*" which is connected with the functional requirement "*evaluation*" through an extension of relationship.

In case of remediation, the functional requirement "remediation" involves the activation of the functional requirement "call tutor" through inclusion relation. This requirement represents the activation of the tutor to help the student to return to its shortcomings in the learning activity.

Another inclusion relation is represented in our figure which represents the actions of the learner in an adaptive system, appearing in the relationship between the functional requirement "call tutor" and requirements "reading the history of the learner" that activates the return of the system to the profile and the course information of the learner. And a requirement "system awareness", that enables the system to follow the course of the learner after remediation.

The Bayesian Network Developed From the Learner Model

The development of Bayesian network based on the use case diagram for modeling the learner in an adaptive educational system passes through two essential steps:

1. Specification of the Model Structure

Taking the case of the node "Learner" to illustrate the stages of development of our Bayesian network representing the model of the learner, notes that this node has three parent nodes (Pretest, Learning Activity and Evaluation), and each of these nodes is composed of child nodes. Links to these nodes are prerequisites relationships:

- **Learning activity:** In this node, all students following the course must go through activities, which are in the adaptive system of two types: static and interactive.
- **Pretest:** All learners, before taking the learning activities of each course must take a pre-test, it consists of two types of evaluation:
  - Knowledge: the student must answer more than 10 questions to measure how his wealth of knowledge. This type of evaluation reflects the evaluation part of the knowledge of the learner.
  - Skills: This is a written proof if the student can apply the knowledge gained in the module. This type of evaluation reflects the part of skills of the learner.
- **Evaluation:** After the student follows the learning activity, it is carried to conduct an evaluation to determine their level of knowledge and skill within the module. The evaluation is essential to guide the course of the learner.

The value that measures the relative importance of each condition varies from 0 to 1, the values of each evaluation element is defined by the teacher. In this case the teacher of the module "Database".

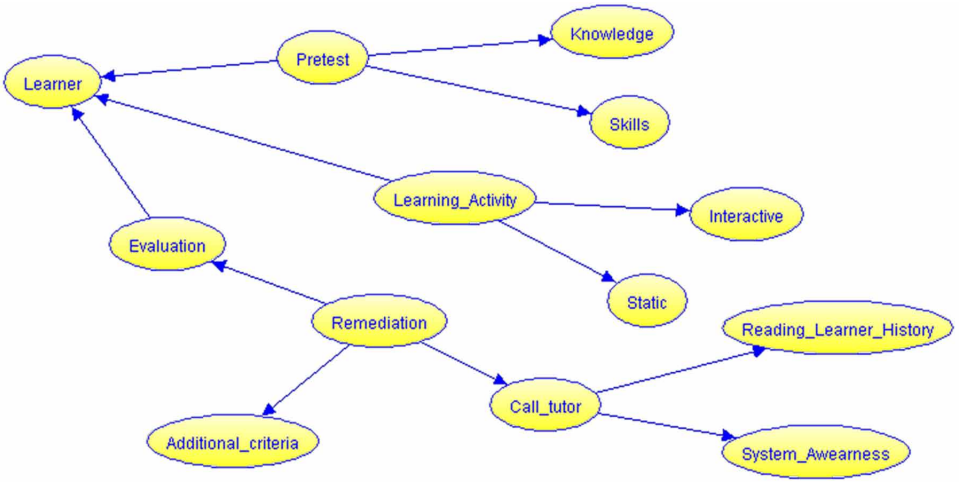
The relationship between the target variable (T) and the evidence variable (E) is from T to E because the process that calculates the posterior probability of target variable is the proof of knowledge of the diagnosis. So if variable evidence has no children, his parents must be the target variables. There are two types of relationships:

- Prerequisites Relations between target variables.
- Diagnostic Relations of target variables to evidence variables. The control of concepts (targets) affects on confidence of evidence. However, if the learner has failed a test, it is not sure of his lack of knowledge or ability because it can make an unexpected error.

2. The Specification of Variable Values

Once the use case diagrams were created, it is easy to create the structure of the Bayesian network using the rules described in the previous sections. Figure 3 represents the Bayesian network built from the use case diagram shown in the previous section. Notice how the conditional independence was directly modeled by applying the rules as shown.

Figure 3. The Bayesian network developed of the Learner model



In the Bayesian network developed, we observe that the node Learner (L) has three parents: Learning Activity (A), Evaluation (E) and Pretest (T) which in turn are corresponding to three weights of prerequisite relationship: w1=0.1, w2=0.5, w3=0.4. Conditional probability of (L) is computed as follows:

$$P\left(L|A,E,T\right) = w1{*}h1 + w2{*}h2 + w3{*}h3$$

where:

$$h1 = \begin{cases} 1 \ if A = L \\ 0 \ otherwise \end{cases}$$

$$h2 = \begin{cases} 1 \ if E = L \\ 0 \ otherwise \end{cases}$$

$$h3 = \begin{cases} 1 \ if T = L \\ 0 \ otherwise \end{cases}$$

We should state that {L, A, E, T} is complete set of mutually exclusive variables, which each also a random and binary variable.

Generalizing about formula below, it is that:

$$P\left(X=1|\,Y1,Y2\ldots Yn\right)=\sum_{i=1}^{n}wi*hi$$

where

$$h1=\begin{cases}1\ \ if Yi=X\\ 0\ \ otherwise\end{cases}$$

With given random binary variables X, Yi. Obviously,

$$P\left(notX|\,Y1,Y2,\ldots,\ \ Yn\right)=1-P(X\mid Y1,Y2,\ldots,Yn)\,.$$

- **The conditional probability table of the node "Learner"**

Table 2 represents the CPT of each child node of the parent node Learner.

Because concepts A, E, T have no prerequisite knowledge for understanding, their CPTs are specified as prior probabilities obeying uniform distribution as stated in "Table 3" (assigned medium value 0.5 in most cases)

- **The conditional probability table of the node "Pretest"**

Table 4 represents the CPT of each child node of the parent node Pretest.

Table 2. The conditional probability table of "Learner" node

A	T	E	P(J=1)	1-P(J=1) P(J=0)
1	1	1	1.0 (0.1*1 + 0.4*1+ 0.5*1)	0.0
1	0	1	0.6 (0.1*1 + 0.4*0+ 0.5*1)	0.4
1	1	0	0.5 (0.1*1 + 0.4*1+ 0.5*0)	0.5
1	0	0	0.1 (0.1*1 + 0.4*0+ 0.5*0)	0.9
0	1	1	0.9 (0.1*0 + 0.4*1+ 0.5*1)	0.1
0	0	1	0.5 (0.1*0 + 0.4*0+ 0.5*1)	0.5
0	1	0	0.4 (0.1*0 + 0.4*1+ 0.5*0)	0.4
0	0	0	0.0 (0.1*0 + 0.4*0+ 0.5*0)	1.0

Table 3. The conditional probability table of "Learner" parents

P(A=1)	P(A=0)	P(T=1)	P(T=1)	P(E=1)	P(E=1)
0.5	0.5	0.5	0.5	0.5	0.5

- **The conditional probability table of the node "Learning activity"**

Table 5 represents the CPT of each child node of the parent node learning activity.

MULTI-ENTITY BAYESIAN NETWORKS

In this part of our chapter, we will present the state of the art on Multi-Entity Bayesian networks, which are considered the new generation of probabilistic

Table 4. The conditional probability table of "Pretest" node

S	P(J=1)	P(J=0) 1-p(J=1)
1	0.2(0.2*1)	0.8
0	0.0(0.8*0)	1.0

D	P(J=1)	P(J=0) 1-p(J=1)
1	0.4(0.4*1)	0.6
0	0.0(0.6*0)	1.0

Table 5. The conditional probability table of "Learning activity" node

S	P(J=1)	P(J=0) 1-p(J=1)
1	0.6(0.6*1)	0.4
0	0.0(0.6*0)	1.0

D	P(J=1)	P(J=0) 1-p(J=1)
1	0.4(0.4*1)	0.6
0	0.0(0.6*0)	1.0

modeling, and on which we based our research for the management of the model of learning in adaptive hypermedia. We will first begin by presenting the first-order logic, which is considered the basis of Bayesian networks, and then we will present Multi-Entity Bayesian networks, their principles and their logic.

First-Order Logic

First-order logic is by far the logical system most commonly used, studied and implemented. First-order logic is a formal system used to define theories in mathematics, computer science, and other scientific fields. It is a very important concept from both a theoretical and a practical point of view. First-order logic can also be used as a rigorous foundation for knowledge representation systems (Laskey, 2008)

A theory in first-order logic consists of axioms, expressed in sentences in the first-order language, in conjunction with sentences derived from axioms according to the rules of reasoning, that is, valid theorems or sentences. In practice, when a first order theory is implemented in a computer, the axioms are stored as data structures and the reasoning that evaluates the truth value of a sentence to the form of a computer program.

Theories are expressed using the first-order logical language. The main components of the first-order logical language are constants, variables, functions, and predicates. Variables are placeholders for constants. The functions return a relative constant of their input arguments. Predicates are an essential component of first-order logic (the reason why it is also called predicate logic), since they are used to define relationships between other components, such as variables and constants. For example, the preaching parents (John, Mary, George), can say that John and Mary are relatives of George. What also makes the first-order logic a strongly expressive language are the rules, such as “brothers (X, Y): - parents (X, X1, X2) AND (Y, X1, X2)”. This rule states that two persons X, Y are siblings if they have the same parents.

An interpretation of a first-order logical theory gives a semantic meaning to each constant, predicate, and function (formulas). Specifically, an interpretation maps each formula to a specific nominal entity, to the constraints of each predicate to relate with other entities belonging to a specific set, and links a function to a domain function. A set containing all the instantiated formulas of a first-order logical theory is called an interpretation.

However, first-order logic does not provide expressivity for modeling uncertain knowledge, let alone a rigorous reasoning mechanism. This is a consequence of the fact that each interpretation mentioned above shares an equal validity with the others. As we will see in the following sections, the key feature of MEBN is the assignment of a probability to each interpretation. This is achieved with Bayesian first order logic (FOBL) (Laskey et al., 2000)

Presentation of Multi-Entity Bayesian Networks

Multi-Entity Bayesian networks are logical systems that integrate first-order logic (FOL) with Bayesian probability theory. Multi-Entity Bayesian networks extend ordinary Bayesian networks to allow representation of graphical models with repeated substructures. Knowledge is coded as a collection of Bayesian network fragments (called MFrags) that can be instantiated and combined to form Bayesian networks specific to the complex situation. A theory of multi-entity Bayesian networks (M-Theory) implicitly represents a joint probability distribution on possibly unlimited numbers of hypotheses and uses Bayesian learning to refine a knowledge base as observations accumulate. The multi-entity Bayesian network provides a logical basis for the emergent collection of highly expressive, probability-based languages. (Costa et al., 2005)

Multi-Entity Bayesian networks (MEBNs) are the result of combining Bayesian networks with first-order logic (FOL). In other words, in a MEBN, Bayesian network capability to model uncertainty is combined with first-order logic expressivity. From the point of view of stochastic Bayesian modeling, the goal of using MEBN is to build a Bayesian Situation-Specific Network (SSBN) that is customized based on the snapshot of the environment in that situation. In multi-entity Bayesian networks, the Bayesian network is extended to a first-order logical Bayesian network (FOBN), which is used to express and represent knowledge. This overcomes the gap in Bayesian networks by being very rigid and inflexible for modeling dynamic environments. (Costa, 2005)

Multi-Entity Bayesian networks integrate first-order logic with Bayesian probability. The logic of Multi-Entity Bayesian networks expresses probabilistic knowledge as a collection of fragments of Multi-Entity Bayesian networks (MFrags) organized into Multi-Entity Bayesian networks (MTheories). An MFrag represents a conditional probability distribution of the instances of its resident random variables taking into account the values of their parent instances in the fragment graphics and given context constraints (Laskey, 2008)

A collection of MFrags represents a joint probability distribution over an unlimited number, possibly infinite, of its random variables. Joint distribution is specified using local distributions with conditional independence relationships implied by fragmented graphics. Contextual terms are used to specify the constraints under which local distributions apply.

A collection of MFrags that satisfies consistency constraints ensuring the existence of a single joint probability distribution on its random variables is called MTheories. MTheories can express probability distributions on the truth values of arbitrary first-order logic sequences and can be used to express domain-specific ontologies that capture statistical regularities in a particular application domain.

In addition, MTheories may represent particular facts relevant to a given reasoning problem. The conditioning of a prior distribution represented by an MTheorie on its results is the basis of the probabilistic inference with the logic of multi-entity Bayesian networks (Carvalho, 2011)

Fragments of Multi-Entity Bayesian Networks

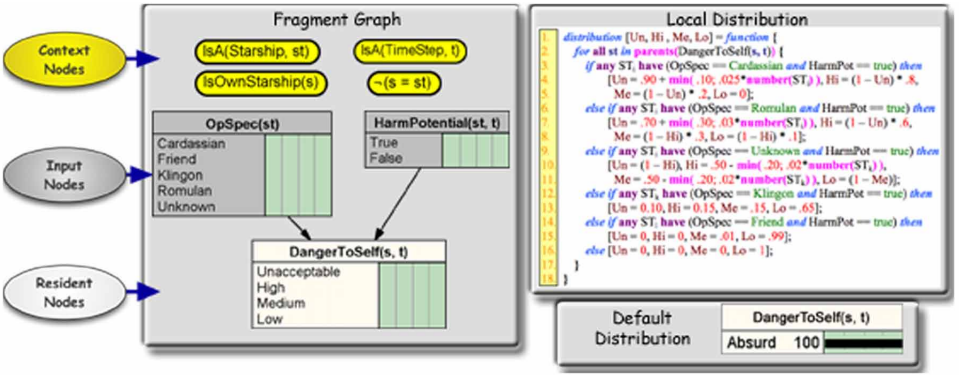
The logic of Multi-Entity Bayesian networks represents the world composed of entities with attributes and related to other entities. Random variables represent features of entities and relationships between entities. The knowledge of attributes and relationships is expressed as a collection of fragments organized in M-Theory. A fragment represents a conditional probability distribution for the cases of its resident RVs given their parents in the fragment graph and the context nodes (Carvalho, 2011)

Like a Bayesian network, an MFrag contains nodes, which represent random variables, arranged in a directed graph whose edges represent direct dependency relationships. An isolated MFrag can be compared to a standard Bayesian network with known values for its root nodes and known local distributions for its child nodes.

For example, the MFrag shown in Figure 4 was taken from a model of a Multi-Entity Bayesian networks on the Star Trek domain and represents knowledge of the degree of danger to which the spacecraft is exposed. The fragment graph has seven nodes. The four nodes at the top of the figure are contextual nodes; the two rectangular nodes shaded under the contextual nodes are the input nodes; and the lower node is a resident node.

A node in an MFrag can have a parentheses list of arguments. These arguments are placeholders for domain entities. For example, the *st* argument

Figure 4. Example of a fragment of multi-entity Bayesian networks (Carvalho et al., 2010)



of the *HarmPotential* node *(st, t)* is a placeholder for an entity that may be harmful, while the t argument is a placeholder for the time step that this instance represents. To refer to an actual entity in the domain, the argument is replaced by a unique identifier. By convention, unique identifiers begin with an exclamation point and no separate entity can have the same unique identifier. The result of the substitution of unique identifiers for the arguments of a random variable is one or more instances of this variable. For example, *HarmPotential (! ST1,! T1)* and *HarmPotential (! ST2,! T1)* are two instances of *HarmPotential (st, t)* that both occur in the time step*!T1*.

The resident nodes of an MFrag have local distributions that define how their probabilities depend on their parent's values in the fragment graph. In a complete M-Theory, each random variable has exactly one domestic MFrag, where its local distribution is defined. The input and context nodes (for example, OpSpec (st) or IsOwnStarship (s)) influence the distribution of resident nodes, but their distributions are defined in their own home MFrags (Carvalho et al., 2010)

Contextual nodes represent conditions that must be satisfied for local influences and distributions of the fragment graph to be applied. Contextual nodes can have a true, false, or absurd value. Context nodes with a true value are considered satisfied. For example, if the unique identifier for *Enterprise (! ST0)* is replaced by the variable s in *IsOwnStarship (s)*, the resulting assumption will be true. If, instead, a unique star identifier (ST1) is used, then this assumption will be false. Finally, if the unique identifier of a *Non-spacecraft (! Z1)* replaces *s*, this statement is absurd (ie it is absurd to wonder if an area in space is its own ship spatial).

To avoid cluttering the graph of fragments, the states of the context nodes are not represented, unlike what happens with the input and resident nodes. This is mainly because they are Boolean nodes whose values are relevant only to decide whether to use the local distribution of a residential random variable or its default distribution. (Wright et al., 2002) (Costa et al., 2009)

MANAGING THE LEARNER MODEL WITH MULTI-ENTITY BAYESIAN NETWORKS

In this part of the chapter, we will first present the fragments that we have developed from the Bayesian Learner Model Network. Then, we will present the complete Multi-Entity Bayesian networks of the learner model based on first-order logic.

Fragments of the Learner Model

In the previous sections of this chapter, we presented the Bayesian network of the learner model that we developed from a use case diagram. To arrive at a multi-entity Bayesian network of the learner model, it is essential to start by first developing the fragments of this network based on the predominant nodes of this network.

The main nodes of our Bayesian network, which will be transformed into fragments of the Multi-Entity Bayesian networks of the learner model, are:

- The pre-test fragment
- The learning situation fragment
- The evaluation fragment

In order to develop the Multi-Entity Bayesian networks of the learner model, it is first necessary to define the context nodes, the input nodes, and the distribution within each resident node of these fragments.

1. Fragment of the Node Pre-Test

For the pre-test node fragment that represents information about the pre-test that the learner must first pass before entering a learning situation. This fragment is composed as we have already shown in the previous sections of

two types of Pre-tests, the first concerns the knowledge of the learner, and the second is a pre-test concerning the skills of the learner.

The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the multi-entity Bayesian network. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the multi-entity Bayesian network.

Figure 5 shows the fragment of the Pre-test node of our multi-entity Bayesian network. There are two random variables in our fragment, is (Knowledge, Abilities) which concerns the determination of the type of Pre-test that the learner must take represented by the input random variable Type *Pre-test (obj).* And the variable *isP (Passed, Failed)* which concerns the validation of the Pre-test by the learner represented by the input random variable *ValidationPre-test (obj).*

2. Fragment of the Node Learning Activity

For the node learning activity fragment, that represents information about the learning activity that the learner must follow during his or her learning path. This fragment is composed as we have already shown in the preceding sections of two types of activities. The first type of activity is interactive, and the second type is static.

The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the multi-entity Bayesian network. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the multi-entity Bayesian network.

Figure 5. The fragment of the node pre-test of the MEBN

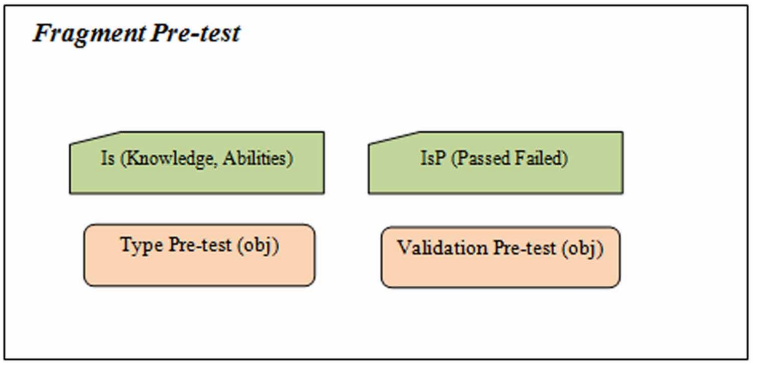


Figure 6. The fragment of the node Learning Activity of the MEBN

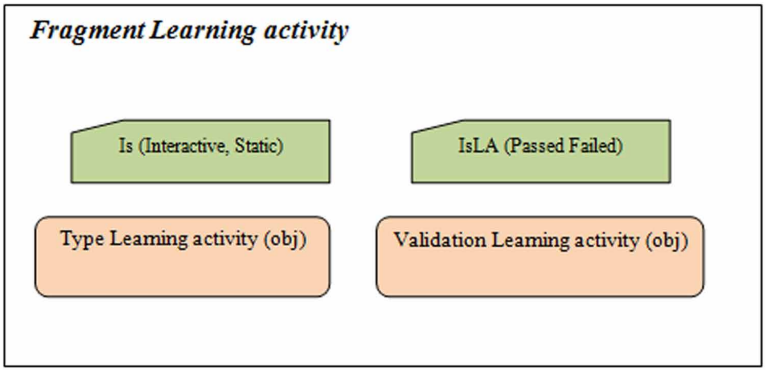


Figure 6 shows the fragment of the learning activity node of our multi-entity Bayesian network. There are two random variables in our fragment, is (Interactive, Static) which relates to the determination of the type of learning activity that the learner must follow represented by the input random variable Type *Learning Activity (obj).* And the variable *isAP (Passed, Failed)* which concerns the validation of the learning activity by the learner represented by the input random variable *Validation Learning Activity (obj).*

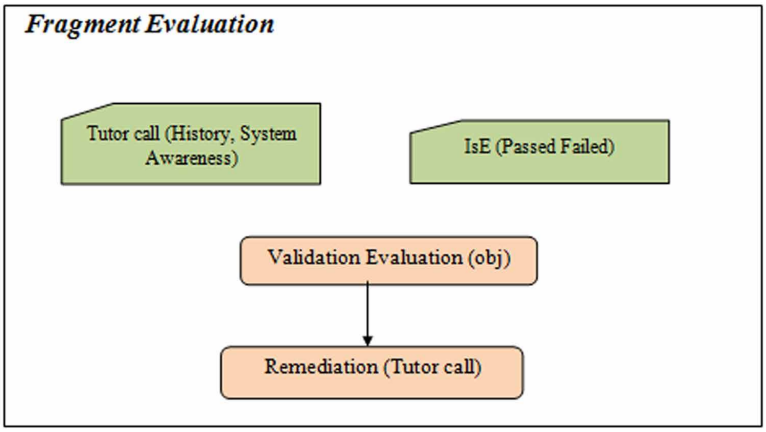
3. Fragment of the Node Evaluation

For the node evaluation fragment, that represents the assessment information that the learner must take at the end of each learning activity during their learning journey. This fragment is composed as we have already shown in the chapters of a primordial relation concerning the call of a tutor to help the learner in case of remediation.

The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the multi-entity Bayesian network. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the multi-entity Bayesian network.

Figure 7 shows the fragment of the node Evaluation of our multi-entity Bayesian network. There are two random variables in our *tutor call(History, System Awareness)* fragment that pertains to a tutor's call to help the learner based on his or her browsing history and to sensitize the system to the remediation case that is represented by the random input variable Remediation

Figure 7. The fragment of node the Learning Activity of the MEBN



(Tutor call). And the variable *isE (Passed, Failed)* which concerns the validation of the evaluation by the learner represented by the input random variable *Validation Evaluation (obj).*

The Random input variable *Remediation (Tutor call)* is related to the conditioning of the input random variable *Validation Evaluation (obj),* which means that remediation is enabled only in the case of failure of the evaluation, this condition requires the tutor's call to help the learner in difficulty.

The Multi-Entity Bayesian Network of the Learner Model

After the development of the three main fragments of our Bayesian network, we will present in this part the complete multi-entity Bayesian network of our learner model. As we defined in the previous sections of this chapter, the knowledge of attributes and relationships is expressed as a collection of fragments organized in M-Theory.

We will begin with a presentation of the learner fragment of our learner model, which concerns the main node of our learner model, its random variables, its output variables, and the probabilistic relationships between the father node and its children. Then we will treat the multi-entity Bayesian network of the learner model that represents all the fragments of the model and the relationships between them.

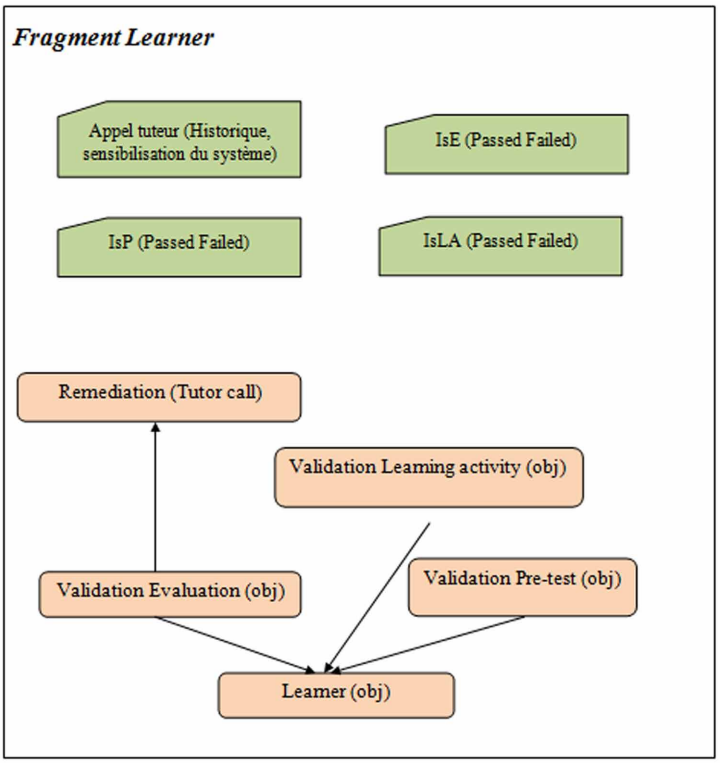
1. Learner's Node Fragment

For the learning node, there are three child nodes of this main node: the Pre-test, the learning activity, and the evaluation, which in turn represents a conditional child node called remediation.

The green flowcharts in our fragment represent the random variables of the context that express the validation conditions of our fragment within the multi-entity Bayesian network. The rounded rectangles in our fragment represent the input random variables, the distribution of its variables will be used in other fragments of the multi-entity Bayesian network.

Figure 8 shows the fragment of the learner node of our multi-entity Bayesian network. There are four random variables in our tutor *call (History, System Awareness)* fragment which concerns a tutor's call to help the learner based on his / her browsing history and to sensitize the system to the case of remediation that is represented by the random input variable Remediation (Tutor call).

Figure 8. The learner fragment of the learner model



And the variable *isE (Passed, Failed)* which concerns the validation of the evaluation by the learner represented by the input random variable *Validation Evaluation (obj).* The variable *isAP (Passed, Failed)* which concerns the validation of the learning activity by the learner represented by the input random variable *Validation Learning Activity (obj)* .And the *variable isP (Passed, Failed)*which the validation of the pre-test performed by the learner represented thanks to the input random variable *Validation Pre-test (obj).*

The learner in this fragment begins by passing the pre-test of the entry through a random variable input *validation pre-test (obj).* After the validation of this condition, the learner is directed to a learning activity, and will be led to validate it by reaching the conditions for success of the random variable *Validation Learning Activity (obj).* And finally, the learner will be led to pass an evaluation in the random variable *Validation Evaluation (obj)*. In case of failure of this assessment, a remediation will be activated in the Random Remediation variable which requires a call to the tutor who will help the learners in difficulty based on their browsing history.

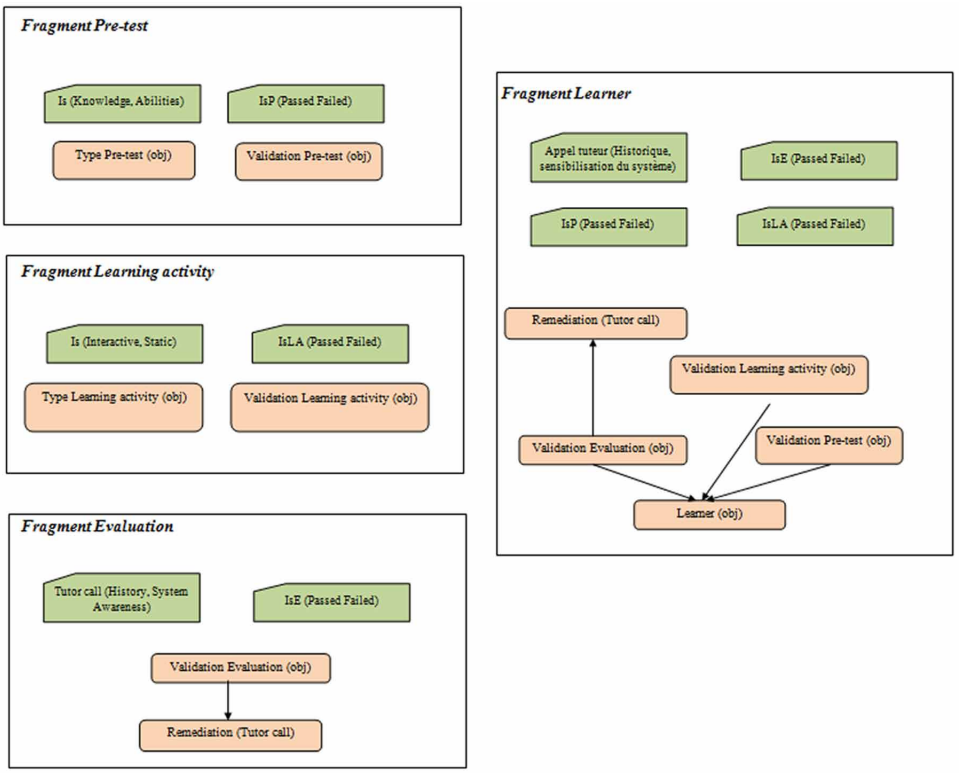
2. The M-Theory of the Learner Model

Figure 9 shows the M-Theory of the learner model, a set of coherent fragments defining a joint distribution on situations involving cases of random variables. There are 3 fragments in our M-theory of the learner model such as the Pre-Test, the Learning Activity as well as the Evaluation, and finally the Learner reference fragment. Each of the MFrags consists of context, input and resident nodes.

The multi-entity Bayesian network of the learner model developed can be used to estimate and predict a learning situation in adaptive hypermedia systems, dynamically tracking in real time all learners' actions during their course. Learning pathways and during their presence in adaptive hypermedia.

The fact that multi-entity Bayesian networks incorporate the ontology concept into their modeling part allows the systematic collection and formal representation of multiple concepts of learner knowledge. Thus, with Multi-Entity Bayesian networks, we also aim to exploit the useful functionality of ontologies to facilitate a practical and non-error-prone development of the part of the representation of learner knowledge within adaptive educational hypermedia. Thus, Multi-Entity Bayesian networks combine, for this specific problem, the advantages of the two worlds, that is, the expression and representation of knowledge on the framework of ontologies and the

Figure 9. The M-Theory of the Learner Model in an Adaptive Hypermedia



uncertainty of modeling using probabilistic models on the framework of Bayesian networks.

All of the elements discussed above represent the essence of this work. The transformation of Bayesian networks developed for the management of the learner model to machine-readable language, such as ontologies, or as we have already proposed, using probabilistic ontologies as a formalism that gives us the possibility of combine Bayesian networks with ontologies (Anouar Tadlaoui et al., 2014; Anouar Tadlaoui et al., 2018)

CONCLUSION

We have already introduced our learner model using Bayesian networks as formalization for learner management. Also, we have covered all phases of initialization and updating of this model thanks to the combination of networks

with other methods and models to ensure a complete management of all areas of the learner model. We wanted to take our work to the next level, to machine-readable modeling. This is why the main hypothesis of this chapter was the management of the learner model based on multi-entity Bayesian networks, for a dynamic and probabilistic management of the learner model in adaptive hypermedia.

The approach that we followed during this report is marked initially by modeling the learner model in three levels: we started with the conceptual level of modeling with the unified modeling language, followed by the modeling model based on Bayesian networks to be able to achieve probabilistic modeling in the three phases of learner modeling. Finally, we have proposed in this last chapter a dynamic and probabilistic modeling of this model using multi-entity Bayesian networks.

This approach is considered very useful for the learner model, especially in the case of a large number of data stored in the system. The transformation of the nodes for fragments gives us the possibility of a separate management of the data of each fragment, keeping at the same time all types of relations of each fragment with the other fragments by using the random variables which exist in several fragments within an M-Theory of the learner model.

REFERENCES

Anouar Tadlaoui, M. (2016). *Gestion d'un modèle d'apprenant dans un système éducatif adaptatif basée sur les réseaux bayésiens*. Academic Press.

Anouar Tadlaoui, M., Aammou, S., Khaldi, M., & Carvalho, R. N. (2016). Learner modeling in adaptive educational systems: A comparative study. *International Journal of Modern Education and Computer Science*, *8*(3), 1–10. doi:10.5815/ijmecs.2016.03.01

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2017). The initialization of the learner model combining the Bayesian networks and the stereotypes methods. *International Journal of Advanced Computer Research*, *7*(33), 200–212. doi:10.19101/IJACR.2017.733024

Anouar Tadlaoui, M., Carvalho, R. N., & Khaldi, M. (2018). A learner model based on multi-entity Bayesian networks and artificial intelligence in adaptive hypermedia educational systems. *International Journal of Advanced Computer Research*, *8*(37), 148–160.

Anouar Tadlaoui, M., Khaldi, M., & Aammou, S. (2014). Towards a Learning model based on Bayesian Networks. In *EDULEARN14 Proceedings* (pp. 3185-3193). IATED.

Anouar Tadlaoui, M., Mohamed, K., & Souhaib, A. (2014). Towards probabilistic ontology based on Bayesian Networks. *International Journal of Software and Web Sciences*, *1*(10), 102–106.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Learner Modeling Based on Bayesian Networks. In E-Learning-Instructional Design, Organizational Strategy and Management. InTech.

Anouar Tadlaoui, M., Souhaib, A., & Mohamed, K. (2015). Developement of Bayesian Networks from Unified Modeling Language for Learner Modelling. *International Journal of Adavanced Computer Science and Applications*, *6*(2).

Carvalho, R. N. (2011). *Probabilistic Ontology: Representation and Modeling Methodology* (PhD dissertation). George Mason University.

Carvalho, R. N., Costa, P. C. G., Laskey, K. B., & Chang, K. C. (2010, July). PROGNOS: predictive situational awareness with probabilistic ontologies. In *Information Fusion (FUSION), 2010 13th Conference on* (pp. 1-8). IEEE. 10.1109/ICIF.2010.5711970

Costa, P. C., Laskey, K. B., Takikawa, M., Pool, M., Fung, F., & Wright, E. J. (2005). MEBN logic: A key enabler for network centric warfare. In *Proceedings of the 178 Tenth International Command and Control Research and Technology Symposium (10th ICCRTS)*. Academic Press.

Costa, P. C. G. (2005). *Bayesian Semantics for the Semantic Web* (PhD dissertation). George Mason University.

Costa, P. C. G., Laskey, K. B., & Chang, K. C. (2009). PROGNOS: Applying Probabilistic Ontologies To Distributed Predictive Situation Assessment In Naval Operations. *Proceedings of the 14th Int. Command And Control Research and Technology Symposium*.

Laskey, K. B. (2008). MEBN: A language for first-order Bayesian knowledge bases. *Artificial Intelligence*, *172*(2-3), 140–178. doi:10.1016/j.artint.2007.09.006

Laskey, K. B., D'ambrosio, B., Levitt, T. S., & Mahoney, S. (2000). Limited rationality in action: Decision Support for military situation assessment. *Minds and Machines*, *10*(1), 53–77. doi:10.1023/A:1008398822124

Souhaib, A. (2013). *Conception de l'intéropérabilité sémantique des systèmes hypermédia adaptatifs éducatifs, basée sur les ontologies*. Academic Press.

Wright, E., Mahoney, S., Laskey, K., Takikawa, M., & Levitt, T. (2002, July). Multi-entity Bayesian networks for situation assessment. In *Information Fusion, 2002. Proceedings of the Fifth International Conference on* (*Vol. 2*, pp. 804-811). IEEE.

ADDITIONAL READING

Brusilovsky, P., & Maybury, M. T. (2002). From adaptive hypermedia to the adaptive web. *Communications of the ACM*, *45*(5), 30–33. doi:10.1145/506218.506239

Bull, S., & Nghiem, T. (2002, June). Helping learners to understand themselves with a learner model open to students, peers and instructors. In Proceedings of workshop on individual and group modelling methods that help learners understand themselves, International Conference on Intelligent Tutoring Systems (Vol. 2002, pp. 5-13).

Dimitrova, V. (2003). STyLE-OLM: Interactive open learner modelling. *International Journal of Artificial Intelligence in Education*, *13*(1), 35–78.

Mabbott, A., & Bull, S. (2006, June). Student preferences for editing, persuading, and negotiating the open learner model. In *International Conference on Intelligent Tutoring Systems*(pp. 481-490). Springer, Berlin, Heidelberg. 10.1007/11774303_48

Montebello, M. (2018). User Profiling and Personalisation. In *AI Injected e-Learning* (pp. 27–37). Cham: Springer. doi:10.1007/978-3-319-67928-0_4

Nguyen, L., & Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, *45*(70), 395–400.

KEY TERMS AND DEFINITIONS

Adaptive Hypermedia Systems: On-line information and help systems, as well as institutional information systems, that provide hyperlinks that are most relevant to the user in an effort to shape the user's cognitive load.

Bayesian Networks: Probabilistic graphical model or a type of statistical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph.

E-Learning: A concept that describes the cognitive science principles of effective multimedia learning using electronic educational technology.

Learner Model: A model that contain all the static information of the learner in an adaptive system and his/her actions during a learning situation.

Learner Profile: A part of the learner model that only contain the static information of the learner that could be gathered before developing a learner model.

Learner Situation: A part of a learning path that the learner takes to achieve a diploma or a certification.

Multi-Entity Bayesian Networks: A logic system that integrates first order logic (FOL) with Bayesian probability theory.

Related Readings

To continue IGI Global's long-standing tradition of advancing innovation through emerging research, please find below a compiled list of recommended IGI Global book chapters and journal articles in the areas of online learning, asynchronous learning experiences, and technological pedagogical content knowledge. These related readings will provide additional information and guidance to further enrich your knowledge and assist you with your own research.

Abdelaziz, H. A. (2014). Creative Design of Interactive eLearning Activities and Materials (IEAM): A Psycho-Pedagogical Model. *International Journal of Technology Diffusion*, *5*(4), 14–34. doi:10.4018/ijtd.2014100102

Abdelmalak, M. M., & Parra, J. L. (2016). Expanding Learning Opportunities for Graduate Students with HyFlex Course Design. *International Journal of Online Pedagogy and Course Design*, *6*(4), 19–37. doi:10.4018/IJOPCD.2016100102

Abera, B. (2014). Applying a Technological Pedagogical Content Knowledge Framework in Ethiopian English Language Teacher Education. In T. Issa, P. Isaias, & P. Kommers (Eds.), *Multicultural Awareness and Technology in Higher Education: Global Perspectives* (pp. 286–301). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5876-9.ch014

Adegbenro, J. B., Gumbo, M. T., & Olugbara, O. O. (2015). Exploring Technological Knowledge of Office Data Processing Teachers: Using Factor Analytic Methods. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 548–576). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch021

Amador, F., Nobre, A., & Barros, D. (2016). Towards a Model of a Didactics of eLearning: An Application to Education for Sustainable Development. In M. Pinheiro & D. Simões (Eds.), *Handbook of Research on Engaging Digital Natives in Higher Education Settings* (pp. 396–415). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0039-1.ch019

Amador, J. M., Kimmons, R., Miller, B. G., Desjardins, C. D., & Hall, C. (2015). Preparing Preservice Teachers to Become Self-Reflective of Their Technology Integration Practices. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 81–107). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch004

Archambault, L. (2014). Teaching Virtually: Strategies and Challenges in the 21st Century Online Classroom. *International Journal of Online Pedagogy and Course Design*, *4*(1), 1–15. doi:10.4018/ijopcd.2014010101

Arinze, B., Sylla, C., & Amobi, O. (2016). Cloud Computing for Teaching and Learning: Design Strategies. In L. Chao (Ed.), *Handbook of Research on Cloud-Based STEM Education for Improved Learning Outcomes* (pp. 159–171). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9924-3.ch011

Aşık, A. (2016). Digital Storytelling and Its Tools for Language Teaching: Perceptions and Reflections of Pre-Service Teachers. *International Journal of Computer-Assisted Language Learning and Teaching*, *6*(1), 55–68. doi:10.4018/IJCALLT.2016010104

Attard, C. (2015). Introducing iPads into Primary Mathematics Classrooms: Teachers' Experiences and Pedagogies. In M. Meletiou-Mavrotheris, K. Mavrou, & E. Paparistodemou (Eds.), *Integrating Touch-Enabled and Mobile Devices into Contemporary Mathematics Education* (pp. 193–213). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8714-1.ch009

Baert, H. (2015). Technology Tools, Proficiency, and Integration of Physical Education Teacher Educators. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 223–254). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch009

Banas, J. R., & York, C. S. (2014). The Impact of Authentic Learning Exercises On Pre-service Teachers' Motivational Beliefs towards Technology Integration. *International Journal of Information and Communication Technology Education*, *10*(3), 60–76. doi:10.4018/ijicte.2014070105

Barakat, M., & Weiss-Randall, D. N. (2016). Through the Eyes of Students and Faculty: A Conceptual Framework for the Development of Online Courses. In V. Wang (Ed.), *Handbook of Research on Learning Outcomes and Opportunities in the Digital Age* (pp. 557–584). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9577-1.ch025

Baran, M. L., & Jones, J. E. (2014). Online Learning: Guidelines for Team Effectiveness. In C. Stevenson & J. Bauer (Eds.), *Building Online Communities in Higher Education Institutions: Creating Collaborative Experience* (pp. 279–292). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5178-4.ch015

Barbour, M. K., Adelstein, D., & Morrison, J. (2014). The Forgotten Teachers in K-12 Online Learning: Examining the Perceptions of Teachers Who Develop K-12 Online Courses. *International Journal of Online Pedagogy and Course Design*, *4*(3), 18–33. doi:10.4018/ijopcd.2014070102

Boboc, M. (2014). Connecting Communication to Curriculum and Pedagogy in Online Environments. In C. Stevenson & J. Bauer (Eds.), *Building Online Communities in Higher Education Institutions: Creating Collaborative Experience* (pp. 132–156). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5178-4.ch007

Borasi, R., Fredericksen, E., & Miller, D. (2017). From 0 to 60: The Case Study of a School of Education's Successful "Online Start-Up". In K. Shelton & K. Pedersen (Eds.), *Handbook of Research on Building, Growing, and Sustaining Quality E-Learning Programs* (pp. 60–83). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0877-9.ch004

Bowers, J., & Kumar, P. (2015). Students' Perceptions of Teaching and Social Presence: A Comparative Analysis of Face-to-Face and Online Learning Environments. *International Journal of Web-Based Learning and Teaching Technologies*, *10*(1), 27–44. doi:10.4018/ijwltt.2015010103

Breen, P. (2014). Philosophies, Traditional Pedagogy, and New Technologies: A Report on a Case Study of EAP Teachers' Integration of Technology into Traditional Practice. In P. Breen (Ed.), *Cases on Teacher Identity, Diversity, and Cognition in Higher Education* (pp. 317–341). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5990-2.ch013

Brockmeier, F. (2017). Service Learning Online: Preparing to Work in Global Societies with E-Service-Learning. In C. Crosby & F. Brockmeier (Eds.), *Student Experiences and Educational Outcomes in Community Engagement for the 21st Century* (pp. 150–172). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0874-8.ch007

Brunvand, S. (2016). Facilitating Student Interaction and Collaboration in a MOOC Environment. In R. Mendoza-Gonzalez (Ed.), *User-Centered Design Strategies for Massive Open Online Courses (MOOCs)* (pp. 1–14). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9743-0.ch001

Bull, P. H., & Patterson, G. C. (2016). Strategies to Promote Pedagogical Knowledge Interplay with Technology. In J. Keengwe & G. Onchwari (Eds.), *Handbook of Research on Active Learning and the Flipped Classroom Model in the Digital Age* (pp. 255–271). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9680-8.ch013

Bush, S. B., Driskell, S. O., Niess, M. L., Pugalee, D., Rakes, C. R., & Ronau, R. N. (2015). The Impact of Digital Technologies in Mathematics Pre-Service Teacher Preparation over Four Decades. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 1–27). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch001

Chen, C. (2016). Effective Learning Strategies for the 21st Century: Implications for the E-Learning. In M. Anderson & C. Gavan (Eds.), *Developing Effective Educational Experiences through Learning Analytics* (pp. 143–169). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9983-0.ch006

Chen, C., Chiu, P., & Huang, Y. (2015). The Learning Style-Based Adaptive Learning System Architecture. *International Journal of Online Pedagogy and Course Design*, *5*(2), 1–10. doi:10.4018/IJOPCD.2015040101

Cheng, H. (2017). A TL-TPACK Model on CSL Pre-Service Teachers' Competencies of Online Instruction. In C. Lin, D. Zhang, & B. Zheng (Eds.), *Preparing Foreign Language Teachers for Next-Generation Education* (pp. 198–225). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0483-2.ch011

Çınar, M., & Tüzün, H. (2016). Web-Based Course Design Models. In M. Pinheiro & D. Simões (Eds.), *Handbook of Research on Engaging Digital Natives in Higher Education Settings* (pp. 374–395). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0039-1.ch018

Conrad, S. S., & Dabbagh, N. (2015). Examining the Factors that Influence how Instructors Provide Feedback in Online Learning Environments. *International Journal of Online Pedagogy and Course Design*, *5*(4), 47–66. doi:10.4018/IJOPCD.2015100104

Courey, S., LePage, P., Blackorby, J., Siker, J., & Nguyen, T. (2015). The Effects of Using Dynabook to Prepare Special Education Teachers to Teach Proportional Reasoning. *International Journal of Web-Based Learning and Teaching Technologies*, *10*(1), 45–64. doi:10.4018/ijwltt.2015010104

Cranton, P., & Thompson, P. (2014). Creating Collaboration in Global Online Learning: Case Studies. In V. Wang (Ed.), *Handbook of Research on Education and Technology in a Changing Society* (pp. 92–103). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6046-5.ch007

de Groot, C., Fogleman, J., & Kern, D. (2015). Using Mobile Technologies to Co-Construct TPACK in Teacher Education. In J. Keengwe & M. Maxfield (Eds.), *Advancing Higher Education with Mobile Learning Technologies: Cases, Trends, and Inquiry-Based Methods* (pp. 195–219). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6284-1.ch011

Deyoe, M. M., Newman, D. L., & Asaro-Saddler, K. (2014). Moving from Professional Development to Real-Time Use: How are we Changing Students? In J. Keengwe, G. Onchwari, & D. Hucks (Eds.), *Literacy Enrichment and Technology Integration in Pre-Service Teacher Education* (pp. 160–182). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-4924-8.ch010

Dick, T. P., & Burrill, G. F. (2016). Design and Implementation Principles for Dynamic Interactive Mathematics Technologies. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 23–51). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch002

Dodd, B. J., Baukal, C. E. Jr, & Ausburn, L. J. (2016). A Post-Positivist Framework for Using and Building Theory in Online Instructional Design. *International Journal of Online Pedagogy and Course Design*, *6*(4), 53–70. doi:10.4018/IJOPCD.2016100104

Driskell, S. O., Bush, S. B., Ronau, R. N., Niess, M. L., Rakes, C. R., & Pugalee, D. K. (2016). Mathematics Education Technology Professional Development: Changes over Several Decades. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 107–136). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch005

Dunston, Y. L., Patterson, G. C., & Bull, P. H. (2016). Faculty Perspectives of Technology-Enhanced Course Redesign. In J. Keengwe & G. Onchwari (Eds.), *Handbook of Research on Active Learning and the Flipped Classroom Model in the Digital Age* (pp. 150–176). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9680-8.ch008

Duvall, M., Matranga, A., Foster, A., & Silverman, J. (2016). Mobile Learning: Technology as Mediator of Personal and School Experiences. *International Journal of Game-Based Learning*, *6*(1), 30–42. doi:10.4018/IJGBL.2016010103

Edson, A. J., & Thomas, A. (2016). Transforming Preservice Mathematics Teacher Knowledge for and with the Enacted Curriculum: The Case of Digital Instructional Materials. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 215–240). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch009

Fasso, W., Knight, C., & Knight, B. A. (2014). A Learner-Centered Design Framework for E-Learning. *International Journal of Online Pedagogy and Course Design*, *4*(4), 44–59. doi:10.4018/ijopcd.2014100104

Felger, J., & Shafer, K. G. (2016). An Algebra Teacher's Instructional Decision-Making Process with GeoGebra: Thinking with a TPACK Mindset. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 493–518). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch019

Fife, E., Nelson, C. L., & Clarke, T. B. (2014). Online Technological Media in the Higher Education Classroom: An Exploratory Investigation of Varied Levels of Twitter Use. *International Journal of Online Pedagogy and Course Design*, *4*(2), 35–45. doi:10.4018/ijopcd.2014040103

Figg, C., & Jaipal-Jamani, K. (2015). Developing Teacher Knowledge about Gamification as an Instructional Strategy. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 663–690). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch025

Finger, G. (2015). Improving Initial Teacher Education in Australia: Solutions and Recommendations from the Teaching Teachers for the Future Project. In N. Ololube, P. Kpolovie, & L. Makewa (Eds.), *Handbook of Research on Enhancing Teacher Education with Advanced Instructional Technologies* (pp. 187–207). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8162-0.ch010

Flores, A., Park, J., & Bernhardt, S. A. (2016). Learning Mathematics and Technology through Inquiry, Cooperation, and Communication: A Learning Trajectory for Future Mathematics Teachers. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 324–352). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch013

Fokides, E. (2016). Pre-Service Teachers, Computers, and ICT Courses: A Troubled Relationship. *International Journal of Information and Communication Technology Education*, *12*(4), 25–36. doi:10.4018/IJICTE.2016100103

Foster, A., & Shah, M. (2016). Knew Me and New Me: Facilitating Student Identity Exploration and Learning through Game Integration. *International Journal of Gaming and Computer-Mediated Simulations*, *8*(3), 39–58. doi:10.4018/IJGCMS.2016070103

Frazier, L. C., & Palmer, B. M. (2015). Effective Online Learning Begins with Effective Teacher Preparation. In T. Heafner, R. Hartshorne, & T. Petty (Eds.), *Exploring the Effectiveness of Online Education in K-12 Environments* (pp. 148–168). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6383-1.ch008

Gallagher-Lepak, S., & Vandenhouten, C. (2016). E-Learning and Faculty Development in Higher Education: A Comprehensive Project. In B. Khan (Ed.), *Revolutionizing Modern Education through Meaningful E-Learning Implementation* (pp. 226–244). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0466-5.ch012

Gautreau, C. S., Stang, K. K., Street, C., & Guillaume, A. (2014). Making the Move: Supporting Faculty in the Transition to Blended or Online Courses. *International Journal of Online Pedagogy and Course Design*, *4*(1), 27–42. doi:10.4018/ijopcd.2014010103

Gikandi, J. W. (2015). Towards a Theory of Formative Assessment in Online Higher Education. In J. Keengwe (Ed.), *Handbook of Research on Educational Technology Integration and Active Learning* (pp. 292–316). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8363-1.ch014

Gikandi, J. W. (2017). Computer-Supported Collaborative Learning and Assessment: A Strategy for Developing Online Learning Communities in Continuing Education. In J. Keengwe & G. Onchwari (Eds.), *Handbook of Research on Learner-Centered Pedagogy in Teacher Education and Professional Development* (pp. 309–333). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0892-2.ch017

Gillow-Wiles, H., & Niess, M. L. (2015). Engaging Google Docs to Support Collaboration and Reflection in Online Teacher Education. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 635–662). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch024

Gillow-Wiles, H., & Niess, M. L. (2016). A Reconstructed Conception of Learner Engagement in Technology Rich Online Learning Environments. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 577–607). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch022

Golden, J. E., & Brown, V. (2017). A Holistic Professional Development Model: A Case Study to Support Faculty Transition to Online Teaching. In C. Martin & D. Polly (Eds.), *Handbook of Research on Teacher Education and Professional Development* (pp. 259–284). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-1067-3.ch014

Goodson-Espy, T., & Poling, L. (2015). Interactive Whiteboards: Preparing Secondary Mathematics Teachers to Avoid Catch-22. In D. Polly (Ed.), *Cases on Technology Integration in Mathematics Education* (pp. 288–307). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6497-5.ch014

Guan, S. (2014). Internet-Based Technology Use in Second Language Learning: A Systematic Review. *International Journal of Cyber Behavior, Psychology and Learning*, *4*(4), 69–81. doi:10.4018/ijcbpl.2014100106

Gupta, S., Taneja, S., & Kumar, N. (2015). Redefining the Classroom: Integration of Open and Classroom Learning in Higher Education. In E. McKay & J. Lenarcic (Eds.), *Macro-Level Learning through Massive Open Online Courses (MOOCs): Strategies and Predictions for the Future* (pp. 168–182). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8324-2.ch010

Hadjileontiadou, S. J., Dias, S. B., Diniz, J. A., & Hadjileontiadis, L. J. (2015). Understanding Online Learning Environments (OLEs). In *Fuzzy Logic-Based Modeling in Collaborative and Blended Learning* (pp. 18–50). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8705-9.ch002

Harkness, S. J. (2014). Program Administration and Implementation of an Online Learning Initiative at a Historically Black College University. In M. Orleans (Ed.), *Cases on Critical and Qualitative Perspectives in Online Higher Education* (pp. 44–60). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5051-0.ch003

Harrington, R. A., Driskell, S. O., Johnston, C. J., Browning, C. A., & Niess, M. L. (2016). Technological Pedagogical Content Knowledge: Preparation and Support of Mathematics Teachers. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 1–22). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch001

Hennessey, S., Olofson, M. W., Swallow, M. J., & Downes, J. M. (2015). Evolving Pedagogy and Practice: The 1:1 Mathematics Classroom through a TPACK Lens. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 577–603). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch022

Hilbert, E., & Mierau, K. (2014). Efficiency and Quality Improvement in Online Course Development. In M. Orleans (Ed.), *Cases on Critical and Qualitative Perspectives in Online Higher Education* (pp. 435–451). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5051-0.ch022

Hsien, O. L., Eak, A. D., Vighnarajah, S., Huah, G. L., & Teik, O. C. (2016). Qualitative Findings on the Dynamics of Online Facilitation in Distance Education. *International Journal of Online Pedagogy and Course Design*, *6*(4), 1–18. doi:10.4018/IJOPCD.2016100101

Huang, C., & Liu, E. Z. (2015). E-Tutor Perceptions towards the Star Rural Area E-Learning Project. *International Journal of Online Pedagogy and Course Design*, *5*(1), 20–29. doi:10.4018/ijopcd.2015010102

Hunter, J. L. (2015). High Possibility Classrooms: A New Model for Technology Integration. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 466–492). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch018

Hurtado, I. G., & Llamas, J. M. (2014). Social Networks in University Classrooms: An Experience of Teaching and Learning with Pre-Service Teachers through Facebook. *International Journal of Online Pedagogy and Course Design*, *4*(3), 34–48. doi:10.4018/ijopcd.2014070103

Jang, J. E., & Lei, J. (2015). The Impact of Video Self-Analysis on the Development of Preservice Teachers' Technological Pedagogical Content Knowledge (TPACK). *International Journal of Digital Literacy and Digital Competence*, *6*(4), 13–29. doi:10.4018/IJDLDC.2015100102

Jang, S., & Tsai, M. (2016). Exploring the Development of Pre-Service Teachers' ICT-TPACK using a Cognitive Stimulation Tool. In E. Railean, G. Walker, A. Elçi, & L. Jackson (Eds.), *Handbook of Research on Applied Learning Theory and Design in Modern Education* (pp. 380–404). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9634-1.ch018

Johnson, G. M., & Cooke, A. (2016). An Ecological Model of Student Interaction in Online Learning Environments. In L. Kyei-Blankson, J. Blankson, E. Ntuli, & C. Agyeman (Eds.), *Handbook of Research on Strategic Management of Interaction, Presence, and Participation in Online Courses* (pp. 1–28). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9582-5.ch001

Khan, K. P. (2017). Improving the Quality of Online Learning Environments: The Value of an Online Specific Design Model. In K. Shelton & K. Pedersen (Eds.), *Handbook of Research on Building, Growing, and Sustaining Quality E-Learning Programs* (pp. 278–300). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0877-9.ch014

Knutas, A., Ikonen, J., Maggiorini, D., Ripamonti, L., & Porras, J. (2016). Creating Student Interaction Profiles for Adaptive Collaboration Gamification Design. *International Journal of Human Capital and Information Technology Professionals*, *7*(3), 47–62. doi:10.4018/IJHCITP.2016070104

Kumi-Yeboah, A. (2015). Learning Theory and Online Learning in K-12 Education: Instructional Models and Implications. In T. Heafner, R. Hartshorne, & T. Petty (Eds.), *Exploring the Effectiveness of Online Education in K-12 Environments* (pp. 126–146). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6383-1.ch007

Lee, K., & Brett, C. (2015). An Online Course Design for Inservice Teacher Professional Development in a Digital Age: The Effectiveness of the Double-Layered CoP Model. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 55–80). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch003

Limone, P., & Pace, R. (2016). Teacher Training and Digital Paths. Revolution in the School: A Project for Lifelong Learning. *International Journal of Digital Literacy and Digital Competence*, *7*(1), 1–18. doi:10.4018/IJDLDC.2016010101

Linton, J., & Stegall, D. (2015). Common Core Standards for Mathematical Practice and TPACK: An Integrated Approach to Instruction. In *Standards and Standardization: Concepts, Methodologies, Tools, and Applications* (pp. 92–107). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8111-8.ch005

Liu, J. C., & Kaye, E. R. (2016). Preparing Online Learning Readiness with Learner-Content Interaction: Design for Scaffolding Self-Regulated Learning. In L. Kyei-Blankson, J. Blankson, E. Ntuli, & C. Agyeman (Eds.), *Handbook of Research on Strategic Management of Interaction, Presence, and Participation in Online Courses* (pp. 216–243). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9582-5.ch009

Lucas, K., & Murdock, J. (2014). Developing an Online Counseling Skills Course. *International Journal of Online Pedagogy and Course Design*, *4*(2), 46–63. doi:10.4018/ijopcd.2014040104

Lyublinskaya, I. (2015). Evolution of a Course for Special Education Teachers on Integrating Technology into Math and Science. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 521–547). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch020

Mac Mahon, B., Grádaigh, S. Ó., & Ghuidhir, S. N. (2016). iTE: Student Teachers using iPad on a Second Level Initial Teacher Education Programme. *International Journal of Mobile and Blended Learning*, *8*(2), 21–34. doi:10.4018/IJMBL.2016040102

Maina, E. M., Wagacha, P. W., & Oboko, R. (2016). Enhancing Active Learning Pedagogy through Online Collaborative Learning. In J. Keengwe & G. Onchwari (Eds.), *Handbook of Research on Active Learning and the Flipped Classroom Model in the Digital Age* (pp. 232–254). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9680-8.ch012

Marshall, A. M., & Callahan, K. M. (2016). Mathematics Teacher Educators' TPACK and MKT Knowledge Domains: Designing Online Discussion Blogs. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 353–380). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch014

Matthews, A., & Kitchin, R. M. Jr. (2015). Examining Design Pattern Strategies as a Means to Achieve Social Presence in the Online Classroom. In R. Wright (Ed.), *Student-Teacher Interaction in Online Learning Environments* (pp. 22–49). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6461-6.ch002

McBroom, E. S., Jiang, Z., Sorto, M. A., White, A., & Dickey, E. (2016). Dynamic Approach to Teaching Geometry: A Study of Teachers' TPACK Development. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 519–550). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch020

McGee, P. (2014). Blended Course Design: Where's the Pedagogy? *International Journal of Mobile and Blended Learning*, *6*(1), 33–55. doi:10.4018/ijmbl.2014010103

Medárová, V. (2014). E-Learning Tools Applied in Teaching English at the University Level. In T. Issa, P. Isaias, & P. Kommers (Eds.), *Multicultural Awareness and Technology in Higher Education: Global Perspectives* (pp. 156–175). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5876-9.ch008

Mellati, M., & Khademi, M. (2015). The Impacts of Distance Interactivity on Learners' Achievements in Online Mobile Language Learning: Social Software and Participatory Learning. *International Journal of Web-Based Learning and Teaching Technologies*, *10*(3), 19–35. doi:10.4018/ijwltt.2015070102

Mishra, P., Henriksen, D., & Mehta, R. (2015). Creativity, Digitality, and Teacher Professional Development: Unifying Theory, Research, and Practice. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 691–722). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch026

Modell, M. G. (2017). Learning to Lead Collaborative Student Groups to Success. In C. Martin & D. Polly (Eds.), *Handbook of Research on Teacher Education and Professional Development* (pp. 187–209). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-1067-3.ch010

Mulder, D. J. (2016). Pre-Service Teachers and Technology Integration: International Cases and Generational Attitudes toward Technology in Education. In J. Keengwe, J. Mbae, & G. Onchwari (Eds.), *Handbook of Research on Global Issues in Next-Generation Teacher Education* (pp. 83–103). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9948-9.ch005

Nicolete, P. C., Bento da Silva, J., Cristiano, M. A., Bilessimo, S. M., Ferreira de Farias, G., & Filho, S. S. (2016). A Remote Mobile Experiment in Brazilian Public Basic Education. In D. Parsons (Ed.), *Mobile and Blended Learning Innovations for Improved Learning Outcomes* (pp. 121–142). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0359-0.ch007

Niess, M. L., & Gillow-Wiles, H. (2016). Mathematics Teachers' Knowledge-of-Practice with Technologies in an Online Masters' Program: Scoop Action Research Experiences and Reflections. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 463–492). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch018

Niess, M. L., & Gillow-Wiles, H. (2017). Innovative Instructional Strategies for an Online Community of Learners: Reconstructing Teachers' Knowledge. In C. Martin & D. Polly (Eds.), *Handbook of Research on Teacher Education and Professional Development* (pp. 499–526). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-1067-3.ch028

Norris, S. E. (2016). Designing Online MBA Programs to Promote Transformative Learning and Knowledge Creation through Project-Based Learning Using the Job Characteristics Model. In V. Wang (Ed.), *Handbook of Research on Learning Outcomes and Opportunities in the Digital Age* (pp. 1–26). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9577-1.ch001

Oh, E. G., & Reeves, T. C. (2015). Collaborating Online: A Logic Model of Online Collaborative Group Work for Adult Learners. *International Journal of Online Pedagogy and Course Design*, *5*(3), 47–61. doi:10.4018/ijopcd.2015070104

Okojie, M. C. (2014). Designing and Delivering Web-Based Instruction to Adult Learners in Higher Education. In J. Keengwe, G. Schnellert, & K. Kungu (Eds.), *Cross-Cultural Online Learning in Higher Education and Corporate Training* (pp. 1–19). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5023-7.ch001

Orellana, A. (2017). A Framework to Assess Appropriate Interaction to Meet Accreditation Quality Guidelines. In K. Shelton & K. Pedersen (Eds.), *Handbook of Research on Building, Growing, and Sustaining Quality E-Learning Programs* (pp. 253–276). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0877-9.ch013

Orrill, C. H., & Polly, D. (2016). Developing Teachers' TPACK for Mathematics through Professional Development: The Case of InterMath. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 433–462). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch017

Ossiannilsson, E. (2015). Quality Enhancement for Mobile Learning in Higher Education. In J. Keengwe (Ed.), *Promoting Active Learning through the Integration of Mobile and Ubiquitous Technologies* (pp. 167–182). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6343-5.ch010

Ouyang, F. (2016). Applying the Polysynchronous Learning to Foster the Student-centered Learning in the Higher Education Context: A Blended Course Design. *International Journal of Online Pedagogy and Course Design*, *6*(3), 52–68. doi:10.4018/IJOPCD.2016070105

Owusu, K. A., Conner, L., & Astall, C. (2015). Contextual Influences on Science Teachers' TPACK Levels. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 307–333). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch012

Papanikolaou, K. A., Makrh, K., Magoulas, G. D., Chinou, D., Georgalas, A., & Roussos, P. (2016). Synthesizing Technological and Pedagogical Knowledge in Learning Design: A Case Study in Teacher Training on Technology Enhanced Learning. *International Journal of Digital Literacy and Digital Competence*, *7*(1), 19–32. doi:10.4018/IJDLDC.2016010102

Patel, K. (2015). Planning, Designing, Implementing, and Managing Social Presence in Online Programs and Online Classes. In R. Wright (Ed.), *Student-Teacher Interaction in Online Learning Environments* (pp. 346–372). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6461-6.ch016

Petrucco, C., & Grion, V. (2015). An Exploratory Study on Perceptions and Use of Technology by Novice and Future Teachers: More Information and Less On-Line Collaboration? *International Journal of Digital Literacy and Digital Competence*, *6*(3), 50–64. doi:10.4018/IJDLDC.2015070104

Picciano, A. G., Seaman, J., & Day, S. L. (2015). Online Learning in Illinois High Schools: The Voices of Principals! In T. Heafner, R. Hartshorne, & T. Petty (Eds.), *Exploring the Effectiveness of Online Education in K-12 Environments* (pp. 1–18). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6383-1.ch001

Polly, D. (2015). Leveraging Asynchronous Online Instruction to Develop Elementary School Mathematics Teacher-Leaders. In P. Ordóñez de Pablos, R. Tennyson, & M. Lytras (Eds.), *Assessing the Role of Mobile Technologies and Distance Learning in Higher Education* (pp. 78–99). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-7316-8.ch004

Polly, D., Binns, I. C., Putman, S. M., Rock, T. C., & Good, A. J. (2015). Developing Technological Pedagogical Content Knowledge in Elementary Education Programs. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 493–520). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch019

Polly, D., Martin, C., Wang, C., Lambert, R. G., Pugalee, D. K., & Middleton, C. W. (2016). The Influence of Professional Development on Primary Teachers' TPACK and Use of Formative Assessment. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 382–405). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch015

Putman, S. M., Kissel, B., Vintinner, J., & Good, A. J. (2015). Online Learning in K-College Classrooms: Students and Teachers Establish Social, Cognitive, and Teaching Presences in Digital Spaces. In T. Heafner, R. Hartshorne, & T. Petty (Eds.), *Exploring the Effectiveness of Online Education in K-12 Environments* (pp. 191–211). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6383-1.ch010

Pytash, K. E., & Testa, E. (2015). Access Denied: Preservice Teachers' Integration of Technology for Teaching Writing. *International Journal of Digital Literacy and Digital Competence*, *6*(4), 49–63. doi:10.4018/IJDLDC.2015100104

Ray, B. B., Hocutt, M. M., & Hooley, D. (2014). Use of an Online Simulation to Promote Content Learning. *International Journal of Online Pedagogy and Course Design*, *4*(1), 43–57. doi:10.4018/ijopcd.2014010104

Razak, R. A., Yusop, F. D., Idris, A. Y., & Halili, S. H. (2016). A Proposed Performance-Based System for Teacher Interactive Electronic Continuous Professional Development (TIE-CPD). *International Journal of Web-Based Learning and Teaching Technologies*, *11*(4), 35–45. doi:10.4018/IJWLTT.2016100103

Reyes, V. C. Jr, Reading, C., Rizk, N., Gregory, S., & Doyle, H. (2016). An Exploratory Analysis of TPACK Perceptions of Pre-Service Science Teachers: A Regional Australian Perspective. *International Journal of Information and Communication Technology Education*, *12*(4), 1–14. doi:10.4018/IJICTE.2016100101

Ritzhaupt, A. D., Poling, N., Frey, C., Kang, Y., & Johnson, M. (2016). A Phenomenological Study of Games, Simulations, and Virtual Environments Courses: What Are We Teaching and How? *International Journal of Gaming and Computer-Mediated Simulations*, *8*(3), 59–73. doi:10.4018/IJGCMS.2016070104

Rosenberg, J. M., & Koehler, M. J. (2015). Context and Teaching with Technology in the Digital Age. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 440–465). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch017

Sankey, M., & Hunt, L. (2014). Flipped University Classrooms: Using Technology to Enable Sound Pedagogy. *Journal of Cases on Information Technology*, *16*(2), 26–38. doi:10.4018/jcit.2014040103

Scheg, A. G. (2014). Examining Guidebooks as an Online Pedagogy Resource. In *Reforming Teacher Education for Online Pedagogy Development* (pp. 77–99). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5055-8.ch004

Seals, C., Horton, A., Berzina-Pitcher, I., & Mishra, P. (2017). A New Understanding of our Confusion: Insights from a Year-Long STEM Fellowship Program. In C. Martin & D. Polly (Eds.), *Handbook of Research on Teacher Education and Professional Development* (pp. 582–604). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-1067-3.ch032

Seifert, T. (2015). Pedagogical Applications of Smartphone Integration in Teaching: Lecturers, Pre-Service Teachers and Pupils' Perspectives. *International Journal of Mobile and Blended Learning*, *7*(2), 1–16. doi:10.4018/ijmbl.2015040101

Semingson, P., Hurlbut, A., Owens, D., & Robertson, M. (2017). Scaffolding Digital Writing and Storytelling in Online-Only Teacher Education Courses. In J. Keengwe & G. Onchwari (Eds.), *Handbook of Research on Learner-Centered Pedagogy in Teacher Education and Professional Development* (pp. 104–127). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0892-2.ch006

Seufert, S., & Scheffler, N. (2016). Developing Digital Competences of Vocational Teachers. *International Journal of Digital Literacy and Digital Competence*, *7*(1), 50–65. doi:10.4018/IJDLDC.2016010104

Shah, M., & Foster, A. (2014). The Inquiry, Communication, Construction and Expression (ICCE) Framework for Understanding Learning Experiences in Games. *International Journal of Virtual and Personal Learning Environments*, *5*(2), 1–14. doi:10.4018/ijvple.2014040101

Sheffield, R., & Quinton, G. (2017). Case Studies of Scaffolded On-Line Inquiry in Primary and Secondary Classrooms: Technology and Inquiry in a Science Context. In N. Ostashewski, J. Howell, & M. Cleveland-Innes (Eds.), *Optimizing K-12 Education through Online and Blended Learning* (pp. 240–255). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0507-5.ch013

Shelton, K., Mason, D., & Cummings, C. (2014). Strategies for Online Course Development to Promote Student Success. In V. Wang (Ed.), *Handbook of Research on Education and Technology in a Changing Society* (pp. 152–164). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6046-5.ch012

Skinner, L., Witte, M. M., & Wohleb, E. (2014). Defining Quality Standards, Guidelines, and Strategies for the Delivery of Successful Online Education in a Changing Society. In V. Wang (Ed.), *Handbook of Research on Education and Technology in a Changing Society* (pp. 190–201). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6046-5.ch015

Smith, N. J., & Bhattacharya, K. (2015). Practical Wisdom of Tool and Task: Meeting the Demands of the Method with Digital Tools in Qualitatively Driven Mixed Methods Studies. In S. Hai-Jew (Ed.), *Enhancing Qualitative and Mixed Methods Research with Technology* (pp. 210–230). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6493-7.ch009

Sorensen, C. (2016). Online Learning at the K-12 Level: An Examination of Teacher Technology Use by Subject Area and Grade Level. *International Journal of Online Pedagogy and Course Design*, *6*(2), 15–28. doi:10.4018/IJOPCD.2016040102

Sprague, D. R., & Katradis, M. (2015). The Transference between Elementary Preservice Teachers' Courses and Technology Use in Teaching. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 108–134). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch005

Suh, J. M., Sprague, D. R., & Baker, C. K. (2016). Transforming Mathematics Teacher Knowledge in the Digital Age through Iterative Design of Course-Based Projects. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 190–214). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch008

Sun, Z., You, J., Song, W., Qu, Z., & Luo, L. (2017). Identifying the Contributors to Improve Mobile-Based TPACK Competency of Elementary School Teachers in China. In C. Lin, D. Zhang, & B. Zheng (Eds.), *Preparing Foreign Language Teachers for Next-Generation Education* (pp. 74–91). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0483-2.ch005

Tammaro, R., & D'Alessio, A. (2016). Teacher Training and Digital Competence: A Pedagogical Recommendation. *International Journal of Digital Literacy and Digital Competence*, *7*(2), 1–10. doi:10.4018/IJDLDC.2016040101

Tankari, M. (2014). Cultural Orientation Differences and their Implications for Online Learning Satisfaction. In J. Keengwe, G. Schnellert, & K. Kungu (Eds.), *Cross-Cultural Online Learning in Higher Education and Corporate Training* (pp. 20–61). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-5023-7.ch002

Thomas, J. A., & Parkison, P. (2015). The Impact upon Comprehension and Reading Tasks of Preservice Elementary Teachers Using a Web 2.0 Reading Extension. *International Journal of Online Pedagogy and Course Design*, *5*(4), 14–26. doi:10.4018/IJOPCD.2015100102

Trespalacios, J., & Rand, J. (2015). Using Asynchronous Activities to Promote Sense of Community and Learning in an Online Course. *International Journal of Online Pedagogy and Course Design*, *5*(4), 1–13. doi:10.4018/IJOPCD.2015100101

Tsai, C., Shen, P., & Lin, R. (2015). Exploring the Effects of Student-Centered Project-Based Learning with Initiation on Students' Computing Skills: A Quasi-Experimental Study of Digital Storytelling. *International Journal of Information and Communication Technology Education*, *11*(1), 27–43. doi:10.4018/ijicte.2015010102

Vasinda, S., Kander, F., & Redmond-Sanogo, A. (2015). University Reading and Mathematics Clinics in the Digital Age: Opportunities and Challenges with iPad Integration. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 135–163). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch006

Villagrasa, S., Fonseca, D., Redondo, E., & Duran, J. (2014). Teaching Case of Gamification and Visual Technologies for Education. *Journal of Cases on Information Technology*, *16*(4), 38–57. doi:10.4018/jcit.2014100104

Wang, L., Wu, Y., & Hu, C. (2016). English Teachers' Practice and Perspectives on Using Educational Computer Games in EIL Context. *International Journal of Technology and Human Interaction*, *12*(3), 33–46. doi:10.4018/IJTHI.2016070103

Wang, W., & Feng, L. (2017). Technology Standards for Chinese Language Teacher Education. In C. Lin, D. Zhang, & B. Zheng (Eds.), *Preparing Foreign Language Teachers for Next-Generation Education* (pp. 38–54). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0483-2.ch003

Wiburg, K., Chamberlin, B., Trujillo, K. M., Parra, J. L., & Stanford, T. (2016). Transforming Mathematics Teaching through Games and Inquiry. In M. Niess, S. Driskell, & K. Hollebrands (Eds.), *Handbook of Research on Transforming Mathematics Teacher Education in the Digital Age* (pp. 52–77). Hershey, PA: IGI Global. doi:10.4018/978-1-5225-0120-6.ch003

Widjaja, A. E., Chen, J. V., & Hiele, T. M. (2016). The Effect of Online Participation in Online Learning Course for Studying Trust in Information and Communication Technologies. *International Journal of Cyber Behavior, Psychology and Learning*, *6*(3), 79–93. doi:10.4018/IJCBPL.2016070106

Wilson, N. S., Zygouris-Coe, V. V., & Cardullo, V. M. (2015). Teacher Development, Support, and Training with Mobile Technologies. In J. Keengwe & M. Maxfield (Eds.), *Advancing Higher Education with Mobile Learning Technologies: Cases, Trends, and Inquiry-Based Methods* (pp. 88–113). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6284-1.ch005

Woodley, X. M., Mucundanyi, G., & Lockard, M. (2017). Designing Counter-Narratives: Constructing Culturally Responsive Curriculum Online. *International Journal of Online Pedagogy and Course Design*, *7*(1), 43–56. doi:10.4018/IJOPCD.2017010104

Wright, M. K. (2016). A Design Theory for Vigilant Online Learning Systems. *International Journal of Information Systems in the Service Sector*, *8*(1), 13–33. doi:10.4018/IJISSS.2016010102

Wright, N. (2015). Vignettes of Pedagogical Practices with iPads: Reinforcing Pedagogy, Not Transforming It. *International Journal of Online Pedagogy and Course Design*, *5*(3), 62–73. doi:10.4018/ijopcd.2015070105

Wright, N. (2015). Vignettes of Pedagogical Practices with iPads: Reinforcing Pedagogy, Not Transforming It. *International Journal of Online Pedagogy and Course Design*, *5*(3), 62–73. doi:10.4018/ijopcd.2015070105

Wright, V. H., & Davis, A. (2016). Integrating Technology in Nurse Education: Tools for Professional Development, Teaching, and Clinical Experiences. In V. Wang (Ed.), *Handbook of Research on Advancing Health Education through Technology* (pp. 23–38). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-9494-1.ch002

Wu, H., Shen, P., Chen, Y., & Tsai, C. (2016). Effects of Web-based Cognitive Apprenticeship and Time Management on the Development of Computing Skills in Cloud Classroom: A Quasi-Experimental Approach. *International Journal of Information and Communication Technology Education*, *12*(3), 1–12. doi:10.4018/IJICTE.2016070101

Xia, B. S. (2017). A Pedagogical Review of Programming Education Research: What Have We Learned. *International Journal of Online Pedagogy and Course Design*, *7*(1), 33–42. doi:10.4018/IJOPCD.2017010103

Yarnall, L., & Fusco, J. (2015). A Framework for Supporting In-Service Teachers to Use Domain-Specific Technologies for Instruction. In M. Niess & H. Gillow-Wiles (Eds.), *Handbook of Research on Teacher Education in the Digital Age* (pp. 604–634). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-8403-4.ch023

Zhang, B. (2015). Bridging the Social and Teaching Presence Gap in Online Learning. In R. Wright (Ed.), *Student-Teacher Interaction in Online Learning Environments* (pp. 158–182). Hershey, PA: IGI Global. doi:10.4018/978-1-4666-6461-6.ch008

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