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Review

Student modeling approaches: A literature review for the last decade

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ABSTRACT

This paper constitutes a literature review on student modeling for the last decade. The review aims at answering three basic questions on student modeling: what to model, how and why. The prevailing student modeling approaches that have been used in the past 10 years are described, the aspects of students' characteristics that were taken into consideration are presented and how a student model can be used in order to provide adaptivity and personalisation in computer-based educational software is highlighted. This paper aims to provide important information to researchers, educators and software developers of computer-based educational software ranging from e-learning and mobile learning systems to educational games including stand alone educational applications and intelligent tutoring systems. In addition, this paper can be used as a guide for making decisions about the techniques that should be adopted when designing a student model for an adaptive tutoring system. One significant conclusion is that the most preferred technique for representing the student's mastery of knowledge is the overlay approach. Also, stereotyping seems to be ideal for modeling students' learning styles and preferences. Furthermore, affective student modeling has had a rapid growth over the past years, while it has been noticed an increase in the adoption of fuzzy techniques and Bayesian networks in order to deal the uncertainty of student modeling.

1. Introduction

In the past decade there has been an enormous growth of the field of computer-based learning that includes e-learning, mobile learning, educational games and standalone educational applications. This has happened due to the rapid and important advances of computer technology and the internet, as well as to the fact that an e-learning environment can be used for tutoring large and heterogeneous groups of students, often, without the limitations of time and place. However, traditional web-based and standalone educational systems still have several shortcomings when compared to real-life classroom teaching, such as lack of contextual and adaptive support, lack of flexible support of the presentation and feedback, lack of the collaborative support between students and systems (Xu, Wang, & Su, 2002). That is the reason why researches in the field of e-learning have expanded their interests on adaptive e-learning, which is suitable for teaching heterogeneous student populations (Schiaffino, Garcia, & Amandi, 2008).

An adaptive system must be capable of managing learning paths adapted to each user, monitoring user activities, interpreting those using specific models, inferring user needs and preferences and exploiting user and domain knowledge to dynamically facilitate the learning process (Boticario, Santos, & van Rosmalen, 2005). In other words, an adaptive educational system has to provide personalization to the specific needs, knowledge and background of each individual student. Creating an adaptive learning system that meets students' requirements can be challenging since students learn with not only different needs, but also different learning characteristics (Lo, Chan, & Yeh, 2012). A solution to this challenge is the technology of student modeling which has been introduced in intelligent tutoring systems (ITS) but its use has been extended to most current educational software applications that aim to be adaptive and personalized.

A student model is the base for personalization in computer-based educational applications. Self (1990) has pointed out that student modeling is a process devoted to represent several cognitive issues such as analyzing the student's performance, isolating the underlying misconceptions, representing students' goals and plans, identifying prior and acquired knowledge, maintaining an episodic memory, and describing personality characteristics. Therefore, a crucial factor for designing an adaptive educational system is the construction of an effective student model. Imagine the student model as an avatar of a real student in the virtual world, the dimensions of the student model correspond to the aspects of the physical student and the properties of the student model represent the characteristics of the real student (Yang, Kinshuk, & Graf, 2010). Student modeling is one of the key factors that affect automated tutoring systems in making instructional

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decisions (Li, Cohen, Koedinger, & Matsuda, 2011), since a student model enables understanding and identification of students' needs (Sucar & Noguez, 2008). Student modeling can be defined as the process of gathering relevant information in order to infer the current cognitive state of the student, and to represent it so as to be accessible and useful to the tutoring system for offering adaptation (Thomson & Mitrovic, 2009).

In order to construct a student model, it has to be considered what information and data about a student should be gathered, how it will update in order to keep it up-to-date, and how it will be used in order to provide adaptation (Millán, Loboda, & Pérez-de-la-Cruz, 2010; Nguyen & Do, 2009). In fact, when a student model is constructed, the following three questions have to be answered: (i) "What are the characteristics of the user we want to model?, (ii) "How we model them?", (iii) "How we use the user model?".

The student's characteristics and data, which are usually represented in a student model, include knowledge level, skills, learning preferences and styles, errors and misconceptions, motivation, affective features such as emotions and feelings, cognitive aspects such as memory, attention, solving, making decisions and analyzing abilities, critical thinking and communication skills, and meta-cognitive aspects like self-regulation, self-explanation, self-assessment and self-management.

There are many approaches to construct a student model: the overlay model which represents the student's knowledge level, the stereotype model that classifies students into groups according to their frequent characteristics, the perturbation model which models the student's knowledge and misconceptions, machine learning techniques for automated observation of students' actions and behavior and for automated induction, cognitive theories that attempt to explain human behavior, fuzzy logic modeling techniques or Bayesian networks for dealing with the uncertainty of student diagnosing, and ontologies for reused student models. Each of the above approaches can be used on its own or can be combined with one or more other approaches, building a hybrid student model, according to a system's needs and aim. By keeping a model for every user, a system can successfully personalize its content and utilize available resources accordingly (Kyriacou, 2008). Therefore, a student model can be used to achieve accurate student diagnosis and predict a student's needs. In return, it offers individualized courses, adaptive navigation support, help and feedback to students, thus allowing them to learn in their own pace.

Student modeling as a research topic has matured sufficiently over the past years and constitutes a very promising technology to be used for personalization and adaptivity of e-learning systems. In this paper, a literature review of student modeling from 2002 up to now is presented. It presents a variety of the prevailing student modeling approaches, the student related data and information that they represent, and the way that a student model is used in order to provide an adaptive learning process. Furthermore, this paper presents the methods that were used in a significant number of adaptive and/or personalized tutoring systems of the past decade for constructing their student models. A wide range of students' characteristics considered in the process of student modeling and the contribution of student models to tutoring systems' adaptation are reviewed. In addition, the paper reviews the possible combinations of student modeling approaches that have been applied to a variety of adaptive and/or personalized educational systems.

The remainder of this paper is organized as follows. In Section 2, the criteria for inclusion in the literature review are presented. In Section 2, the students' characteristics that should be taken into consideration during the design of a student model are presented. In Section 4, eight commonly used approaches of student modeling are presented. In Section 5, it is showed how a system can use its student model in order to provide adaptivity. In Section 6, the approaches of student modeling are discussed and a comparison and contrast of them in relation to student modeling characteristics is made. Finally, in Section 7, the conclusions drawn from this work are given.

2. Criteria for inclusion in the literature review

The literature review that is presented and discussed in this paper has been based on an extensive search for relevant papers that were published in the last decade. The main criterion for inclusion of papers in the literature review was the search engine that was used to find them. Mostly, the listing systems appeared in the Scopus. Scopus is the world's largest abstract and citation database of peer-reviewed literature and it is considered as one of the most valid search engine for research papers. In particular, 89.47% of the adaptive and/or personalized systems that are listed below are results of the Scopus search engine. These systems have been published in quality journals or have been presented at significant international conferences.

In addition, a significant percentage of the systems reviewed have been evaluated by their respective authors. In particular, the systems that have been evaluated and are included in the present survey constitute 82.90% of the total systems. The rest systems, which have not been evaluated, have been found, however, in Scopus, which ensures a preliminary selection of research database of papers. These papers represent trends, which have not been established yet.

3. Students' characteristics to model

A significant initial stage of constructing a student model is the selection of appropriate students' characteristics that should be considered. The question: "what aspects of the student should we model in a specific intelligent tutoring system?" has to be answered when a new student model is built (Gonzalez, Burguillo, & Llamas, 2006). According to Yang et al. (2010) in order to carry out the personalization efficiently, the student model needs to consider both domain dependent and domain independent characteristics. Also, some of these characteristics are static while others are dynamic. According to Jeremić, Jovanović, and Gasěvić (2012) static features, such as email, age, tongue language etc., are set before the learning process takes place, in most cases using questionnaires, and they usually remain unchanged throughout the learning session, although some of these data can be changed directly by a student through available options menu, while dynamic features come directly from the student's interactions with the system and are those that the system constantly updates during learning sessions based on the collected data.

Therefore, the challenge is to define the dynamic student's characteristics that constitute the base for the system's adaptation to each individual student's needs. These characteristics include knowledge and skills, errors and misconceptions, learning styles and preferences, affective and cognitive factors, meta-cognitive factors. Knowledge refers to the prior knowledge of a student on the knowledge domain as well as her/his current knowledge level. This is usually measured through questionnaires and tests that the student has to complete during the learning process. Furthermore, through these tests as well as observing student's actions, the system can identify the misconceptions of students. Learning style refers to individual skills and preferences that affect how a student perceives, gathers and processes learning materials (Jonassen & Grabowski, 1993). According to Popescu (2009) some learners prefer graphical representations, others prefer audio materials and others prefer text representation of the learning material, some students prefer to work in groups and others learn better alone. Adapting courses to the learning preferences of the students has a positive effect on the learning process, leading to an increased efficiency, effectiveness and/or learner satisfaction (Popescu, Badica, & Moraret, 2010). A proposal for modeling learning styles, which are adopted by many ITSs, is the Felder–Silverman learning style (FSLSM). FSLSM classifies students in four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global (Felder & Silverman, 1988; Felder & Soloman, 2003). Another method for modeling learning styles is the Myers-Briggs Type Indicator (MBTI) (Bishop & Wheeler, 1994), which identifies the following eight categories of learning styles: extrovert, introvert, sensing, intuitive, thinking, feeling, judging, perceiving.

Given that there is evidence that experienced human tutors monitor and react to the emotional state of the students in order to motivate them and to improve their learning process (Johnson, Rickel, & Lester, 2000; Lehman, Matthews, D'Mello, & Person, 2008), a tutoring system should interpret the emotional state of students and adapt its behavior to their needs, giving an appropriate response for those emotions (Katsionis & Virvou, 2004). Therefore, affective factors are student characteristics that should be considered to build a student model. The affective states can be the following: happy, sad, angry, interested, frustrated, bored, distracted, focused, confused (Balakrishnan, 2011. Rodrigo et al. (2007) have found that some of these emotions, like boredom or frustration, lead students to an off-task behavior. Off-task behavior means that students' attention becomes lost and they engage in activities that neither have anything to do with the tutoring system nor include any learning aim (Cetintas, Si, Xin, & Hord, 2010). Among typical off-task behavior examples are surfing the web, devoting time to off-topic readings, talking with order students without any learning aims (Baker, Corbett, Koedinger, & Wagner, 2004). These behaviors are associated with deep motivational problems (Baker, 2007), and consequently, modeling affective factors can be a base for modeling students' motivation.

The most common characteristics of a student that are described in a student model are the student's cognitive features. These features refer to aspects such as attention, knowledge, ability to learn and understand, memory, perception, concentration, collaborative skills, abilities to solve problems and making decisions, analyzing abilities, critical thinking. However, students need not only to have cognitive abilities, but they also need to be able to critically assess their knowledge in order to decide what they need to study (Mitrovic & Martin, 2006). Thereby, adaptive and/or personalized tutoring systems must consider students' meta-cognitive skills. According to Flavell (1976) meta-cognition concerns to the active monitoring, regulation and orchestration of information processes in relation to cognitive objects on which they bear. In other words, the notion of meta-cognition deals with students' ability to be aware of and control their own thinking, for example, how they select their learning goals, use prior knowledge or intentionally choose problem-solving strategies (Barak, 2010). Some meta-cognitive skills are reflection, self-awareness, self-monitoring, self-regulation, self-explanation, self-assessment, and self-management (Pẽna & Kayashima, 2011).

4. Student modeling approaches

4.1. Overlay

One of the most popular and common used student models is the overlay model. It was invented by Stansfield, Carr, and Goldstein (1976) and has been used in many systems ever since. The main assumption underlying the overlay model is that a student may have incomplete but correct knowledge of the domain. Therefore, according to the overlay modeling, the student model is a subset of the domain model (Martins, Faria, Vaz de Carvalho, & Carrapatoso, 2008; Vélez, Fabregat, Nassiff, Petro, & Fernandez, 2008), which reflects the expert-level knowledge of the subject (Brusilovsky & Millán, 2007; Liu & Wang, 2007). The differences between the student's and the expert's set of knowledge are believed to be the student's lack of skills and knowledge, and the instructional objective is to eliminate these differences as much as possible (Bontcheva & Wilks, 2005; Michaud & McCoy, 2004; Staff, 2001). Consequently, the domain is decomposed into a set of elements and the overlay model is simply a set of masteries over those elements (Nguyen & Do, 2008). The pure overlay model assigns a Boolean value, yes or no, to each element, indicated whether the student knows or does not know this element, while in its modern form, an overlay model represents the degree to which the user knows such a domain element by using a qualitative measure (good–average–poor) or a qualitative measure such as the probability that the student knows the concept (Brusilovsky & Millán, 2007). It is obvious that the overlay model technique requires that the domain model of the adaptive and/or personalized tutoring system represents individual topics and concepts. Thereby, its complexity depends on the granularity of the domain model structure and on the estimate of the student knowledge (Martins et al., 2008). So, the overlay model can represent the user knowledge for each concept independently and this is the reason for its extensive use.

Kassim, Kazi, and Ranganath (2004) used an overlay student model in a web-based intelligent learning environment for digital systems (WILEDS) in order to represent dynamically the emerging knowledge and skills of each student. Also, in MEDEA (Carmona & Conejo, 2004) student modeling is performed by an overlay model in which for each domain concept an estimation of the student knowledge level on this concept is stored. InfoMap (Lu, Ong, & Hsu, 2007; Lu, Wu, Wu, Chiou, & Hsu, 2005), which is designed to facilitate both human browsing and computer processing of the domain ontology in a system, uses an overlay student model in combination with a buggy model for identification of the deficient knowledge. Another adaptive tutoring system that performs student modeling through an overlay student model is ICICLE (Michaud & McCoy, 2004). ICICLE's student model attempts to capture the user's mastery of various grammatical units and thus can be used to predict the grammar rules s/he is most likely using when producing language. Kumar (2006a, 2006b) has used overlay technique for student modeling in programming tutors. Glushkova (2008) applied a qualitative overlay student model for modeling learners' knowledge level to DeLC system. However, because she wanted to model, also, learners' manner of access to training resources, their preferences, habits and behaviors during the learning process, she combined the overlay model with stereotype modeling (stereotypes are referred below). Furthermore, LS-Plan (Limongelli, Sciarrone, Temperini, & Vaste, 2009), which is a framework for personalization and adaptation in e-learning, uses a qualitative overlay model. IWT (Albano, 2011) models competence in mathematics in an e-learning environment through an overlay model, which applies an ontology-based representation of the domain knowledge. Also, Mahnane, Laskri, and Trigano (2012) build an adaptive hypermedia system that integrates thinking style (AHS-TS) by applying an overlay model. Finally, PDinamet (Gaudioso, Montero, & Hernandez-del-Olmo, 2012) is a web-based adaptive learning system for the teaching of physics in secondary education, which uses an overlay model in order to provide effective and personalized selection of the appropriate learning resources.

It is obvious from the applications of the overlay model that it does not allow representing neither the incorrect knowledge that the student acquired or might have acquired, nor the different cognitive needs, preferences and learners' behavior and personality. As Rivers (1989) point out, overlay models are inadequate for sophisticated models because they do not take into account the way users make inferences, how they integrate new knowledge with knowledge they already have or how their own representational structures change with learning. That is the reason why many adaptive and/or personalized tutoring systems perform student modeling, combing overlay model with other student modeling approaches like stereotypes, perturbation and fuzzy techniques.

4.2. Stereotypes

Another common used approach of student modeling is stereotyping. Stereotypes were introduced to user modeling by Rich (1979) in the system called GRUNDY. The main idea of stereotyping is to cluster all possible users of an adaptive system into several groups according to certain characteristics that they are typically shared. Such groups are called stereotypes. More specifically, a stereotype normally contains the common knowledge about a group of users. A new user will be assigned into a related stereotype if some of his/her characteristics match the ones contained in the stereotype. According to Kay (2000) the stereotype has a set of trigger conditions $\{tM_i\}$, where each $\{tM_i\}$ is a Boolean expression based upon components of the student model, and a set of retraction conditions, $\{rM_i\}$. The primary action of a stereotype is illustrated by Eq. (1) and a stereotype is deactivated when any of the retraction conditions becomes true (Eq. (2)).

$$if\ \exists i, tM_i = \text{true} \rightarrow \text{active}(Mg) \quad (1)$$

$$\exists\, j, rM_j = \text{true} \rightarrow \text{not activate}(M) \quad (2)$$

The stereotype is a particularly important form of reasoning about users and also student modeling with stereotypes is often a solution for the problem of initializing the student model by assigning the student to a certain group of students (Tsiriga & Virvou, 2002).

Stereotypes have been used for student modeling in many adaptive and/or personalized tutoring systems and often they are combined with other methods of user modeling. INSPIRE (Grigoriadou, Kornilakis, Papanikolaou, & Magoulas, 2002; Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003) is an intelligent system for personalized instruction in a remote environment, which classifies knowledge on a topic to one of the four levels of proficiency (insufficient, rather insufficient, rather sufficient, sufficient). Except of stereotypes, it uses, also, a fuzzy approach to deal with the uncertainty of student diagnosis, as well as an overlay model. Web-PTV (Tsiriga & Virvou, 2003a, 2003b), which teaches the domain of the passive voice of the English language, provides individualized tutoring and advice through the student model that is based on stereotypes and a machine learning technique. Carmona, Castillo, and Millán (2008) used a stereotype-like approach, which classifies students in four dimensions according to their learning styles, in combination with Bayesian networks in order to design a system that is able to select the more adequate objects for each student. A stereotype-like approach was used, also, in WELSA for adapting the courses to the learning preferences of each student (Popescu, Badica, & Moraret, 2009). AUTO-COLLEAGUE (Tourtoglou & Virvou, 2008; Tourtoglou & Virvou, 2012) that is an adaptive and collaborative learning environment for UML performs student modeling through a hybrid student model based on perturbation and the stereotype-based modeling technique. The stereotypes of AUTO-COLLEAGUE are related to three aspects of the performance of the trainee (the level of expertise, the performance type and the personality). Also, Chrysafiadi and Virvou (2008) developed a three-dimensional stereotype approach (1st dimension: knowledge level, 2nd dimension: type of programming errors, 3rd dimension: previous knowledge) for a web-based educational application that teaches the programming language Pascal (Web_Tutor_Pas), in order to adapt its responses to each individual student dynamically. Moreover, Kofod-Petersen, Petersen, Bye, Kolås, and Staupe (2008) adopted the stereotyping approach for modeling the learners of their intelligent learning environment. Another adaptive tutoring system that uses stereotypes in order to provide an individualized learning environment is CLT (Durrani & Durrani, 2010), which is a C++ tutor. Finally, a stereotype-like approach of student modeling is used in Wayang Outpost, which is a software tutor that helps students learn to solve standardized-test type of questions, in particular for a math test called Scholastic Aptitude Test, and other state-based exams taken at the end of high school in the USA, in order to discern factors that affect student behavior beyond cognition (Arroyo, Meheranian, & Woolf, 2010).

The advantages of using the stereotype technique are that the knowledge about a particular user will be inferred from the related stereotype(s) as much as possible, without explicitly going through the knowledge elicitation process with each individual user and the information about user groups/stereotypes can be maintained with low redundancy (Zhang & Han, 2005). Furthermore, Kay (2000) reports that an appealing property of the stereotype is that it should enable a system to get started quickly on its customized interaction with the user.

However, stereotypes deal with problems as well. Stereotype approach is quite inflexible due to the fact that stereotypes are constructed in a hand-crafted way before real users have interacted with the system and they are not updated until a human does so explicitly (Tsiriga & Virvou, 2002). Moreover, Kass (1991) argues that stereotypes suffer from two problems. First, in order to use them, the set of system users must be divisible into classes; however, such classes may not exist. Second, even if it is possible to identify classes of system users, the system designer must build the stereotypes; this is a process that is both time-consuming and error-prone.

4.3. Perturbation

A perturbation student model is an extension of the overlay model that represents the student's knowledge as including possible misconceptions as well as a subset of the expert's knowledge (Mayo, 2001). It represents learners as the subset of expert's knowledge, like the overlay model, plus their mal-knowledge (Nguyen & Do, 2008). This extension allows for better remediation of student mistakes, since the fact that a student believes something that is incorrect is pedagogically significant (Surjono & Maltby, 2003). The perturbation student model is useful for diagnostic reasoning. According to Martins et al. (2008), the perturbation student model is obtained by replacing the correct rules with the wrong rules, which when applied they lead to the answers of the student. Since there can be several reasons for a student wrong answer (several wrong values that lead to the student answer) the system proceeds to generate discriminating problems and presents them to the student to know exactly the wrong rules that this student has.

The collection of mistakes included in a perturbation model is usually called bug library and can be built either by empirical analysis of mistakes (enumeration) or by generating mistakes from a set of common misconceptions (generative technique). For enumerative modeling, the system developers analyze the model and determine possible errors students can make or are prone to make (Smith, 1998). The theory used on most existing systems is the enumerative bug theory, which is also known as the "buggy" model because it was first used in the intelligent tutoring system called BUGGY (Brown & Burton, 1975). However, enumerative modeling techniques suffer from costly computational requirements. Furthermore, as Clancey (1988) points out, not all students may fit the program's pre-enumerated set of bugs and he adds that a more capable program would attempt to generate a description of bugs from patterns in a particular student's behavior and a model of how bugs come about. This is called generative modeling, in which the system uses a cognitive model to detect students' errors. Errors are regarded as failed extrapolation of the concepts learned, and if the general form of the extrapolation errors can be found, then the majority of the errors can be explained (Mayo, 2001).

The past decade many adaptive and/or personalized tutoring systems have embedded a perturbation student model for reasoning the students' behavior. Surjono and Maltby (2003) used a perturbation student model to perform a better remediation of student mistakes. LeCo-EAD (Faraco, Rosatelli, & Gauthier, 2004) modeled students' knowledge and misconceptions through an enumerative perturbation student model, which included both correct and incorrect knowledge propositions, in order to provide personalized feedback and support to the distant students in real time. An enumerative perturbation student model was also applied by Lu et al. (2005) in an intelligent tutoring system that taught basic arithmetic to children (InfoMap). Their perturbation student model, which involved 31 types of addition errors and 51 types of subtraction errors, allowed the reasoning of students' errors and helped the system to expand the explanation during the feedback to the students. Finally, Baschera and Gross (2010) used a perturbation student model for spelling training, which represented student's strength and weaknesses, in order to allow for appropriate remediation actions to adapt to students' needs.

4.4. Machine learning techniques

Student modeling involves a process of making inferences about the student's behavior taking into account her/his knowledge level, her/his cognitive abilities, her/his preferences, her/his skills, her/his aptitudes e.t.c. The processes of observation of student's action and behavior in an adaptive and/or personalized tutoring system, and of induction, should be made automated by the system. A solution for this is machine learning, which is concerned with the formation of models from observations and has been extensively studied for automated induction (Webb, 1998). Observations of the user's behavior can provide training examples that a machine learning system can use to induce a model designed to predict future actions (Webb, Pazzani, & Billsus, 2001).

According to Sison and Shimura (1998), machine learning or machine-like techniques have so far been used in two areas of student modeling research:

(a) To induce a single, consistent student model from multiple observed student behaviors.
(b) For the purpose of automatically extending or constructing from scratch the bug library of student modelers.

Hence, the use of machine learning techniques in student modeling has become increasingly popular. Web-EasyMath (Tsiriga & Virvou, 2002; Tsiriga & Virvou, 2003c) uses a combination of stereotypes with the machine learning technique of the distance weighted k-nearest neighbor algorithm, in order to initialize the model of a new student. The student is first assigned to a stereotype category concerning her/his knowledge level and then the system initializes all aspects of the student model using the distance weighted k-nearest neighbor algorithm among the students that belong to the same stereotype category with the new student. Baker et al. (2004) applied a machine learning model in order to identify if a student is gaming the intelligent tutoring system in a way that leads to poor learning. Furthermore, Baker (2007) constructed a machine learning model that can automatically detect when a student using an intelligent tutoring system is off-task, i.e. engaged in behavior which does not involve the system or a learning task. In ADAPTAPlan (Jurado, Santos, Redondo, Boticario, & Ortega, 2008) fuzzy logic was used to evaluate students' assignments and to update the student model with their preferences by means of machine learning techniques. A machine learning technique was used, also, in the adaptive hypermedia educational system GIAS (Castillo, Gama, & Breda, 2009), in combination with stereotypes. The adaptation techniques of GIAS are focused on the appropriate selection of the course's topics and learning resources, based on the student's goals, knowledge level, learning style. Wang, Yang, and Wen (2009) adopted support vector machines, a machine learning method based on statistical learning theory, in order to provide personalized learning resource recommendation. POOLE III (Inventado, Legaspi, The Duy Bui, & Suarez, 2010) used a combination of Bayesian networks and machine learning technique in order to observe students' reactions while using an intelligent tutoring system and adjust feedback automatically to each individual learner. Similarly, Baker, Goldstein, and Heffernan (2010) applied a student model based on a combination of Bayesian networks and machine learning technique. The machine learning constitutes the student model able to assess the probability that a student learned skill at a specific problem step and thus the system can predict the student knowledge. In addition, Al-Hmouz, Shen, Yan, and Al-Hmouz (2010), Al-Hmouz, Shen, Yan, and Al-Hmouz (2011) combined two machine learning techniques in order to model the learner and all possible contexts related to her/his current situation in an extensible way so that they can be used for personalization. Cetintas et al. (2010) used machine learning techniques for the performing of the automatic detection of off-task behaviors in intelligent tutoring systems. SimStudent (Li et al., 2011) used a machine learning technique in order to construct student models automatically and improve the accuracy of prediction of real students learning performance. Finally, Balakrishnan (2011) build a student model upon ontology of machine learning strategies in order to model the effect of affect on learning and recognize for any learning task, what learning strategy, or combination thereof, is likely to be the most effective.

4.5. Cognitive theories

Many researchers (e.g. Salomon, 1990; Welch & Brownell, 2000) point out that technology is effective when developers thoughtfully consider the merit and limitations of a particular application while employing effective pedagogical practices to achieve a specific objective. That is the reason that many researchers adopt cognitive theories in student models. A cognitive theory attempts to explain human behavior during the learning process by understanding human's processes of thinking and understanding. The Human Plausible Reasoning (HPR) theory, the Multiple Attribute Decision Making (MADM) theory, the Ortony, Clore, and Collins (1988) (OCC) theory and the Control-Value theory are some cognitive theories that have been used in student modeling.

Particularly, the Human Plausible Reasoning (HPR) theory (Collins & Michalski, 1989) is a domain-independent theory originally based on a corpus of people's answers to everyday questions, which categorizes plausible inferences in terms of a set of frequently recurring inference patterns and a set of transformations on those patterns (Burstein & Collins, 1988; Burstein, Collins, & Baker, 1991). It serves the purpose of adding more "human" reasoning to the computer and this is the reason that it has been used in F-SMILE (Virvou & Kabassi, 2002). The student model in F-SMILE uses a novel combination of HPR with a stereotype-based mechanism, in order to generate default assumptions about learners until it acquires sufficient information about each individual learner.

The Multiple Attribute Decision Making (MADM) involves making preference decisions (such as evaluation, prioritization, and selection) over the available alternatives that are characterized by multiple, usually conflicting attributes (Hwang & Yoon, 1981). Web-IT used MADM in combination with stereotypes for the automatic selection of the most appropriate advice to be given to a user who is having problems with the interaction (Kabassi & Virvou, 2004). Furthermore, Alepis, Virvou, and Kabassi. (2008) have described a novel mobile educational system that incorporates bimodal emotion recognition through a multi-criteria theory.

In addition, the OCC cognitive theory of emotions (Ortony et al., 1988), which allows modeling possible emotional states of students, has been used by Conati and Zhou (2002) for recognizing user emotions for their educational game prime climb. VIRGE is another ITS-game which has adopted OCC theory in order to provide important evidence about students' emotions while they learn (Katsionis & Virvou, 2004; Virvou, Katsionis, & Manos, 2005). Moreover, Hernández, Sucar, and Arroyo-Figueroa (2010) applied an affective student model combining the OCC theory with Bayesian Networks. The OCC theory has also used in a Mobile Medical Tutor (MMT) for modeling possible states that a tutoring agent may use for educational purposes (Alepis & Virvou, 2011). Finally, the emotional student model of PlayPhysics (Muñoz, Mc Kevitt, Lunney, Noguez, & Neri, 2011) uses, except of Bayesian Networks, the Control-Value theory (Pekrun, Frenzel, Goetz, & Perry, 2007), which is an integrative framework that employs diverse factors, e.g. cognitive, motivational and psychological, to determine the existence of achievement emotions.

4.6. Constraint-Based Model

The Constraint-Based Model (CBM) has been proposed by Ohlsson (1994). It is based on Ohlsson's theory of learning from errors (Ohlsson, 1996), which proposes that a learner often makes mistakes when performing a task, even when s/he has been taught the correct way to it. In CBM constraints are used to represent both domain and student knowledge. According to Martin (1999) a constraint is characterized by a relevance clause and a satisfaction clause: the relevance clause is a condition that must be true before the constraint is relevant to the current solution, and once it has been met, the satisfaction clause must be true for the solution to be correct. In other words, in CBM each constraint represents a bug in the form "when 'satisfaction clause' fails to hold true for 'relevance condition', the learner has introduced a bug". Consequently, in CBM the domain knowledge is represented as set of constraints and the student model is the set of constraints that have been violated.

Therefore, the CBM approach provides a theoretically sound and practical solution to the intractable problem of student modeling (Ohlsson & Mitrovic, 2006). According to Mitrovic, Mayo, Suraweera, and Martin (2001), the most important advantages of CBM are: its computational simplicity, the fact that it does not require a runnable expert module, and the fact that it does not require extensive studies of student bugs as in enumerative modeling. These advantages have lead researchers to apply the CBM approach to tutoring systems in a variety of domains. One such system is the SQLT-Web, which is a web-enabled intelligent tutoring system that teaches the SQL database language (Mitrovic, 2003). It observes students' actions and adapts to their knowledge and learning abilities, modeling the student with the CBM approach. KERMIT, which is an ITS that teaches conceptual database design, maintains two kind of student models: short-term, which is implemented as CBM, and long-term ones that is implemented as an overlay model (Suraweera & Mitrovic, 2004). Another system that uses CMB for student modeling is COLLECT-UML, which is an ITS that teaches object-oriented design using Unified Modeling Language (Baghaei, Mitrovic, & Irwin, 2005). Furthermore, the CBM approach has been used in J-LATTE, which is an ITS that teaches a subset of the Java programming language (Holland, Mitrovic, & Martin, 2009). INCOM is another tutoring system in the field of programming, which has used the CBM approach to diagnose the student's errors (Le & Menzel, 2009). Finally, Weerasinghe and Mitrovic (2011) have adopted CBM, in order to model the student's knowledge in EER-Tutor, which is another ITS that teaches conceptual database design and the early standalone version of which was KERMIT.

4.7. Fuzzy student modeling

Learning is not a "black and white" paper, but it is a complex process. Determining a student's knowledge is not a straightforward task, since it often depends on and is reflected through things that cannot be directly observed and measured (Jeremić et al., 2012). Especially in an intelligent tutoring system, where there is no direct interaction between the teacher and the student and technical difficulties, such as network congestion, cause difficulties and problems in gathering information about students' mental state and behavior, the presence of uncertainty in student diagnosis is increased (Grigoriadou et al., 2002). One possible approach to encounter this uncertainty is fuzzy logic that was introduced by Zaheh (1965) as a methodology for computing with words, which cannot be done equally well with other methods (Zadeh, 1996), since the fuzzy logic based methods are more consistent with the human-being decision-making process (Shakouri & Tavassoli, 1998). Fuzzy logic is able to handle uncertainty in everyday problems caused by imprecise and incomplete data as well as human subjectivity (Drigas, Argyri, & Vrettaros, 2009). According to them, a fuzzy set is defined as an ordered set $(x, u_A(x))$, where $x \in X$ and $u_A(x) \in [0,1]$, equipped with a membership function $\mu_A(x)$: $X \to [0,1]$, where

$$\mu_A(x) = \begin{cases} 1, & x \text{ absolutely in } A \\ 0, & x \text{ absolutely not in } A \\ (0,1), & x \text{ partially in } A \end{cases}$$

Value $u_A(x)$ is called degree of membership or membership value.

Fuzzy logic techniques can be used to improve the performance of an educational environment, in which decisions about the learning material that should be delivered and the feedback and advices that should be given to each individual learner, have to be taken, since according to Shakouri and Menhaj (2008) an algorithm based on fuzzy decision making helps to select the optimum model considering a set of criteria and model specifications. Indeed as Chrysafiadi K. and M. (2012) showed, the integration of fuzzy logic into the student model of an ITS can increase learners' satisfaction and performance, improve the system's adaptivity and help the system to make more valid and reliable decisions. Therefore, several researchers have incorporated fuzzy logic techniques in student modeling, due to its ability to naturally represent human conceptualizations.

Xu et al. (2002) used fuzzy models to represent a student profile in order to provide personalized learning materials, quiz and advices to each student. In F-CBR-DHTS (Tsaganoua, Grigoriadou, Cavoura, & Koutra, 2003) the diagnosis of students' cognitive profiles of historical text comprehension was done with fuzzy techniques. Moreover, TADV (Kosba, Dimitrova, & Boyle, 2003, 2005) includes a student model which combines an overlay model with fuzzy techniques, to represent the knowledge of individual students and their communication styles. Kavcic (2004) succeeded to provide personalization of navigation in the educational content of InterMediActor system through the construction of a navigation graph and the adoption of fuzzy logic into student reasoning. A fuzzy-based student model was applied, also, by Stathacopoulou, Magoulas, Grigoriadou, and Samarakou (2005) to a discovery-learning environment that aimed to help students to construct the concepts of vectors in physics and mathematics. The use of fuzzy techniques allowed the diagnostic model to some extent imitate teachers in diagnostic students' characteristics, and equips the intelligent learning environment with reasoning capabilities that can be further used to drive pedagogical decisions depending on the student learning style. In addition, Salim and Haron (2006) constructed a framework for individualizing the learning material structure in an adaptive learning system, which utilized the learning characteristics and provide a personalized learning environment that exploit pedagogical model and fuzzy logic techniques. Jia, Zhong, Zheng, and Liu (2010) applied fuzzy set theory to the design of an adaptive learning system in order to help learners to memory the content and improve their comprehension. Furthermore, Goel, Lallé, and Luengo (2012) used fuzzy logic representation for student modeling. This fuzzy student model facilitated student reasoning based on imprecise information coming from the student–computer interaction and performed the prediction of the degree of error a student makes in the next attempt to a problem. Finally, DEPTHS (Jeremić et al., 2012), which is an intelligent tutoring system for learning software design patterns, models the student's mastery and cognitive characteristics through a combination of stereotype and overlay modeling with fuzzy rules that are applied during the learning process to keep student model update.

4.8. Bayesian networks

Another well-established tool for representing and reasoning about uncertainty in student models is Bayesian networks (Conati, Gertner, & Vanlehn, 2002). A Bayesian network (BN) is a directed acyclic graph in which nodes represent variables and arcs represent probabilistic dependence or causal relationships among variables (Pearl, 1988). The causal information encoded in BN facilitates the analysis of action sequences, observations, consequences and expected utility (Pearl, 1996). In student modeling nodes of a BN can represent the different components/dimensions of a student such as knowledge, misconceptions, emotions, learning styles, motivation, goals etc. Mayo and Mitrovic (2001) has classified Bayesian student modeling approaches into three types, according to how the structure of the network and prior, conditional probabilities are elicited. These types of Bayesian student models are expert-centric models, which use experts to specify the structure of the network and its corresponding initial prior and conditional probabilities, efficiency-centric models that restrict the structure of the network in order to maximize efficiency, and data-centric models, which use data from previous experiment and/or pre-tests to generate the network and its probabilities.

Bayesian networks have attracted a lot of attention from theorists and system developers due to their sound mathematical foundations and also for a natural way of representing uncertainty using probabilities (Jameson, 1996; Liu, 2008). The attractiveness of Bayesian models comes from their high representative power and the fact that they lend themselves to an intuitive graphical representation, as well as the fact that they offer a well defined formalism that lends itself to sound probability computations of unobserved nodes from evidence of observed nodes (Desmarais & Baker, 2012). Furthermore, the presence of capable and robust Bayesian libraries (e.g. SMILE), which can be easily integrated into the existing or new student modeling applications, facilitates the adoption of BNs in student modeling (Millán et al., 2010).

In Andes, which is a tutoring system for Newtonian physics, students' reasoning is performed by a constrained-based model (Shapiro, 2005). In this system, also, a probabilistic student model with Bayesian networks is used in order to manage uncertainty (Conati et al., 2002). Millán and Pérez-de-la-cruz (2002) improved the accuracy and efficiency of the diagnosis process through a student model, which applied Bayesian networks and Adaptive Testing Theory. Also, Bunt and Conati (2003) used Bayesian networks to model the students of an intelligent exploratory learning environment for the domain of mathematic functions, which was named Adaptive Coach for Exploration (ACE). They built a student model capable of detecting when the learner is having difficulty exploring and of providing the types of assessments that the environment needs to guide and improve the learner's exploration of the available material. A Bayesian student model was applied in an assessment-based learning environment for English grammar, which is called English ABLE and was used by pedagogical agents to provide adaptive feedback and adaptive sequencing of tasks (Zapata-Rivera, 2007). AMPLIA, which is an intelligent learning environment employed as a resource in medical students' training, supports the development of probabilistic diagnostic reasoning and modeling of diagnostic hypotheses through a hybrid student model that combines Bayesian networks with cognitive theories (Viccari, Flores, Seixas, Gluz, & Coelho, 2008). Moreover, eTeacher (Schiaffino et al., 2008) used Bayesian networks in order to detect a student's learning style automatically from the student's actions. Similarly, modeling of student's learning style was performed using Bayesian networks in DesignFirstITS, which is an ITS that helps novices to learn object oriented design by creating UML class diagrams (Parvez & Blank, 2008). Furthermore, Conati and Maclaren (2009) developed a probabilistic model of user affect, which recognizes a variety of user emotions by combining information on both the causes and effects of emotional reactions within a Dynamic Bayesian Network. A similar significant attempt to recognize and convey emotions in order to enhance students' learning and engagement was done by Muñoz, Mc Kevitt, Lunney, Noguez, and Neri (2010) in PlayPhysics, an emotional game-based learning environment for teaching physics. Furthermore, Millán et al. (2010) used Bayesian networks as a practical tool for student modeling in order to provide personalized instruction to the domain of engineering. Similarly, in TELEOS a Bayesian network based student model was used in order to explicitly diagnose the student's knowledge state and cognitive behavior (Chieu, Luengo, Vadcard, & Tonetti, 2010). Hernández et al. (2010) developed an affective model (ABM) for intelligent tutoring systems, which was based on an affective student model that was represented as a dynamic Bayesian network. In addition, a Bayesian student model was used in Crystal Island, which is a game-based learning environment, in order to predict student affect and improve learning and motivation (Sabourin, Mott, & Lester, 2011). Another Bayesian student model was applied to AdaptErrEx in order to model learners' skills and misconceptions (Goguadze, Sosnovsky, Isotani, & McLaren, 2011). Finally, INQPRO system predicts the acquisition of scientific inquiry skills, which are composed of implicit skills as hypothesis formulation, variable identification, data comparison and drawing conclusion, by modeling students' characteristics with Bayesian networks (Ting & Phon-Amnuaisuk, 2012).

4.9. Ontology-based student modeling

Recently a lot of research has been done on the crossroad of user modeling and web ontologies, since both disciplines attempt to model real world phenomena qualitatively and due to the fact that the majority of user modeling projects have been deployed on the web and web ontologies are becoming defacto standard for web-based knowledge representation (Sosnovsky & Dicheva, 2010). The fact that an ontology supports the representation of abstract enough concepts and properties so as to be easily reused and, if necessary, extended in different application contexts, enables the reasoning on the information represented in the ontology (Clemente, Ramírez, & de Antonio, 2011). Therefore, ontologies seem to can help to student reasoning. Winter, Brooks, and Greer (2005) analyzed the ways ontologies can help student modeling. Among the advantages of ontology-based models they named ‘‘formal semantics, easy reuse, easy probability, availability of effective design tools, and automatic serialization into a format compatible with popular logical inference engines’’. Moreover, according to Peña and Sossa (2010) meta-data and ontologies facilitate building a large-scale web of machine-readable and machine-understandable knowledge, and therefore they facilitate the reuse and the integration of resources and services, so that web-based educational systems and student models can provide better applications.

Several student models have been built based on ontologies. The Personal Reader uses semantic web technologies and ontologies in order to represent information about learners, which is needed to recommend appropriate learning resources relevant to user interests, learner performance in different courses within one domain or different domains, user goals and preferences (Dolog, Henze, Nejdl, & Sintek, 2004). Pramitasari, Hidayanto, Aminah, Krisnadhi, and Ramadhanie (2009) developed a student model ontology based on student performance as representation of prior knowledge and learning style, in order to create personalization for e-learning system. Also, OPAL is an ontology-based framework which provides content presentation and navigation assistance depending on the requirements of individual users and it adapts specifically to a learner’s knowledge and interests of the subject (Cheung, Wan, & Cheng, 2010). Peña and Sossa (2010) adopted a semantic representation and management of student models with ontologies in order to represent learners’ knowledge, personality, learning preferences and content, and to deliver the appropriate option of lecture to students. MAEVIF makes sensible tutoring decisions and provide the most suitable feedback to the student in each moment through a student model which is based on ontologies and diagnosis rules (Clemente et al., 2011). Finally, Nguyen, Vo, Bui, and Nguyen (2011) introduced an ontology-based student model used in a Social Network for Information Technology Students (SoNITS) to help the organization of knowledge and the reasoning on skill relationships.

5. How a student model is used

It has been said that a well-designed tutoring system actively undertakes two tasks: that of the diagnostician, discovering the nature and extent of the student’s knowledge, and that of the strategist, planning a response using its findings about the learner (Glaser, Lesgold, & Lajoie, 1987; Michaud & McCoy, 2004; Spada, 1993). This is the main role of student model, which is the base for personalization in intelligent tutoring systems (Devedzic, 2006). The information of a student model is used by the system

Table 1a
2002–2008.

	Overlay	Stereotypes	Perturbation	Machine learning	Cognitive theories	Constraint-based	Fuzzy	Bayesian networks	Ontology-based
Web-EasyMath		X		X					
Andes						X		X	
Millán & Perez de la Cruz, 2002					X			X	
Xu et al., 2002							X		
Conati & Zhou, 2002					X				
F-SMILE		X			X				
INSPIRE	X	[a]					X		
Web-PTV		X		X					
Surjono & Maltby, 2003	X	X	X						
SQLT-Web						X			
ACE								X	
F-CBR-DHTC		[a]					X		
TADV	X						X		
LeCo-EAD			X						
WILEDS	X								
MEDEA	X								
InterMediActor	X						X		
The personal reader	X								X
Baker et al., 2004				X					
KERMIT	X					X			
ICICLE	X	X							
Web-IT		X			X				
VIRGE					X				
Stathakopoulou, Magoulas, Grigoriadou & Samaracou, 2005							X		
COLLECT-UML						X			
InfoMap	X		X						
Kumar, 2006a; Kumar, 2006b	X								
Salim & Haron, 2006		[a]					X		
English ABLE								X	
Baker, 2007				X					
DeLC	X	X							
AUTO-COLLEAGUE		X	X						
Kofod-Petersen et al., 2008		X							
Web_Tutor_Pas		X							
AMPLIA					X			X	
Carmona et al., 2008		[a]						X	
Alepis et al., 2008					X				
DesignFirstITS								X	
ADAPTAPlan				X			X		
e-Teacher								X	

[a] Stereotype-like.

in order to adapt its responses to each individual student dynamically providing personalized instruction, help and feedback.

The student model is used for accurate student diagnosis in order to predict students' needs and adapt the learning material and process to each individual student's learning pace. It is used to produce highly accurate estimations of the student's knowledge level and cognitive state in order to deliver to them the most appropriate learning material. Furthermore, an adaptive and/or personalized tutoring system can consult the student model in order to recognize the learning style and preferences of a student and make a decision about the learning strategy that is likely to be the most effective for her/him. Moreover, by predicting of student affective state, an adaptive and/or personalized educational system can select appropriate learning methods in order to increase the effectiveness of tutorial interactions and improve the learning and motivation. In addition, a student model can be used for identifying the student's strength and weaknesses in order to provide her/him individualized advice and feedback. Also, by identifying the meta-cognitive skills of a learner, the system can provide her/him with more complicated tasks and proper learning methods in order to enhance deep learning and help her/him to become a better learner.

6. Comparative discussion

The aim of this paper is to discover the tendencies that there are on student modeling the past years. For this reason a search of the student modeling techniques that have been used by researchers as well as the student's characteristics that they have chosen to model was conducted. The results of the findings are presented in the following tables. To be more specific, Table 1a presents the student modeling approaches that have been used in a variety of adaptive and/or personalized tutoring systems from 2002 up to 2008, Table 1b presents the student modeling approaches that have been used in the development of adaptive and/or personalized tutoring systems from 2009 up to now, Table 2a presents the student's characteristics that have been modeled by the student model of several adaptive and/or personalized tutoring systems from 2002 up to 2008, and Table 2b presents the student's characteristics that have attracted the interest of many researchers the past 5 years concerning the student model. The data in these tables are presented with chronological order.

Firstly, a comparative discussion about the student modeling techniques was made. As it is presented in Tables 1a and 1b, the most common used student modeling techniques are the overlay and stereotype modeling. Indeed, the years 2002 up to 2007 the overlay student model was used more usually. Furthermore, the use of the perturbation student model was most common until 2007, while the use of machine learning techniques and the integration of cognitive theories seem to be stable during the past 10 years. Moreover, the years 2002 up to 2007 researchers preferred to integrate fuzzy logic techniques into the student model in order to deal with the uncertainty of student's diagnosis. However, the past 5 years a probabilistic model has been added to researchers' preferences for dealing with the uncertainty. This probabilistic model is Bayesian student model, which is based on

Table 1b
2009–2012.

	Overlay	Stereotypes	Perturbation	Machine learning	Cognitive theories	Constraint-based	Fuzzy	Bayesian networks	Ontology-based
GIAS		X		X					
LS-Plan	X								
Pramitasari et al., 2009									X
Wang et al., 2009				X					
Conati & Maclaren, 2009								X	
J-LATTE						X			
INCOM						X			
WELSA		[a]							
CLT		X							
ABM					X			X	
Baschera & Gross, 2010			X						
Cetintas et al., 2010				X					
POOLE III				X				X	
Baker et al., 2010				X				X	
Al_Hmouz et al., 2010		[a]		X					
Jia et al., 2010							X		
Millán et al., 2010								X	
PlayPhysics					X			X	
Peña & Sossa, 2010									X
TELEOS								X	
OPAL	X								X
Wayang outpost		[a]							
SimStudent				X					
Balakrishnan, 2011				X					X
EER-Tutor						X			
Crystal Island								X	
AdaptErrEx								X	
IWT	X								X
MAEVIF									X
SoNITS									X
DEPTHS	X	X					X		
MMT					X				
AHS-TS	X	[a]							
PDinamet	X								
Goel et al., 2012							X		
INQPRO								X	

[a] Approach-like (stereotype-like or perturbation-like).

Table 2a
2002–2008.

	Knowledge	Errors/ misconceptions	Learning styles & preferences	Other cognitive aspects	Affective features	Moti-vation	Meta-cognitive features
Web-EasyMath	X						
Andes	X	X		X			X
Millán & Perez de la Cruz, 2002	X	X					
Xu et al., 2002	X			X			
Conati & Zhou, 2002					X		
F-SMILE	X	X					
INSPIRE	X		X				
Web-PTV	X			X			
Surjono & Maltby, 2003	X	X	X				
SQLT-Web	X						
ACE	X		X				
F-CBR-DHTC	X			X			
TADV	X		X				
LeCo-EAD	X	X					
WILEDS	X						
MEDEA	X						
InterMediActor	X						
The personal reader	X		X				
Baker et al., 2004	X	X				X	
KERMIT	X	X					
ICICLE	X						
Web-IT	X			X			
VIRGE	X				X		
Stathakopoulou, Magoulas, Grigoriadou & Samaracou, 2005	X		X	X		X	
COLLECT-UML	X						
InfoMap	X	X					
Kumar, 2006a; Kumar, 2006b	X						
Salim & Haron, 2006			X				
English ABLE	X						
Baker, 2007					X	X	
DeLC	X		X	X			
AUTO-COLLEAGUE	X	X		X	X		
Kofod-Petersen et al., 2008				X	X		
Web_Tutor_Pas	X	X					
AMPLIA	X			X			
Carmona et al., 2008			X				
Alepis et al., 2008					X		
DesignFirstITS	X		X				
ADAPTAPlan	X		X	X			
e-Teacher	X		X				

Bayesian networks. Also, an interest has started to arise, mainly the past two years, about the ontology-based student model.

Furthermore, many researchers have used a hybrid student model, which brings together various features of different techniques of student modeling, in order to combine various aspects of student's characteristics. So, there are hybrid student models that combine overlay with stereotype modeling techniques, or stereotypes with machine learning techniques, or an overlay student model with fuzzy logic techniques, or Bayesian networks with machine learning algorithms. The above combinations of student modeling techniques are just some examples. In Table 3 the possible combinations that have been applied to a variety of adaptive and/or personalized tutoring systems from 2002 up to now are presented. To be more specific, in this table the percentages of the adaptive and/or personalized tutoring systems that have used each combination of student modeling approaches are presented. To be informed about the tendency that there is in student modeling techniques' combinations, each row of the Table 3 should be read. For example, by reading the first row, the reader is informed about the fact that the most common used combination of an overlay student model is with stereotypes (43.75%), while no one adaptive and/or personalized tutoring system has used a compound student model which brings together an overlay model with machine learning algorithms or Bayesian networks. Moreover, a frequent combination of an overlay student model is with fuzzy logic techniques. Also, some researchers have attempted to combine overlay with perturbation model or ontologies. Therefore, an overlay student model usually is combined with stereotypes or fuzzy logic techniques. Stereotypes are blended, mainly, with overlay but they are also combined with machine learning or fuzzy logic techniques. Perturbation student model is combined only with overlay and stereotypes. Machine learning techniques are used mostly to support stereotype modeling but there is also an interest to combine them with Bayesian networks. Cognitive theories are applied with Bayesian Networks and stereotypes. Constraint-Based Modeling is combined with overlay modeling and Bayesian Networks. Fuzzy logic usually is used with overlay or stereotype student models. Bayesian networks are blended, mainly, with machine learning techniques and cognitive theories, but also researchers used them in combination with stereotypes or Constraint-Based Models. Finally, ontologies are primarily combined with overlay student modeling. It has to be referred that attempts to construct a hybrid student model that combines more than two student modeling techniques, have also be made, but they are few and they are usually limited to the combination of overlay model with stereotypes and fuzzy logic techniques.

The need for blended student models arises from the need to model a variety of student's characteristics. It has been proven that some student model approaches are ideal for representing some particular aspects of the student's characteristics. For example,

Table 2b
2009–2012.

	Knowledge	Errors/ misconceptions	Learning styles & preferences	Other cognitive aspects	Affective features	Moti-vation	Meta-cognitive features
GIAS	X		X	X			
LS-Plan	X		X				
Pramitasari et al., 2009	X		X				
Wang et al., 2009	X		X	X			
Conati & Maclaren, 2009					X		
J-LATTE	X	X					
INCOM	X	X					
WELSA			X				
CLT	X			X			
ABM	X		X	X	X		
Baschera & Gross, 2010	X	X					
Cetintas et al., 2010	X					X	
POOLE III	X				X		
Baker et al., 2010	X						
Al_Hmouz et al., 2010	X		X	X			
Jia et al., 2010	X		X	X			
Millán et al., 2010	X	X		X	X	X	X
PlayPhysics	X				X	X	
Peña & Sossa, 2010	X		X	X			
TELEOS	X			X			
OPAL	X		X			X	
Wayang Outpost	X				X		X
SimStudent	X						
Balakrishnan, 2011	X	X			X		
EER-Tutor	X	X					
Crystal Island					X		
AdaptErrEx	X	X					
IWT	X		X				X
MAEVIF	X		X				
SoNITS	X						
DEPTHS	X		X	X			
MMT					X	X	
AHS-TS	X		X	X			
PDinamet	X						
Goel et al., 2012	X						
INQPRO	X						

Table 3
Tendencies on blended student models.

	Overlay (%)	Stereotypes (%)	Perturbation (%)	Machine learning (%)	Cognitive theories (%)	Constraint-Based (%)	Fuzzy (%)	Bayesian networks (%)	Ontology-based (%)
Overlay		43.75	6.25	0	0	6.25	25	0	18.75
Stereotypes	31.58		10.53	21.05	10.53	0	21.05	5.26	0
Perturbation	50	50		0	0	0	0	0	0
Machine learning	0	50	0		0	0	12.5	25	12.5
Cognitive theories	0	33.33	0	0		0	0	66.67	0
Constraint-based	50	0%	0	0	0		0	50	0
Fuzzy	44.44	44.44	0	11.11	0	0		0	0
Bayesian networks	0	12.50	0	25	50	12.50	0		0
Ontology-nased	75	0	0	25	0	0	0	0	

the overlay student model is useful for the representation of the student's mastery on the domain knowledge, stereotypes are ideal to represent student's learning styles, the perturbation student model specializes in detecting the student's misconceptions, cognitive theories, such as OCC theory, seem to have been established as a standard method for emotion recognition, Constraint-Based Modeling identifies the student's knowledge, fuzzy and probabilistic student modeling approaches are ideal for representing more abstract and subjective aspects of the student's characteristics such as affective, cognitive and meta-cognitive features. Tables 2a and 2b that are presented above have been constructed, in order to detect the tendency of student modeling techniques in relation to student modeling characteristics. It is concluded that the years 2002 up to 2008, the researchers were focused, primarily, on modeling the knowledge level, the errors and misconceptions, and the learning styles of students. That is, maybe, the reason for the increasing use of overlay, perturbation and stereotype student modeling approaches these years. The following years the interest of modeling the student's learning styles and preferences, and other cognitive aspects, continued to grow. Also, the interest on modeling motivation, affective aspects and meta-cognitive features of students has arisen. That is why researchers have turned their interest to new student modeling approaches, such as Bayesian networks and ontology-based techniques.

Table 4 was constructed in order to make a comparative discussion about the student modeling techniques in relation to student

Table 4
Student modeling approaches in relation to student modeling characteristics.

	Knowledge (%)	Errors/ misconceptions (%)	Learning styles & preferences (%)	Other cognitive aspects (%)	Affective features (%)	Moti-vation (%)	Meta-cognitive features (%)
Overlay	20	0	17.95	9.09	0	10	20
Stereotypes	14.44	5.26	25.64	33.33	16.67	0	0
Perturbation	2.22	26.32	0	0	0	0	0
Machine learning	13.33	10.53	10.26	15.15	16.67	30	0
Cognitive theories	6.67	10.53	0	9.09	33.33	20	0
Constraint-based	7.78	26.32	0	0	0	0	0
Fuzzy	10	0	17.95	18.18	0	10	0
Bayesian networks	16.67	15.80	12.82	12.12	27.78	20	60
Ontology-based	8.89	5.26	16.67	3.03	5.36	10	20

modeling characteristics. This table presents the percentage of student modeling approaches that have been used the past decade, in order to model particular student's characteristics. The most preferred technique for representing the student's mastery on the domain knowledge is the overlay student model. Furthermore, it seems that the representation of student's errors and misconceptions is performed better by a perturbation student model or a constraint-based student model. Stereotyping seems to be ideal for modeling student's learning styles, preferences and other cognitive factors such as memory, attention and perception. Due to the uncertainty that characterizes students' cognitive aspects; many researchers chose to integrate fuzzy logic techniques into the student model. In addition, Bayesian networks are preferred for modeling affective aspects of student's characteristics, such as emotions and feelings, and meta-cognitive aspects, such as self-regulation, self-explanation and self-assessment, while motivation seems to be modeled better by machine learning techniques. Another approach that seems to be ideal for performing affective student modeling is the utility of cognitive theories. The ontology-based student model does not seem to prevail in the modeling of a particular student's characteristic, This happens, maybe, because it is a new student modeling approach and there is no an adequate number of researches and applications on this domain.

7. Conclusions

Our target in this paper was to present a literature review of student modeling from 2002 up to now. The students' characteristics and data that should be gathered and represented by a student model were analyzed, the most prevailing approaches of student modeling of the past decade were presented and how a student model can be used by an adaptive and/or personalized tutoring system for adaptation was showed. A student model can represent a wide range of students' characteristics. The most common aspects of a student that have been modeled are knowledge state and learning preferences. Moreover, a research trend to represent students' emotions and affective aspects has arisen in the past years. It is prudent to develop domain-independent methods for providing user modeling capabilities. This is achieved by domain-independent authoring tools which help the instructors to create adaptive and/or personalized tutoring systems that may model learners' characteristics and their reasoning abilities.

In addition, many researchers have combined different student modeling techniques in order to build hybrid student models which represent a variety of students' characteristics. This way, the student model can exhibit a variety of unique individual characteristics and preferences of each learner. The student models of a large number of adaptive and/or personalized tutoring systems were reviewed and the different approaches that were applied to construct them were compared.

In conclusion our review has revealed that the majority of personalized and adaptive tutoring systems use an overlay model to represent the student's knowledge, while they use a perturbation model to identify the student's misconceptions. Furthermore, learning styles and preferences are usually modeled with stereotyping. Also, affective student modeling is performed successfully through the utility of cognitive theories and/or Bayesian networks. A significant conclusion is that there is an increase in the adoption of fuzzy logic techniques and Bayesian networks in the development of a student model in order to deal with the uncertainty of learning and student diagnosing processes. Finally, several researchers have shown great interest in ontology-based student modeling due to the fact that this technique offers the ability to represent student models in a more abstract way which allows their reuse.

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