Towards a Context-Aware Adaptive e-Learning Architecture

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Abstract. E-learning is increasingly becoming the preferred delivery mode in learning institutions as it allows any time anywhere learning. However, content delivery, access, distribution and personalization are still a challenge. Moreover, ambiguity of students during decision making for their preferred courses has not been addressed. This paper proposes an adaptive e-learning model, an architecture for the adaptation of learning course materials considering students' profiles and their context information. Integration of fuzziness with processes of customization and selection of adequate material for the user creates a chance to build truly personalized and adaptive systems. This adaptive model is helpful in recommending course materials to students or adapting them depending on their context. It complements instructors' efforts in the delivery of learning materials relevant to their personal profiles. An AeLModel architecture is presented taking a full advantage of ontology, tagging, and users' feedback represented with linguistic descriptors and quantifiers. A prototype was developed and tested using 20 students in a class to assess this model's usability in addition to its adherence to content adaptation, resulting in a 77% of acceptance. It is recommended for this to be used in improving learning processes.

Keywords: e-Learning · Semantic Web · Context-awareness
Context · Adaptation

1 Introduction

The ever-changing state of portable devices in the recent time, coupled with the fact that most of them are pervasively connected to the internet, allows learning to take place anywhere and at any time [32]. This has made it possible for learning management systems (LMS) to provide learning contents to students even outside a school environment. Closely related to this is Ubiquitous Learning, whereby the process of learning can take place virtually everywhere and this can be integrated with people's daily lives [32]. Furthermore, possibility of exploring context awareness in the learning environment and adapting learning to the users' needs and surroundings [5] has increased in the recent times. In mobile learning environment, different context data can be explored.

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Portable devices being in use for supporting teaching and learning is no longer new. Mobile learning reality has been made possible by the fact that wireless infrastructure is widely deployed and adoption of handheld computing devices is rapid. Mobile-based learning systems development is discussed in [3,9,27,31]. These systems create practical mobile learning environments that enable students to enjoy the learning mobility with ease. However, when students relocate to areas that are not covered by the local area network, the systems experience challenges, among them the learning functions being disabled leading to inability of tracking the students' learning behaviors, delivery of content, and synchronization of data. Additionally, context-awareness, a concept that is useful in enhancing the learning systems' usability as discussed in [17,30,33,37] is proposed in this work. It is also possible to take the same concept into account in the course caching strategy design for which the main parameters are related context information [8,13].

According to the works in [1], the student context could encompass users' surroundings thus, location information, the learning objective, historical knowledge and preferences. Accordingly, adaptation of content, could personalize the learning object in a bid of meeting this context. As an example, as quoted from [1], *"if a learner, driving to school may need information pertaining to the course in which the leaner will have an examination in a few minutes, an application in the learner's mobile phone, using context awareness, can suggest an LO related to the examination. Since the learner is currently driving, the object can be adapted to audible format and transmitted via Bluetooth to the car sound system"*.

Ontology as a concept of Semantic Web is also proposed in one of the classic works [6] as an idea of machine-process-able information. This form of representation enabled better and more semantic-oriented processing of information, as well as reasoning about it. Its application to e-Learning created opportunities for building systems that were capable of analyzing students' needs and behaviors, and more accurate selection of learning materials. These capabilities notwithstanding, there is a need to deal with missing or inaccurate data [36]. Uncertainty is brought by students when they imprecisely express their needs and opinions. The decisions they make in regard to selection of the most suitable alternatives heavily depend on current circumstances, their understanding of situations, and their needs and requirements—things that are 'equipped' with ambiguity [22].

In this paper, first, we describe an architecture for constructing adaptive human-centric e-Learning systems—systems with capabilities to recognize students's contexts and adapt to students' needs and preferences considering their fuzzy nature in decision making. Such systems combine (1) technologies of the Semantic Web—ontology and forms of its representation, (2) aspects of social software—blogs and tagging, and (3) techniques of Computational Intelligence (CI)—fuzziness and MCDM. Additionally, instructors are also provided with the abilities to enter their suggestions and recommendations and observe students' learning activities and comment on them. Secondly, we propose a model named adaptive e-Learning Model (AeLModel), which depending on the students' context (profile), adapts course materials. In this way, learning is enhanced. The following question is answered: *Putting into consideration the students' context, how could a model for adapting learning materials that is relevant and satisfies the student be developed?* In the process of developing AeLmodel we did not find any other model appropriate for this task. Additionally, existing propositions were not available for either extension or reuse.

Organization of the remainder of this paper is as follows: Sect. 2 discusses related work. Section 3 describes adaptive e-learning concept in some details. Section 4 discusses the technologies and the methodology approach for our study. Section 5 describes the learning model. Sections 6 and 7 present the model's evaluation, results, and concluding remarks.

2 Related Work

Development of e-Learning systems and supporting these technologies represents an ongoing challenge of fundamental interest and practical relevance. Existing approaches in this area are quite diversified enjoying the reliance on various methodologies and effective algorithmic developments. A substantial number of them adhere to the fundamentals of general schemes of web technologies. The domain of e-Learning is expanding quite fast.

In [7,20] it is stated that E-learning allows students to study without the limitations of time and space which is beneficial to some extent. Those studies suggest that ideal systems should classify students and should also provide necessary amount of learning materials that are tailored for the individual student's needs. The 'one size fits all' philosophy results in too much information for users and lacks personalization [4]. However, personalization can bring improvements in Learning Management Systems (LMS). According to [7], LMS in this category do not satisfy the constraints to develop and manage contents to meet the demand of learning institutions. Moreover, most LMS do not provide complete learning solutions [20]. They are unable to provide adequate mechanisms for maintaining consistent instructional presentation or adapting that content to the needs of students. E-learning mode of training is touted as a solution to the above issues. However, student imprecise decision making nature is not managed—hence losing many of them in the process.

According [1], the Semantic Web based on semantic web-rule language (SWRL) rules, providing knowledge representations formats—Resource Description Framework (RDF)[1] and ontology—is already entrenched in e-Learning applications. Features such as formal taxonomies expressed with web ontology languages RDFS and OWL,[2] with rules represented using the web rule language RuleML,[3] have been used in the representation and the dynamic construction of shared and re-usable learning content [14].

1 http://www.w3.org/RDF/.
2 http://www.w3.org/TR/owl2-overview/.
3 http://ruleml.org/.

Social networks are among the emerging technologies which can be tapped into when developing education portals. They can provide a platform for exchange of information, and communication between authors, teachers, and educational institutions [21,39]. These network platforms allow for *"combining educational portals, ontologies, and search agents with functions such as Web mining, and knowledge management to create, discover, analyze, and manage the knowledge of different domains presented in educational material"* [22].

Multiple aspects of e-Learning have been addressed by techniques involving fuzziness. Fuzzy-based methods are used for user profiling, determining students' profiles, evaluating quality of e-Learning systems, as well as enhancing their capabilities. In [19], fuzzy terms were used to describe pedagogical resources as well as users' profiles.

It is apparent that a proper representation of data and adequate processing of information are necessary steps leading towards knowledge-oriented systems. The ability to find and represent different types of relations between pieces of information is a necessary condition for creating semantically conscious applications. This semantic awareness allows for more accurate identification of relevant information. At the same time building any type of system that interacts with a human requires ability to handle imprecision and ambiguity. In this regard we believe that the application of fuzziness and approximate reasoning creates a promising avenue of introducing human aspects to software systems and could lead to the development of more human-conscious-like systems. This aspect is apparently missing in the reviewed works.

3 Concept

Ultimately, our work aims to develop a detailed architecture for development of human-centric adaptive e-learning models. For human-centric aspects to be realized, utilization of fuzziness and approximate reasoning that are able to express and process ambiguity and imprecision—two very characteristic features of human selection and decision-making activities—is needed. We suggest that combining these techniques with RDF and ontology-based representations of knowledge and elements of social networks—blogging and tagging—can lead to a new way of designing e-Learning Systems. Moreover, development of such a system can be a basis upon which to draw conclusions of immediate practical relevance to creation of such applications.

Different from other approaches reported in the literature, this paper considers uncertainty aspects of human nature as imprecision, insufficient available information, and approximate reasoning in order to ensure engaging and comfortable, yet practical and efficient learning environment. Key issues of the proposed architecture include: (1) undisputed ambiguity and imprecision of information provided and used by humans; (2) multiplicity of sources of information influencing the content and (3) the form of course materials that has the following components:

- Personal preferences and feedback, i.e. a student's goals and learning style, as well as the student's involvement in content annotation, tagging, and contributions to blogs;
- Required material, suggestions, and constraints provided by instructors;
- Feedback, content annotations, notes, and evaluations contributed by peer students.

These information sources are often ambiguous. However, they determine relevant components of domain knowledge, greatly influencing the choice of the teaching material considered most appropriate to the student. A variety of ways exist for performing this selection process with varying levels of accuracy and levels of importance assigned to each of these sources. For instance, in courses that are fundamental and need a rigorous approach, the suggestions and constraints imposed on the content by instructors will have higher priority, influence, and precision than preferences provided by the student, as well as the feedback provided by peer students. Construction of course materials becomes flexible with adoption of such approach.

4 Methods and Techniques

4.1 Fuzziness and Semantic Web

Fuzzy theory has proven advantages for dealing with imprecise and uncertain decision situations and models human reasoning in its use of approximate information [34]. Incorporating fuzzy logic in students' decision-making techniques can address the problem on unreliability due to insufficiency in amount of information students have at the point of making decisions. Fuzziness provides a unique approach for dealing with the very human concept of imprecision. Abilities to use such imprecise terms as much, so-so and linguistic quantifiers like more than, most, least, any make fuzzy-based methods most suitable for dealing with human evaluation of different items and their description. Fuzzy set theory implements grouping of data with boundaries that are not distinctly defined. This leads to a critical aspect of fuzziness which is its ability to express levels of membership of terms to specific concepts. Using fuzzy-based mechanisms for processing and reasoning, deduction of new facts and their levels of belonging to specific categories, as well as precision levels of their descriptions is possible.

Software technologies can provide a comprehensive approach to knowledge representation. Ontology is the basic framework usable in representation of concepts, their definitions and instances, in addition to how the concepts are linked and dependent on each other. In some contexts, ontology definition uses the concept of Resource Description Framework (RDF) represented in triple as the foundation of knowledge representation. In this case, the triple is in the form of subject-predicate-object, where: subject identifies the object being described; predicate is the piece of data in the object that a value is given to; and the actual value of the attribute is the object. For instance, the triple 'Anne loves movies' has 'Anne' as its subject, 'loves' as predicate, and 'movies' as object.

The process of tagging is simply labeling or annotation of resources [18] which is performed by users that use tags to easily and freely and without any knowledge of any taxonomies or ontologies annotate resources. These tags are used to represent those strings considered by users, appropriate descriptions of resources. On the other hand, resources could be any items that have been posted and are accessible by users and can lead to an interesting way of describing resources [24,34]. Those technologies are applied to design and develop elements and features of adaptive e-Learning models.

4.2 Categorization of Students

Another very essential aspect of this work is the identification of categories of students. All students have different learning traits. The differences have been categorized by educators as learning styles, cognitive styles, multiple intelligences or cognitive traits. In creating adaptive learning systems, two approaches have been used: (1) at the outset, cognitive/learning styles are assessed and then the system is presented to match the students' profiles, or (2) having no preset initialization of the system, only allowing adaptations to occur based on the students' use of the system. A test of both approaches is necessary in order understand their advantages and disadvantages.

For the former approach, the exact method for characterizing student profiles is the subject of debates by professionals in education sector. This has been so because some student assessment approaches rely on cognitive style measures arising from psychological theory [29], that is, as discussed in [22], measures of general cognitive tendencies or approaches that endure across numerous types of stimuli. Other assessments modes focus on learning styles, categorizations of students' preferences in educational contexts and finally, some methods employ the measurement of basic cognitive traits (e.g. working memory capacity) as a means to predict what material and style of presentation is desirable for a particular student [12]. From a theoretical standpoint it appears none of these approaches have been unchallenged in regards to their validity and reliability [29].

From the foregoing, the inconclusive nature of research in these areas is vivid. To address this state of affairs, this paper proposes creation of coherence between the initially derived student profiles and the mechanisms for updating their profiles which already exist within a particular adaptive system. A choice of a cognitive style measure that reflects the specific mechanisms in the adaptive system created in this work is taken. This is necessitated as it makes it possible to be modified in a bid to limit the demands of assessment on the student in the initial phase of using the system. Furthermore, for the assessment of the structure of content, the holistic/analytic dimension on the Cognitive Styles Analysis (CSA) [26] is relied upon.

4.3 Representation of Course Material

Students are able to experience new interaction mechanisms with the learning environment with the proliferation of digital technology systems in education. In this regard, of great importance to the teaching process is the effectiveness of digital media. This paper explores how digital representation of material selectively extends but also constrains what a student sees, experiences and has access to, and how it enhances but also shapes instructors' representations and presentations of their knowledge in an e-Learning system. Some of the critical parts of a learning process in whichever level of education are activities such as taking notes, marking important and/or difficult parts of presented materials, and writing feedback comments (i.e. confirmation, corrective, explanatory, diagnostic, and elaborative information). The proposed framework is equipped with a number of techniques and methods, such as content annotation, blogs, and tagging, to allow users to label the teaching material and provide their opinions about its content with particular emphasis put on the use of nonintrusive ways of inputting information, for instance, via voice.

Information provided by users is stored using the knowledge representation schema based on ontology and RDF triples. Algorithms are used to process users' inputs and to annotate course materials with terms and keywords reflecting users' opinions and notes.

4.4 Personalization and Context Dependence

One of the essential challenges of e-Learning systems is to satisfy students' needs and preferences. It is of critical importance to be able to properly elicit and store information about students, their likes and dislikes, and what kind of methods, techniques and media they enjoy during learning activities. The techniques should ensure utilization of two types of information:

- Student's needs, what he/she already knows, his/her goals, things already done, things left to do, timing, ability to learn, ways of learning, most suitable media (slides, notes, short lectures);
- Current context, such as: time of a day, an amount of time a student can spend, place, ability to listen or watch. Special mechanisms and techniques are used to keep track of things that work for the student, i.e. likes, comments, and information about favorite instructors.

All information about an individual student is stored in a specialized ontology. Such ontology is created and maintained for each student. The mechanisms that support storing imprecise (fuzzy-based) information are developed. Students are able to provide their priorities regarding needs and preferences in a suitable form. Special mechanisms for estimating relevance of that information are proposed and validated.

4.5 Instructors' Input Mechanism

The involvement of instructors in the education process is irreplaceable. Therefore, the proposed framework provides a number of ways that an instructor can monitor students' activities and act accordingly. Instructors are able to query the system for items related to available materials and students taking their courses, as well as read comments provided by students and related to the material they prepared. The system also allows instructors to enter answers to students' questions, suggest alternative material to students, and correct them.

4.6 Individual and Collaboration-Based Material Selection

The process of selecting most suitable lecture materials, i.e. choice between multiple versions, multiple sections, multiple media, etc., is the most critical part of any AeLModel-based system. Multiple sources of information about lecture materials have to be evaluated and ranked based on:

- Multiple criteria provided by the student, including student's goals and profile (preferences, likes/dislikes), as well as comments and notes given to similar course materials;
- Instructors' suggestions, recommendations, and constrains, including instructors' notes, observations and expertise, are used as important selection criteria;
- Multiple evaluations of possible material, including the process of collecting students' feedback via social software methods, lead to an extensive annotation of material; also a schema for integrating annotations and extracting most common opinions is required; those opinions play the role of criteria during a selection process.

The proposed selection methods mimic human-amenable aggregation processes from students', other users', and instructors' points of view. The levels of importance are taken into consideration. The methods have to deal with imprecision information (evaluations, criteria, annotation), different priorities, and constraints. This paper examines the following aggregation approaches: fuzzy-based methods; evidence theory; different aggregation techniques including linguistic based aggregation. Overall, the proposed selection mechanisms perform decision-making tasks taking into account:

- What the instructor thinks is important;
- What is important for the student;
- What peers think is important.

5 Description of the Learning System

The architecture of the AeLModel-based system is presented in Fig. 1. In a nutshell, the system knows what the student wants (student's profile) and likes

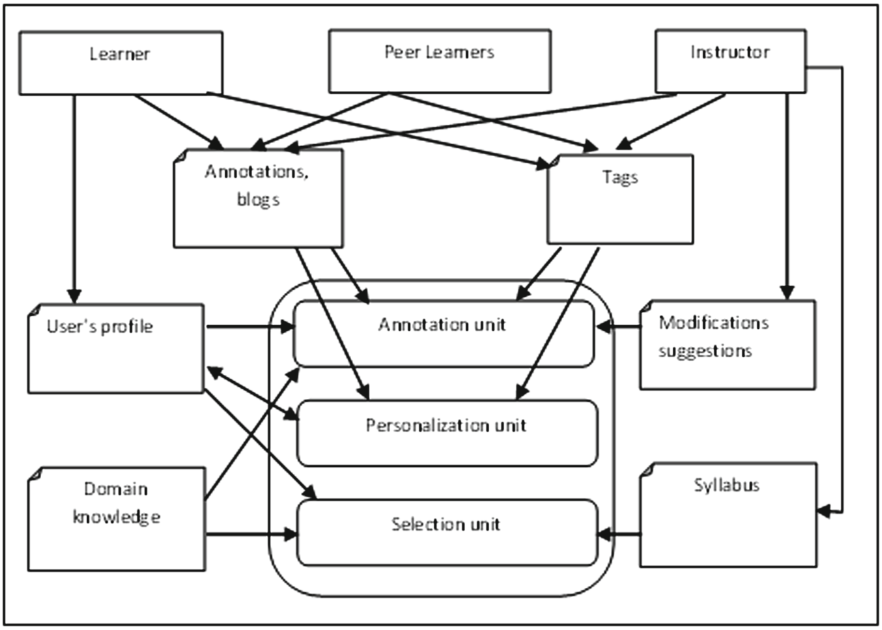

Fig. 1. Architecture of AeLModel-based system

(annotations, blogs, tags), knows what instructors suggest and recommend (modifications, suggestions, annotations, blogs, tags), and knows what peer students say about available material (annotations, blogs, tags). Based on that knowledge and syllabi, the system provides the student with most suitable alternatives regarding sets of education material. The system allows students to make notes and record opinions. At the same time instructors have the ability to monitor the student and provide modifications and additions to the material the student is currently using.

In order to accomplish that, all the tasks performed by the system are divided into three categories:

– Multi-domain annotation of course material stored in a repository combined with techniques and methods of extracting important options based on tag clouds, blogs and students' notes; instructors' suggestions and constrains are also used to annotate available material;
– Personalization that leads to creation and updating of student's profile that contains information about student's preferences, needs, likes or dislikes;
– Prioritization-based multi-criteria selection that performs selection of most suitable material based on student's profile, peer students' opinions, and instructors' inputs.

The annotation activities are presented in Fig. 2. All annotation is performed on course material stored in the repository of the system, and it reflects three

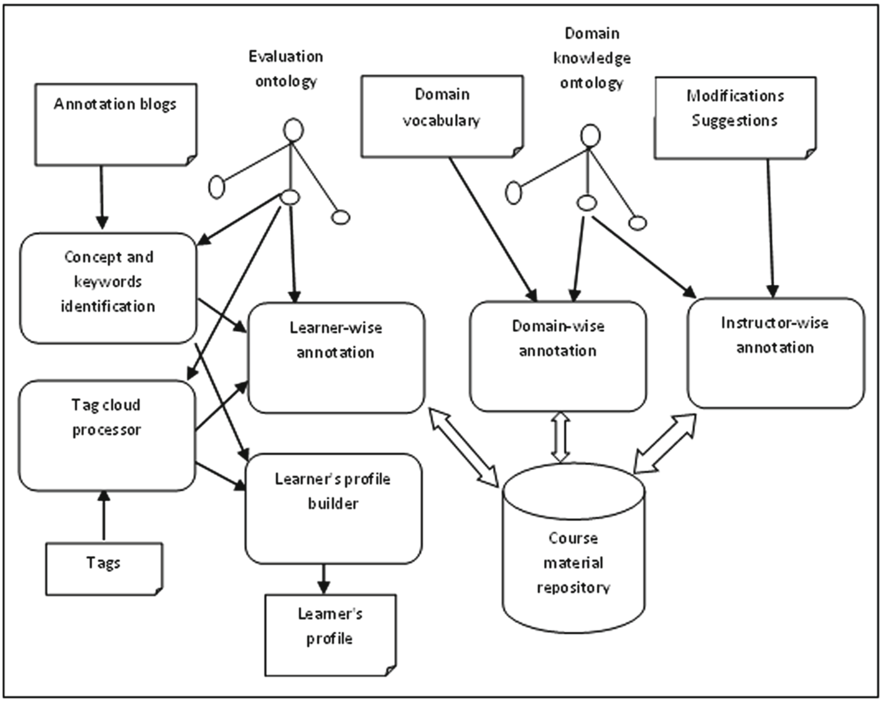

Fig. 2. Annotation activities of AeLModel-based system

domains (dimensions): students', instructors', and knowledge relevant to course topics.

The students-wise annotation is supported by such processes as identification of concept and keywords in annotations and blogs, as well as analysis of tag-clouds. The instructor-wise annotation takes into account all requirements and recommendations provided by instructor. The domain-wise annotation leads to annotation of all repository materials with terms originated from specific knowledge domains.

In the end, all materials are annotated with three types of terms originated from three sources of annotations. The personalization activity is also shown in Fig. 2. It uses results of the same process as annotation: concept and keyword identification and analysis of tag-clouds to extract information that is related to a single student. This information is used for updating of the student's profile. Both annotation and personalization process are continuously performed to keep annotations and profile up-to-date.

The multi-criteria selection mechanisms are presented in Fig. 3. The first step in the process selects a few sets of alternative materials. The selection uses the annotated course material and is based on student's needs and goals and provided syllabi. An important element is extraction of evaluations of those materials done by other students. The last and most important step of selection

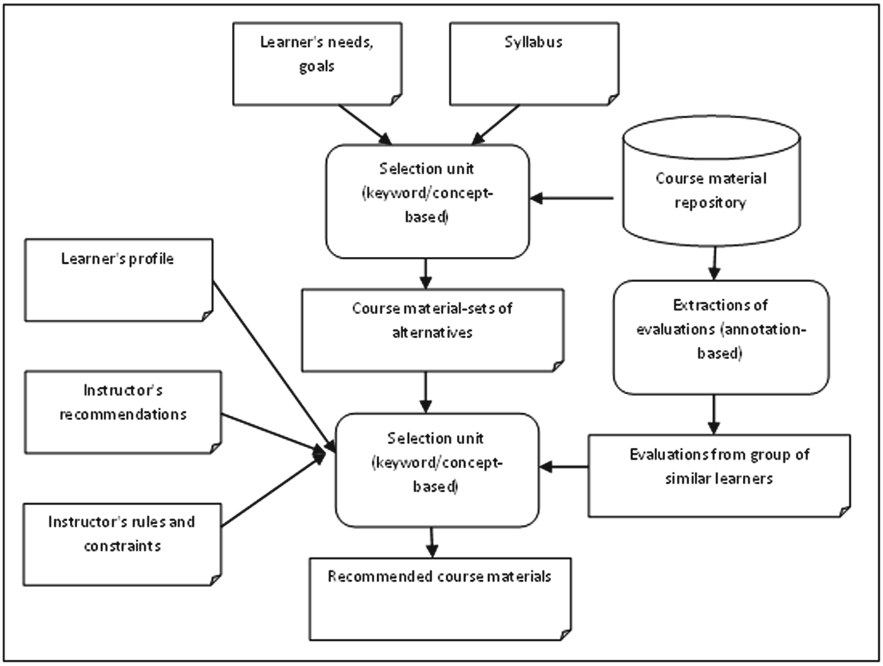

Fig. 3. Selection processes

is identification of the most suitable material. This step relies on a number of different decision-making methods that are able to deal with multiple criteria with multiple levels of priorities [35], imprecise information and human-amenable aggregation of evaluations [23,25]. These processes can use different sources of information, for example RSS-feeds, and different analysis techniques including formal ones, for example FCA [16].

6 Model Evaluation and Results

6.1 AeLModel Evaluation

Model evaluation is a critical component while developing applications. This model is evaluated by analyzing the quality and the fidelity that it provides to fulfill the proposed objective. To accomplish this, a *prototype was developed* and used by undergraduate students taking a course in database systems.[4] An experiment was done with 20 Computer Science undergraduate students, who had experience in e-learning. The experiment was divided into pre-test and post-test. During the pre-test stage, the students were allowed to use the AeLModel application for learning the database systems course. To do this, the application

[4] The prototype software is available from the authors upon request.

Table 1. Questionnaire

Q. no.	Statement
1	The course material was appropriately adapted to my profile
2	The course material content was suitable to me
3	The course material was available in the device I was using to access it and was in the right format
4	This model was helpful in my learning and can be useful in online learning (within or outside the premises)
5	This model stirred in me greater interest to learn
6	I could understand easily the content displayed
7	The model can facilitate independent study in disregard to location
8	It was easy to use the model
9	Access of learning material through the model was quick
10	My learning experience was better using the model than other modes I have previously used

was installed to both mobile (Android) and laptops with internet access, and these were given to the students. These devices using web services accessed the course materials stored in a repository. For the post-test, at the end of the semester, participants were asked to fill a questionnaire developed based on the work in [28] in regard to the suitability of the model in answering the research question. Ten statements were worded, and the students rated them using a Likert scale [15]. The scale had five (scoring) choices: 'completely agree' (5), 'agree' (4), 'neutral' (3), 'disagree' (2), and 'completely disagree' (1).

We employed the Cronbach alpha method [10] to test the reliability of the questionnaire administered. This was important as it allowed estimation of the correlation between the responses given by participants. According to [10,11] reliability test results should be more than or equal to 0.7 for them to be acceptable. For our survey the test resulted in 0.8, confirming its reliability. Tables 1 and 2 present the statements in and the results obtained from the survey respectively.

The formulated statements are shown in Table 1. In Table 2 they are represented in the first column, followed by percentages of responses by participants to each item in the following columns, in regard to the Likert scale. For better analysis of the responses, weight average value (WAV) of the items was calculated. The greatest satisfaction to students when they use the model is shown when the WAV value is closer to L(5), while a value closer L(1) indicates the satisfaction level in reverse. For this survey, WAV values were greater than L(3), indicating approval of the model by the students and that they were satisfied in using it.

Results from this survey show that the statement regarding 'presentation' (Q.2) scored lowest. However, its value of 3.32 is above mean and satisfactory

Table 2. Percentage of responses computed from the Questionnaire, with WAV = weight average value = (5A + 4B + 3C + 2D + 1E)/12, where A, B, C, D, E are the number of responses in Likert scale L(5)–L(1) with 12 interviewees according to [38]

Response	L(5)	L(4)	L(3)	L(2)	L(1)	WAV
Q.1	26	67	7	0	0	4.17
Q.2	7	54	16	16	7	3.32
Q.3	24	66	7	2	1	4.16
Q.4	59	23	9	1	8	4.26
Q.5	48	48	1	0	1	4.49
Q.6	48	24	24	2	0	4.24
Q.7	44	32	18	6	0	4.09
Q.8	15	65	18	2	0	4.01
Q.9	16	66	17	0	0	4.00
Q.10	40	40	10	3	7	4.09

as it is closer to L(5) than L(1). These results also show the summary of affirmative responses from participants regarding the use of AeLModel. It is shown that there are high incidences of 'agree' and 'completely agree' as responses for statements Q.5 and Q.6 essentially explaining the enhancement of the students' personal interest and understanding by the model. The usability characteristic of the model tested by statements Q.8 and Q.9, was approved by majority of the participants, although it also obtained the highest number of users that were neutral. This could be associated with the fact that a significant number of participants considered that this being just an experiment and the time frame, it would not have been appropriate to evaluate this feature. Notably, adaptation and performance represented by statements Q.1 and Q.9 respectively was good and therefore students who participated in the survey were satisfied with the model. Finally, most participants were satisfied with statement Q.10, stating that the model eased their learning process.

It is noted that our survey employed a relatively small sample and used the Likert scale as a non-parametric scale. Two samples were formed: one with concordant responses ('completely agree' and 'agree') and the other discordant responses ('completely disagree' and 'disagree'). Due to this, the Mann-Whitney-Wilcoxon test [2] was applied to determine the distribution similarity level between the samples using 0.05 as value of significance. Furthermore, the use of R,[5] a statistics software, resulted in the negative. Consequently it is shown that the model of distribution followed by the two sample groups is dissimilar. This means that sample values are independent, effectively showing that inference of any conclusion about one sample that does depend on the results of the other sample.

[5] http://www.r-project.org/.

7 Conclusions

One of the strengths of the proposed architecture for development of e-Learning systems is its multidisciplinary nature. This work leads to interesting results in several important areas:

Ontology and RDF triples: those are new and conceptually challenging forms of knowledge representation; activities related to adaptation of these forms to e-Learning systems and their integration with interactive systems should lead to improvements in system's abilities to store, access and analyze information;

Blogs and tagging: incorporation of these activities with e-Learning systems should improve agility of e-Learning systems and their ability to absorb users' feedback, additionally their integration with new forms of knowledge representation should lead to a better analysis of information embedded in blog posts and used tags;

Fuzziness and multi-criteria decision making, as the core technologies of the framework, should play an critical role in the process of creating more human-centric systems; at the same time the framework should provide an evidence of necessity of application of these techniques to development of real-world system able to support users' activities in a personalized way; the combination of fuzziness with the new forms of knowledge representation (ontology and RDF triples) should increase the presence of CI technologies on the Web.

The proposed e-Learning architecture constitutes a very important step towards direct application of fuzziness and new forms of knowledge representation to 'real world' needs of e-Learning systems. The architecture also addresses the challenges imposed by human-centric systems.

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