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Evaluating the integration of fuzzy logic into the student model of a web-based learning environment

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ABSTRACT

In this paper, we evaluate the effectiveness and accuracy of the student model of a web-based educational environment for teaching computer programming. Our student model represents the learner's knowledge through an overlay model and uses a fuzzy logic technique in order to define and update the student's knowledge level of each domain concept, each time that s/he interacts with the e-learning system. Evaluation of the student model of an Intelligent Tutoring System (ITS) is an aspect for which there are not clear guidelines to be provided by literature. Therefore, we choose to use two well-known evaluation methods for the evaluation of our fuzzy student model, in order to design an accurate and correct evaluation methodology. These evaluation models are: the Kirkpatrick's model and the layered evaluation method. Our system was used by the students of a postgraduate program in the field of Informatics in the University of Piraeus, in order to learn how to program in the programming language C. The results of the evaluation were very encouraging.

1. Introduction

The last decades the interest on web-based learning environments and tools has been witnessed a rapid growth. However, web-based learning environments deal with the varying backgrounds and heterogeneous needs of learners. Student's individual differences play a central role in web-based learning (Graf & Kinshuk, 2010), and a way to deal with these is the Intelligent Tutoring Systems (ITS), which belong to an advanced generation of computer-based instruction systems that provide students with highly personalized learning experience by adapting the content and its presentation to the student's needs and preferences (Jeremić, Jovanović, & Gašević, 2012). Therefore, the need of developing a web-based educational system that can offer dynamic adaptation to each individual student is arisen.

Adaptive e-learning is suitable for teaching heterogeneous student populations in higher education (Schiaffino, Garcia, & Amandi, 2008). 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). So, when creating an adaptive web-based educational application, we have to focus on the student model, which is a core component in any intelligent or adaptive tutoring system that represents many of the student features such as knowledge and individual traits (Brusilovsky & Millán, 2007). 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 ITS for offering adaptation (Thomson & Mitrovic, 2009). The most widely used technique in the field of user modeling is the overlay model. The main idea of the overlay modeling is that the learner model is a subset of the domain model (Martins, Faria, Vaz de Carvalho, & Carrapatoso, 2008; Vélez, Fabregat, Nassiff, Petro, & Fernandez, 2008). However, student modeling, in many cases, deals with uncertainty and one possible approach to encounter this is fuzzy logic. Integrating fuzzy logic into the student model of an ITS is a good idea, since the fuzzy logic based methods are more consistent with the human-being decision-making processes (Shakouri & Tavassoli, 2012).

Although, the adaptation generated by user modeling techniques often tend to improve the user-system interaction, most of the time the exploitation of such techniques makes the system more complex and consequently, it should be evaluated whether the adaptivity really improves the system and whether the user really prefers the adaptive version of it (Gena, 2005). The evaluation of adaptive systems is a difficult task due to the complexity of such systems, as shown by many studies (Lavie, Meyer, Beugler, & Coughlin, 2005; Markham et al., 2003; Missier & Ricci, 2003). Thereby, evaluators need to ensure that correct evaluation methods and measurement metrics are used (Mulwa, Lawless, Sharp, & Wade, 2011). In Intelligent Tutoring Systems community, the common practice of evaluation is to perform experiment with a

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particular set of users (Jeremić, Jovanović, & Gasěvić, 2009). However, there is no standard agreed measurement framework for assessing the value and effectiveness of the adaptation yielded by adaptive systems. Therefore, it is important to not only evaluate but also to ensure that the evaluation uses the correct methods, since an incorrect method can lead to wrong conclusions (Gena & Weibelzahl, 2007).

In the view of the above, in this paper we describe and evaluate the integration of fuzzy logic into the student model of a web-based educational-environment for teaching the programming language C. To be more specific, we use an overlay student model for representing each individual knowledge level and needs. The update of the student model is based on the mechanism of rules over the fuzzy sets that are used to describe the student's knowledge level of each domain concept of the knowledge domain, which we have described in previous work (Chrysafiadi & Virvou, 2010). So, the student modeling and the adaptation decision making incorporate fuzzy logic. For the evaluation of the effectiveness and efficiency of our student model and for the estimation of the success of adaptation, which is achieved via the system's student model, we used a combination of two well-known and used models for evaluation: the Kirkpatrick, 1979 and the layered evaluation method (Brusilovsky, Karagiannidis, & Sampson, 2004). The Kirkpatrick's model is ideal for measuring the effectiveness of training programs and the layered evaluation method is an approach of evaluating the success of adaptation that is offered by an adaptive learning system.

The remainder of this paper is organized as follows. In Section 2, we present and discuss related work in the adaptive learning systems, student modeling and evaluation methods of adaptive systems and user modeling. In Section 3, we describe the student model of our web-based educational application and in Section 4 we show how it evolves by integrating fuzzy logic into it. In Section 5, we describe the evaluation method that we used in order to assess the effectiveness and efficiency of our student model. Also, in this section we quote and discuss the results of our evaluation. Finally, in Section 6, we give the conclusion drawn from this work.

2. Related work

A web-based educational system is used by students with different needs and cognitive abilities. Therefore, it is not effective all the learners to follow the same instructional model, since provision of the same instructional conditions to all students can be pedagogically ineffective (Akbulut & Cardak, 2012). This lead to the use of Adapative Education Hypermedia Systems, which provide methods to personalize system through tailoring the content presentation, navigation, and services according to individual characteristics such as user's background, previous knowledge, interests and other preferences (Ghazal, Yuosof, & Zin, 2011). So, personalization is a key in the adaptive web-based educational applications and according to Devedzic (2006), it relies on the student modeling.

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). The most commonly used technique of student modeling is the overlay model, which focuses on the comparison between the student model and the expert domain knowledge (Castillo, Gama, & Breda, 2009). The overlay model can represent the user knowledge for each concept independently and this is the reason for its extensive use in e-learning (Kahraman, Colak, & Sagiroglu, 2007; Limongelli, Sciarrone, Temperini, & Vaste, 2009). Thereby, in our system we use a qualitative weighted overlay model that determine which domain concepts and at what degree is known by a learner by describing the knowledge level of each concept with a qualitative value and a weight of this value.

Determining a student's knowledge is a complex process, which is characterized with human subjectivity. So, it is fraught with uncertainty and one possible approach to deal with this is fuzzy logic, which was introduced as a methodology for computing with words in order to handle uncertainty. An algorithm based on fuzzy decision making helps to select the optimum model considering a set of criteria and model specifications (Shakouri & Menhaj, 2008). Consequently, fuzzy logic techniques seem to be ideal for analyzing the students' knowledge level, needs and behavior and for making the right decision about the instructional model that has to be applied for each individual learner. That is the reason for applying fuzzy logic techniques in many adaptive e-learning systems (Alves, Amaral, & Pires, 2008; Jili, Kebin, Feng, & Huixia, 2009; Jurado, Santos, Redondo, Boticario, & Ortega, 2008; Sevarac, 2006). In the view of the above, we decided to apply fuzzy logic to determine the learner's knowledge level of each domain concept, to update the student model and to make decisions about the adaptation of the instruction.

In general, the fact that adding a user model to any software system will most likely make it more complex, less predictable and more buggy, leads us to ask whether or not the user model will actually improve the system (Chin, 2001). So, student models' evaluation is particularly important in the case of adaptive systems. An assessment of the student model that SQL-Tutor uses is presented in Mitrovic, Marting, and Mayo (2002). Also, Weibelzahl and Weber (2003) performed the evaluation of the accuracy of the student model of an adaptive learning system, called the HTML-Tutor. A more recent attempt to assess the effectiveness and the accuracy of the student model, which was applied in an intelligent tutoring system for learning software design patterns, was done by Jeremić et al. (2009).

Although there are many evaluation methods available in literature review, there is a not clear guideline for the selection of the right evaluation method of student modeling. However, we have to ensure that the evaluation methods that we use are correct, since a well designed evaluation should provide the evidence if a specific approach has been successful and of potential value to others (Dempster, 2004). That is the reason for choosing to use a combination of two well-known and used techniques in order to assess our system's student model. The one evaluation model that we use is the Kirkpatrick, 1979. It defines four levels of evaluation:

- *Evaluation of reaction:* It is examined what the learners thought and felt about the training. A typical instrument for gathering information regarding students' reactions is questionnaires.
- *Evaluation of learning:* It assesses the extent to which the learners gain knowledge and skills. At this level, each student's learning should be measured by quantitative and objective means.
- *Evaluation of behavior:* It examines what changes in job performance resulted from the learning process.
- *Evaluation of results:* It assesses the effects on the business, organization or environment resulting from the trainee's performance.

The second evaluation model that we selected is a model-based evaluation approach, which is called the layered evaluation framework (Brusilovsky et al., 2004). According to this framework the success of adaptation is addressed at two distinct layers:

- *Layer 1: Evaluation of user modeling.* At this layer only the user modeling process is being evaluated. Here the question can be stated as: "are the conclusion drawn by the system concerning

the characteristics of the user-computer interaction valid?"or "are the user's characteristics being successfully detected by the system and stored in the user model?"
- *Layer 2: Evaluation of adaptation decision making.* At this layer only the adaptation decision making is being evaluated. The question here can be stated as: "are the adaptation decisions valid and meaningful for the given state of the user model?"

Therefore, we use the above evaluation methods in order to measure the effectiveness of the training program, as well as the efficiency and variety of the adaptation decisions that the system makes, when we incorporate fuzzy logic into the student model.

3. Student model

To achieve adaptivity, the system should be informed about each individual learner's knowledge, needs, characteristics and misconceptions. Therefore, we have to construct a student model, which is a core component in any intelligent or adaptive tutoring system that represents many of the student's features such as knowledge and individual traits (Brusilovsky & Millán, 2007), and has been called "the key to individualized knowledge-based instruction (Millán, Loboda, & Pérez-de-la-Cruz, 2010). According to Nguyen and Do (2009) and Millán et al., 2010 when modeling a user we have to take into consideration what information and data about user should be gathered, how the user model will be updated in order to keep it up-to-date, and how it will be used. Consequently, the problem of user modeling is described by the following three questions: (i) "What are the characteristics of the user we want to model?", (ii) "How we model them?", (iii) "How we use the user model?".

In our e-learning environment we want to model the cognitive states of each learner, so as the system can recognize when a learner learns or not, forgets or assimilates concepts of the domain knowledge. In order to model the user knowledge we use an overlay model (Fig. 1). The idea of overlay modeling is to represent an individual user's knowledge as a subset of the domain model that resembles expert knowledge of the subject (Nguyen & Do, 2008). The domain is decomposed into a set of elements and the overlay model is simply a set of masteries over those elements (Nguyen & Do, 2009). The overlay model of our system is updating each time the learner interacts with the system, obtaining information about the learner's performance by the results of a test that s/he has to complete at the end of each instructional process. There is a threshold to the percentage of errors that a learner can do, in order her/his performance in a domain concept to be considered successful. In particular, a domain concept is considered as learned for a student, when s/he does up to 20% errors, otherwise the domain concept is considered to be not learned. Therefore, the overlay student model of our web-based educational application is the subset of the domain knowledge, which includes only those concepts that is considered as learned.

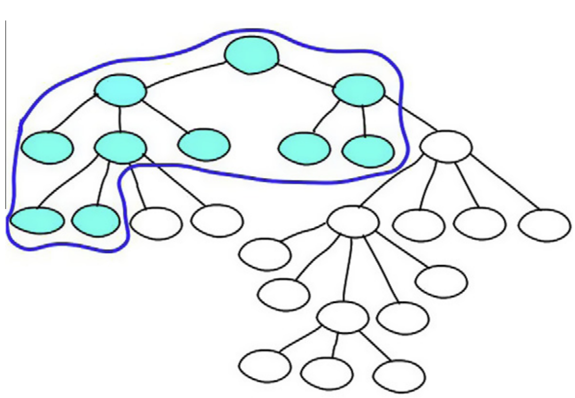

Fig. 1. Pure overlay model.

We have to notice that in the intermediate, advanced and expert levels of knowledge the tests become more complex and include exercises that combine elements of chapters that a user has been taught in a previous level. For example, an exercise with a sorting algorithm requires knowledge on variable declaration, selection and iteration statements and arrays. Therefore the learner's score on these elements triggers the system to infer whether or not the learner has forgotten a domain concept. In particular, if the learner makes more than 20% errors in these concepts, then the system infers that the learner has forgotten the corresponding chapter and responds directly to this situation by removing some elements from her/his overlay model. Consequently, the student overlay model of our system can be expanded or decreased. So, the system advices the overlay student model in order to provide personalized instruction.

4. Integration of fuzzy logic into the student model

Learning is not a "black and white" paper, but it is a complex and continuous process. It is not precise to say that a domain concept is learned or unknown, since a part of it may be unsatisfactory known and another part may be well known. The learning process is a continuous process and consequently the state of student's knowledge level has variances, since an unknown domain concept can become unsatisfactory known, known, or learned, during the learning process or a known domain concept can become unsatisfactory known if the student forgets it. Furthermore, the knowledge of a domain concept may be affected by the knowledge of another domain concept. To be more specific, if a student knows the domain concept A, it may mean that a percentage of its related domain concept B is already known by the student and so it is possible that s/he does not need to read the domain concept B. For example, if a learner excels at calculating an average in a for loop, then it means that s/he knows well, also, how to calculate a sum in a for loop, so s/he should not read the corresponding chapter. In addition, if the knowledge level of the domain concept B is reduced, it is possible that the learner has to revise the domain concept A. Thereby, the knowledge level of a domain concept can either increase or decrease the knowledge level of a depended domain concept.

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). Therefore, student's knowledge cannot be considered as a variable which takes concrete values, since its determinations deals with uncertainty and human subjectivity. One possible approach to encounter this, is fuzzy logic, which was introduced in order to handle uncertainty in everyday problems caused by imprecise and incomplete data, as well as human subjectivity (Drigas, Argyri, & Vrettaros, 2009). We define the following four fuzzy sets for describing student knowledge of a domain concept:

- **Unknown (Un):** the degree of success in the domain concept is from 0% to 60%.
- **Unsatisfactory Known (UK):** the degree of success in the domain concept is from 55% to 75%.

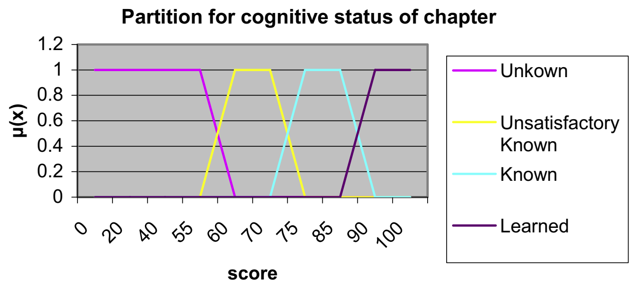

Fig. 2. Partition for cognitive status of chapter.

- **Known (K):** the degree of success in the domain concept is from 70% to 90%.
- **Learned (L):** the degree of success in the domain concept is from 85% to 100%.

The membership functions for the four fuzzy sets are depicted in Fig. 2, and are the following:

$$\mu_{\mathrm{Un}}(x) = \begin{cases} 1, & x \leqslant 55 \\ 1-(x-55)/5, & 55 < x < 60 \\ 0, & x \geqslant 60 \end{cases}$$

$$\mu_{\mathrm{K}}(x) = \begin{cases} (x-70)/5, & 70 < x < 75 \\ 1, & 75 \leqslant x \leqslant 85 \\ 1-(x-85)/5, & 85 < x < 90 \\ 0, & x \leqslant 70 \text{ or } x \geq 90 \end{cases}$$

$$\mu_{\mathrm{UK}}(x) = \begin{cases} (x-55)/5, & 55 < x < 60 \\ 1, & 60 \leqslant x \leqslant 70 \\ 1-(x-70)/5, & 70 < x < 75 \\ 0, & x \leq 55 \text{ or } x \geq 75 \end{cases}$$

$$\mu_L(x = \begin{cases} (x-85)/5, & 85 < x < 90 \\ 1, & 90 \leqslant x \leqslant 100 \\ 0, & x \leq 85 \end{cases}$$

where x is the student's degree of success in a domain concept.

The following expressions stand:

Table 1
Increase on the knowledge level of depended domain concepts.

Domain concept	$(\mu_{\mathrm{Un}}, \mu_{\mathrm{UK}}, \mu_{\mathrm{K}}, \mu_{\mathrm{L}})$	
	Before	After
Calculating sum in a for loop	(1, 0, 0, 0)	(0, 0, 0.4, 0.6)
Calculating average in a for loop	(1, 0, 0, 0)	(0, 0, 0.51, 0.49)
Counting in a for loop	(1, 0, 0, 0)	(0, 0, 0.73, 0.27)
Calculating sum in a while loop	(1, 0, 0, 0)	(0, 0, 0.4, 0.6)
Counting in a while loop	(1, 0, 0, 0)	(0, 0, 0.73, 0.27)
Calculating average in a while loop	(1, 0, 0, 0)	(0, 0, 0.77, 0.23)

Table 2
Reduce of the knowledge level of depended domain concepts.

Domain concept	$(\mu_{\mathrm{Un}}, \mu_{\mathrm{UK}}, \mu_{\mathrm{K}}, \mu_{\mathrm{L}})$	
	Before	After
Finding max/min	(0, 0, 0.2, 0.8)	(0, 0.6, 0.4, 0)
Calculating max/min in for loop	(0, 0, 0.63, 0.37)	(0, 0.6, 0.4, 0)
Calculating max/min in a while loop	(0, 0, 0.63, 0.37)	(0, 0.6, 0.4, 0)

$\mu_{\mathrm{Un}}, \mu_{\mathrm{UK}}, \mu_{\mathrm{K}}, \mu_{\mathrm{L}}$ € [0,1]
$\mu_{\mathrm{Un}} + \mu_{\mathrm{UK}} + \mu_{\mathrm{K}} + \mu_{\mathrm{L}} = 1$
if $\mu_{\mathrm{Un}} > 0 \rightarrow \mu_{\mathrm{K}} = \mu_{\mathrm{L}} = 0$
if $\mu_{\mathrm{UK}} > 0 \rightarrow \mu_{\mathrm{L}} = 0$
if $\mu_{\mathrm{K}} > 0 \rightarrow \mu_{\mathrm{Un}} = 0$
if $\mu_{\mathrm{L}} > 0 \rightarrow \mu_{\mathrm{Un}} = \mu_{\mathrm{UK}} = 0$

Therefore, a quadruplet $(\mu_{\mathrm{Un}}, \mu_{\mathrm{UK}}, \mu_{\mathrm{K}}, \mu_{\mathrm{L}})$ is used to express the student knowledge of a domain concept, the values of which are determined by the above membership functions.

Moreover, we use the fuzzy rules that we have described in a previous work (Chrysafiadi & Virvou, 2010), in order to describe how the knowledge level of a domain concept causes increase or decrease on the knowledge level of the related with this concept, concepts. According to these rules, if a student is being examined in the chapter "calculating sum in a for loop" and is doing 12% errors ($x = 88\%$), then this chapter from 100% Unknown is becoming 40% Known and 60% Learned. However, except of this chapter, changes on the knowledge level of all the related with this domain concept, concepts occur as depicted in Table 1.

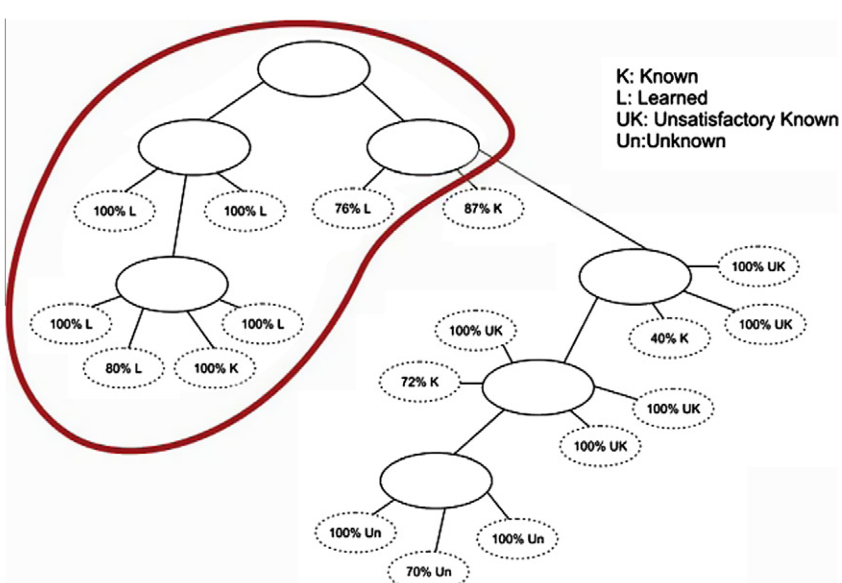

Fig. 3. The qualitative weighted overlay model.

So, all the related domain concepts become learned without the system advises the student to read them. Lets the quadruplet for the domain concept "calculating max/min in a for loop" is (0, 0, 0.63, 0.37) and the results of the test for student A show that s/he did 28% errors ($x = 72\%$) on this concept. Then, according to the fuzzy rules the knowledge level of this domain concept will be reduced, as well as the knowledge level of all the related domain concepts, which either precede or follow the above domain concept (Table 2).

Thereby, the learner has to revise and the three domain concepts.

Consequently, our pure overlay model is evolving into a qualitative weighted overlay model. A qualitative weighted overlay model is an extension of the pure overlay model that can distinguish several levels of user's knowledge about each concept representing user knowledge of a concept as a qualitative value (Brusilovsky & Anderson, 1998; Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003). In our overlay model in order to represent user knowledge of a concept, we use a qualitative value (unknown, unsatisfactory known, known, learned) combined with a percentage from 0 to 100% that points the weight of a qualitative value for a concept (Fig. 3). For example, if the quadruplet (0, 0.38, 0.72, 0) defines the knowledge level of concept C_i, then in the overlay model the corresponding with this domain concept, node will be characterized as 72%known. So C_i is not considered as assimilated. In order to be considered as assimilated, it must become 100% known (0, 0, 1, 0) or a portion of it has to be known and the remain has to be learned $(0, 0, x, 1 - x)$, hence it will be characterized as $(1 - x)\%$ Learned.

5. Evaluation

The adaptation generated by user modeling techniques often tend to improve the user-system interaction. Since most of the time exploitation of such techniques makes the system more complex, it should be evaluated whether the adaptivity really improves the system and whether the user really prefers the adaptive version of it (Gena, 2005). An evaluation offers information to make decision about using the product or not (Phillips & Gilding, 2003). According to Mulwa, Lawless, Sharp, and Wade (2011) there is no standard agreed measurement framework for assessing the value and effectiveness of the adaptation yielded by adaptive systems. Indeed, the most common method for the evaluation of an Intelligent Tutoring System (ITS) is empirical approaches (Aïmeur & Frasson, 2000; Weber & Specht, 1997). Empirical evaluations refer to the appraisal of a theory by observation in experiments (Mulwa et al., 2011). Consequently, the only way to verify the quality of the adaptation that is provided by our fuzzy student model is to evaluate the system in real conditions.

5.1. The method

For the evaluation of our student model we use a combination of the Kirkpatrick (1979), which is the most well-known and used model for measuring the effectiveness of training programs, with the layered evaluation (Totterdell, 1990). In particular, we use the first two levels of evaluation of the Kirkpatrick's model and the second phase of the layered evaluation model as Brusilovsky et al. (2004) have defined. The evaluation of behavior and the evaluation of results levels of the Kirkpatrick's model were omitted due to the fact that they need at least a two year evaluation period (Jeremić et al., 2009) and the students which participated in the empirical evaluation of this study would have already graduated. Also, we omitted the interaction assessment phase of the layered evaluation because we want to evaluate only the integration of fuzzy logic in the student model, which changes the decision-making processes that the system follows in order to define the knowledge level of learners each time. Both student models (this without the fuzzy logic and this with the fuzzy logic) detect and maintain learners' characteristics with the same way. Therefore, we have to evaluate the adaptation decision-making phase. Consequently, the method that we applied to evaluate the effectiveness of the integration of the fuzzy logic into the student model is consisted of:

i. Analyzing the learners' reactions to the e-learning environment. For gathering this kind of information we used a questionnaire (Appendix A). The questions were close-ended based on Likert scale with five responses ranging from "Very much" (5) to "Not at all" (1). The questions were divided into two sections based on the type of information we were interested in. The questions of the first section were related to the effectiveness of the training program. The second section was aimed at evaluating the adaptivity of the system.
ii. Conducting an experiment with an experimental group (the group of students which used the system with the fuzzy student model for learning programming) and a control group (the group of students which used the system with the student model from which fuzzy logic was absent, for learning programming). According to Grubišić, Stankov, Rosić, and Žitko (2009) experiment used in the e-learning systems' effectiveness evaluation change the independent variable (tutoring strategy) while measuring the depended variable (effects on learning). In our study, the independent variable is the student model and the dependent variables are:

- The evaluation of learning, which is determined by measuring the learner's performance. Learner's performance is referred to how well the students understood the facts and techniques presented in the learning material. It is measured by learner's results on the final test of each learning session in combination with the times that s/he needed to read the corresponding with the test chapters. In particular, we use a weight $w = 5\%$, according to which the percentage of errors (er) increases when the reading times (rt) increase. The math type is $VMP = er + w * rt$, where VMP is the Variable Measuring Performance. For example, three students did 20% errors in the domain concept I. However, student A read it once, student B three times and student C did not read it at all. So, for student A is $VMP = 20 + 5 * 1 = 25\%$, for student B is $VMP = 20 + 5 * 3 = 35\%$ and for student C is $VMP = 20 + 5 * 0 = 20\%$. Consequently, student's C performance is the better.
- The appropriateness of adaptation decisions, which answers to the question if the adaptation decisions that the system makes improve the quality of the user's interaction with the system. The integration of fuzzy logic into our system forces it to decide which domain concepts are learned or not, which concepts have to be revised and which domain concepts have been forgotten by a learner. Therefore, we have to measure the system's navigation efficiency, which is referred to how many times the system advices each learner to read or revise a domain concept until it will be considered as learned. Furthermore, we want to check the reliability of the system when it decides that a domain concept does not need more reading. As a result, we define the following two variables:

o *VMNE (Variable Measuring Navigation Efficiency):* It defines the navigation efficiency of the system, calculating the mean of times that the system advises a student to read or revise each domain concept until it is considered as learned. The fewer the reading times, the more efficient the navigation support of the system.

o *VCR (Variable Consolidating Reliability)*: It defines system's reliability, calculating the mean of times that each student is advised to revise a domain concept, which was considered as learned in a previous interaction with the system, multiplied with a defined weight. More concretely, each time a learner "returns" to a learned domain concept to revise it, we consider that the system's reliability reduces 10%. If the learner needs to revise more than one time the specific domain concept after her/his return to this, until it is considered as learned again, the system's reliability reduces 5% multiplied with the times of revision. In general, the VCR is calculated by the formula $VCR = 10 * ret + (trev - ret) * 5$, where ret is the times of "return" to a domain concept and trev is the times of revise after returning. For example, student A returned two times to the domain concept I (ret = 2) and the first time of these s/he needed to revise it three times until it is considered learned again (trev = 3 + 1 = 4). The VCR for student A is $VCR = 10 * 2 + (4 - 2) * 5 = 30\%$. So, the system's reliability reduces by 30%. Thus, as higher the value of VCR is, as less reliable the system is.

5.2. The test-bed

Our system with the fuzzy student model (Fuz-C) was used by a group of fifty three students for learning the programming language C. This is done during a postgraduate program in the field of informatics at the University of Piraeus. Learners had different backgrounds. Physic science, mathematic science, computer science, technical sciences, education, human science, social science are some of learners' backgrounds. After their participation in the training program, the learners completed the questionnaire that is displayed in Appendix A. So, we registered and analyzed the learners' reactions to the e-learning environment. Furthermore, we measured the values of the dependent variables (VMP, VMNE, VCR) for this system and we compared them with the values of the corresponding variables that were derived from the use of a similar learning system from which fuzzy logic was absent (No-Fuz-C). No-Fuz-C was used for teaching the programming language C in a group of sixty four students of the same postgraduate program.

5.3. Results and discussion

Learner's reactions to using the above e-learning environment for learning programming are positive. The results of the questionnaire reveal that the users were very satisfied with the educational software and its contribution to the learning process. Also, learners estimate that the adaptation of the learning process in their needs is very satisfied. The results of the questionnaire are depicted in Fig. 4. This information is easy to collect, but does not tell enough about the training success.

For more concrete estimation results we conducted the experimental research and measured the variables VMP, VMNE and VCR for the group A that was consisted of the 64 students of the

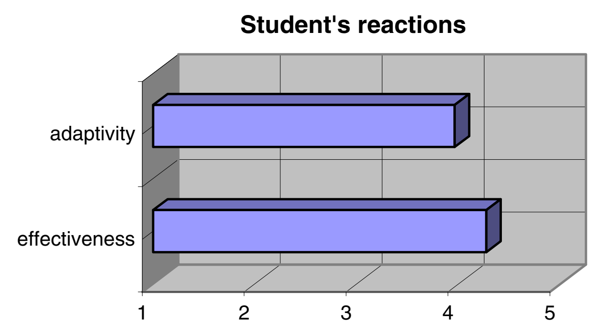

Fig. 4. Results of the questionnaire.

Group Statistics

	group of work	N	Mean	Std. Deviation	Std. Error Mean
VMP	group A	64	14,1239	6,51175	,81397
	group B	53	9,4038	5,79469	,79596
VMNE	group A	64	1,1719	,30157	,03770
	group B	53	,1698	,38460	,05283
VCR	group A	64	80,00	87,885	10,986
	group B	53	42,92	64,565	8,869

Fig. 5. Results of the experimental research.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
VMP	Equal variances assumed	1,103	,296	4,101	115	,000	4,72013	1,15107	2,44008	7,00019
	Equal variances not assumed			4,146	114,380	,000	4,72013	1,13846	2,46492	6,97534
VMNE	Equal variances assumed	,097	,756	15,794	115	,000	1,00206	,06345	,87639	1,12774
	Equal variances not assumed			15,440	97,557	,000	1,00206	,06490	,87327	1,13086
VCR	Equal variances assumed	3,785	,054	2,553	115	,012	37,075	14,525	8,305	65,846
	Equal variances not assumed			2,626	113,480	,010	37,075	14,119	9,105	65,046

Fig. 6. Results of the independent-samples *T*-test.

postgraduate program in the field of informatics at the University of Piraeus, which used No-Fuz-C and for the group B that was consisted of the fifty three students of the same postgraduate program, which used Fuz-C. The results are depicted in Fig. 5. We notice that the mean of VMP for group A is higher (14.1239) than the corresponding mean for group B (9.4038), which means that students' performance improves integrating the fuzzy logic into the student model. Furthermore, VMNE for group B is lower (0.1698) than the corresponding mean for group A (1.1719), which means that the navigation support is more effective using fuzzy logic techniques in the decision-making process about the navigation support. Moreover, the mean of VCR for group B is lower (42.92) compared with the VMR for group A (80.0). So, the system's reliability increases about 46.35% integrating fuzzy logic into the student model.

However, how can we be sure that the different averages scores are not occurred by chance or due to differences on the education, knowledge level and abilities of the learners of the two groups? How can we be sure that the different mean scores are not a result of the different amount of participants in the two groups? To ensure this we choose the statistical method of "Independent-sample *T*-test", which used to test whether the different average scores of two groups, represents a real difference between the two populations, or just a chance difference in our samples (Carver & Nash, 2009; Norusis, 2009). It uses the Levene's test for equality of variances to determine the "sig." value that indicates how likely we could have gotten the results by chance. If "sig." is less than 0.05 the two variances are significantly different. If it is greater than 0.05 the two variances are not significantly different, that is the two variances are approximately equal. So, in order to ensure that the above results were not occurred randomly, we have to see the "sig." value of each Levene's test (Fig. 6). If it is greater than 0.05 means that the variability in two groups is about the same. As we notice, this value is greater than 0.05 for all our variables. So, the variances are assumed to be equal and consequently we read the top line of the independent samples test for each variable. Then, we focus on the value of "sig. (2-tailed)", which will tell us if the two means are statistically different. If this value is greater than 0.05, we can say that there is no statistically difference between our means and we can conclude that the difference is likely due to chance. In our results, we notice that the "sig. (2-tailed)" value is 0 for both VMP and VMNE, and 0.12 for VCR. Thus, the differences between our means are statistically significant for our variables and are not a result of chance. Therefore, the evaluation test proved that the integration of fuzzy logic into the student model improves the learners' performance and the system's adaptivity, as well as increases the validity of the system's decisions.

6. Conclusions

This paper presents the evaluation of the integration of a fuzzy logic technique into the student model of a web-based educational environment for teaching the programming language C. The student model of our system is based on an overlay model, which represents the knowledge level of the learner. The determination of the student's knowledge level of each domain concept, as well as the updating of the student model and the decision-making about the instruction model that the system should follow for each individual learner, are based on the fuzzy logic technique that we incorporate into the student model. The evaluation approach that we adopted, can be applied for the evaluation of the student model of any ITS. To be more specific, we used the first two levels (evaluation of reaction and evaluation of learning) from the Kirkpatrick's model, which is a well-known method for measuring the effectiveness of training programs, in order to assess the learners' satisfaction and feelings about the e-learning environment, as well as the system's effectiveness to improve learners' knowledge. Furthermore, we used the evaluation of adaptation decision-making level of the layered evaluation framework that is an approach for evaluating the student model's success in making valid and meaningful adaptation decisions.

For applying, the above evaluation methods we used a questionnaire and we conducted an experiment. In particular, our e-learning system was used by a group of students of a postgraduate program in the field of Informatics, for learning the programming language C. Another group of students of the same postgraduate program used another version of our educational application, from which the fuzzy logic technique was absent. Then, the students of the first group completed the questionnaire in order to state their reaction to the system. Moreover, we compared the learners' performance of the two groups, as well as the navigation efficiency and decisions' reliability of the two systems.

The results of the evaluation were very encouraging. We showed that the integration of fuzzy logic into the student model of an ITS increases the learners' satisfaction and performance, improves the system's adaptivity and helps the system to make more valid and reliable decisions. Consequently, fuzzy logic is an ideal approach to deal with the uncertainty that characterizes the learning process in web-based educational applications.

Appendix A

	Questions	Degree
Effectiveness	Does the educational software meet your expectations?	4
	Does the educational software help you understanding the logic of programming?	4
	Do you think that this educational software is useful as an educational "tool"?	4
	Do you think that the use of this educational software is a waste of time?	1
	After the end of the educational process, do you feel that you have assimilated all the subjects that you are taught?	4.34
Adaptivity	Does the program correspond to your knowledge level each time?	4
	Does the program correspond to your educational needs level each time?	4
	How time do you spend on issues that you already known?	2
	Does the test adapt to your educational needs?	3.78
	Do you thing that each time you go to a next level, you have known adequately all the subjects of the previous chapters ?	4.1
	Does your return to a previous level, that happened each time the system discovered that you made errors of previous chapters, help you learning programming?	3.86

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