IDD Personalization Framework for e-Learning

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Abstract

This paper focuses on the development of an IDD personalization framework for personalizing an E-Learning System. The paper begins with a problem domain together with a brief description of e-learning systems and its diffusion in the present day educational system based on the proposed learning approach model. The paper then concentrates on the method of identification questions into different level of difficulties and applies the categorized questions into the IDD model. The design of the IDD model will be revised and discussed together with the personalized learning assessment module via IDR table before a conclusion and future enhancement are presented.

Keywords: E-Learning, Learning Approach Model, IDD personalization model, Increment & Decrement reference (IDR) table, Difficulty level model and fuzzy.

1. Introduction

E-learning can be defined as a technology-based learning in which learning materials are delivered electronically to remote learners via a computer network [10]. For a more precise definition, E-learning can be described as the delivery of formal and informal training activities, processes, communities and events via the use of all electronic media like Internet, Intranet, Extranet, CD-ROM, video tape, DVD, TV, cell phones, personal digital assistant (PDA) etc. [4]. Many people believe that through electronic devices such as the Internet, learners can freely absorb new knowledge without the restriction of time and place [5].

Many methods and studies have been done with the intention of accomplishing an effective learning in both classroom and non-classroom environments [11, 12]. Generally, those approaches can be classified into the learning approach model which has been restructured in Fig1. There are four learning approaches. Learner Oriented Approach which focus on recognition of unique skills, passions, and characteristics of each learner, Content Oriented Approach which concentrates on course design honors to individual learning styles, Teacher Oriented Approach which concentrate on interactive and behavioral education between teachers and learners as well as among learners and learners, selection suitable assignments and activities and lastly Environment Oriented Approach which focuses on developing learning process, technology access, and varied learning environments.

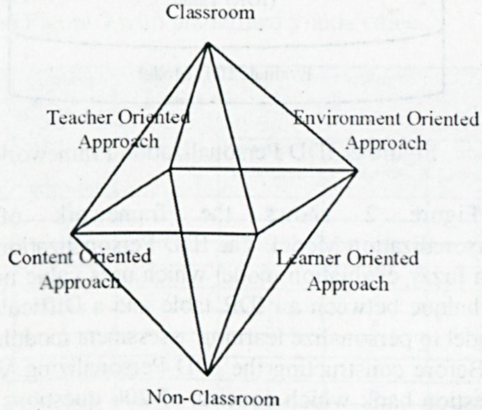

Figure 1. Learning Approach Model

Basically, many researchers have proposed and applied various methods, models and solutions in e-learning system based on the learning approach model which has been stated above. However, in the year 2004, Dolog and Sintek [2] managed to point out that personalization learning method for learners is the most significant factor among other approaches. Derntl and Motschnig-Pitrik [1] have highlighted also the fact that much research has been devoted to producing e-learning content, describing it with metadata and to constructing e-learning platforms. However, less attention has been paid to using technology to improve the learning process in terms of depth and scope. According to [6], an E-learning system should accommodate different learning styles and foster learning through a variety of activities that apply to different learning styles. Generally, learners prefer to learn at their chosen rate and select the learning materials which meet their level of knowledge, interest

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and what they need to know to perform more effectively in their particular activity [3].

However, most of the researches which have been carried out emphasize on the technical aspects of e-learning and subsequently the psychological aspects of e-learners have been neglected. As a result, the purpose of this paper is on providing a mechanism whereby an e-learning system can be personalized to cater for the individual learner's learning ability and patterns. In the following section, the framework of the IDD personalization model which has been designed to accommodate each individual learner's personal learning pattern will be described.

2. IDD Personalization Framework

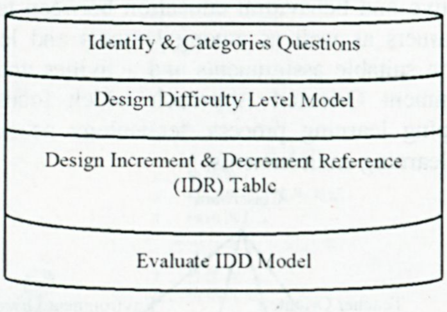

Figure 2. IDD Personalization Framework

Figure 2 shows the framework of IDD Personalization Model. The IDD Personalization Model is a fuzzy evaluation model which uses value matching technique between an IDR table and a Difficulty level model to personalize learning assessment module.

Before constructing the IDD Personalizing Model, a question bank which consists of 200 questions mainly on Cisco Certified Networking Associate (CCNA) Topics has been identified for test-bed purposes. Those questions have been distributed to lecturers and students (undergraduate and postgraduate) primarily from computer science and information technology domain within the Faculty of Computer Science and Information Technology, University of Malaya, Malaysia using survey method as to get the question to be evaluated for its difficulty level. The level of difficulty for each question was then categorized into easy, moderate and tough levels.

	Category		
	I	II	III
Weight	0.5	1.0	1.5

Table 1. Weight for Different Group of Evaluator

In order to balance up the difference in knowledge during the evaluation process among the different group of evaluators, a categorical approach has been used. All the evaluators were categorized into 3 categories after pilot testing with 150 samples using interview and observation methods before defining Table 1. In general, the knowledge on CCNA subjects for 1st year and 2nd year students are inadequate and their knowledge level is about the same. As a result, 1st year and 2nd year students are categorized into Category I. For students from 3rd year and onwards, they have a better knowledge on CCNA subjects and their knowledge level is about the same in general according to the survey result. Therefore, students from 3rd year and onwards are categorized into Category II. While category III evaluators consists of lecturers and postgraduate students who have better knowledge on CCNA subjects.

Due to the fact that there is an obvious knowledge gap between the observations in 3 categories, a heuristic approach with weight of 0.5, 1.0 and 1.5 have been exploited to the above mentioned categories respectively. The difficulty level of each question is then determined by normalizing each survey result in cooperating with matching the normalize value to the normal distribution graph at Figure 3. As if the normalize value of a question is greater or equal to 1σ, in between -1σ and $+1\sigma$, and less than or equal to -1σ, that question will be categorized into tough, moderate and easy category respectively. The rationale of normalizing and performing value matching with normal distribution graph is to fine tune and balance up the gap between experience and less experience evaluators. The range of each difficulty in Figure 3 has been tested and identified using the heuristic approach. From the testing, approximately 15.8% of the sampling falls into the tough or easy region.

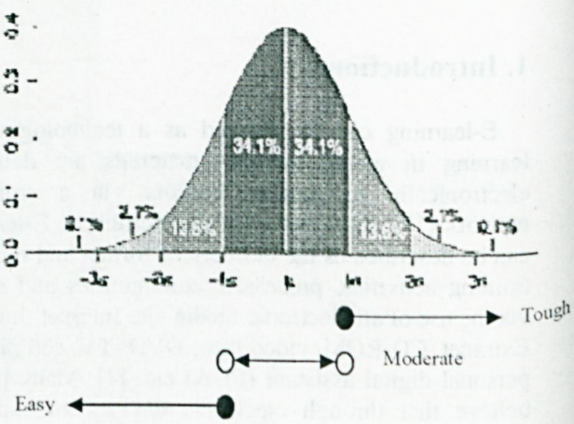

Figure 3. Difficulty Level Determination Using Normal Distribution Graph [9]

Once the test questions have been labeled accordingly, an assortment of questions to the learners are founded based on the rules at [7, 13]. A generic difficulty level diagram was then deployed using the fuzzy model. The purpose of having a difficulty level model is to classify and obtain the number of easy, moderate and tough questions that are randomly generated from the question bank to be set into an assessment. The following sections depict the design of the Difficulty level Model and the corresponding of Difficulty level Model with IDR Table. Several testing have been conceded for reliability testing of the IDD Personalizing Model

3. Difficulty Level Model

Difficulty Level (DL) Model was proposed at [7]. Essentially the DL Model manages to support up to m difficulty levels and n number of questions. However, there are two saturated levels (0 and n) positioned at the y-axis. The saturated levels are used to determine the number of maximum and minimum questions to be set in an assessment. Figure 4 shows the generic difficulty level diagram.

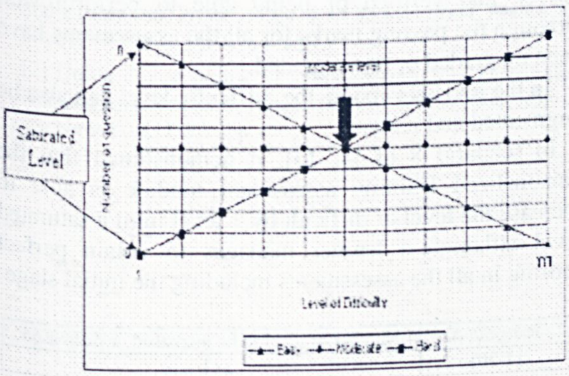

Figure 4: Generic Difficulty Level Diagram

The DL Model has been verified and examined using 10 as the maximum number of questions at y-axis and 10 difficulty level ranges at x-axis [7]. Figure 5 shows the test-bed graph for the difficulty level model.

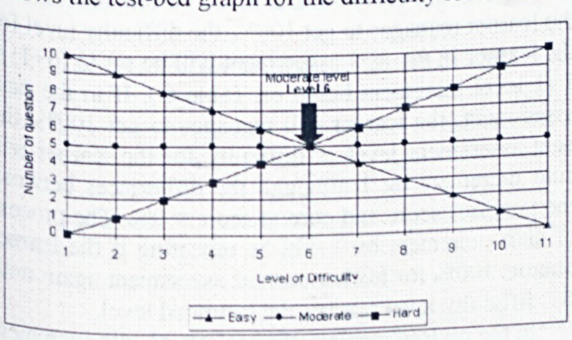

Figure 5. Test-bed graph [7]

4. Personalized Learning Assessment Module Via IDR Table

An IDR table at Table 2 has been constructed based on the incorporation of difficulty level model which was stated at Figure 4.

Range (%)	Number of level to be increased or decreased	Difficulty Level	Number of		
			Easy Questions	Moderate Questions	Hard Questions
+100 / (m/2) per range	+ (Max level - Mid level) / (m/2)	(Max level -Min level) / m per level	Refer to test bed	Refer to test bed	Refer to test bed
0	0				
-100 / (m/2) per range	- (Mid level - Min level) / (m/2)				

Denote
m: Range of intended difficulty level

Table 2. Generic Increment & Decrement Reference (IDR) Table

The range at Table 2 refers to the score range which can be categorized into positive, neutral and negative regions. Each score range will be used to determine the numbers of increment or decrement levels for an assessment module. After determining the difficulty level, the number of easy, moderate and hard questions will then be generated accordingly based on each individual learner's personal learning pattern. Figure 3 is the test-bed IDR table which has been generated based on Figure 5 with predefined y-axis value.

Range (%)	Number of level to be increased or decreased	Difficulty Level	Number of		
			Easy Questions	Moderate Questions	Hard Questions
81-100	+5	11	0	5	10
61-80	+4	10	1	5	9
41-60	+3	9	2	5	8
21-40	+2	8	3	5	7
1-20	+1	7	4	5	6
0	0	6	5	5	5
-(1-20)	-1	5	6	5	4
-(21-40)	-2	4	7	5	3
-(41-60)	-3	3	8	5	2
-(61-80)	-4	2	9	5	1
-(81-100)	-5	1	10	5	0

Table 3. Test-bed IDR Table [7]

Several researches at [8] which have been carried out are based on the test-bed IDR Table at Table 3. Below are the revised summary of the scenarios which has been discussed in [7] and have been fine tuned in [8, 13].

For scenario 1, 2 and 3, an assumption of the passing marks for all assessments were set to be 80% and with difficulty level number 10. In Scenario 1 [8, 13], a learner has resumed with previous score of 90% together with difficulty level 9. From Table 3, 2 easy questions, 5 moderate questions and 8 hard questions will be given to the learner in the next assessment. If the learner only manages to get 60% of the score, the range between current score and the previous score will be (60-90) = -30%. The negative region has indicated that there should be a decrement of level once the learner retakes the assessment (A prerequisite for learner before the learner is able to proceed to the next assessment.).

Range (%)	Number of level to be increased or decreased
-(21-40)	-2

Table 4. Zoom in Range for -(21-40)

Based on the zoom in range at Table 4, 2 difficulty levels will be decreased (from level 9 to level 7). From the question pool result at Table 3, the learner will be given 4 easy questions, 5 moderate questions and 6 hard questions in the retake assessment.

As for scenario 2 [8, 13], the learner manages to score 95% after retaking the assessment. The score difference is now (95%-80%) = 15%. The previous score of the learner is still 80%. Once the learner has passed the current assessment, the current score of the assessment will become the previous score for the learner. The reason of applying this ruling is to prevent the fluctuation of enormous gaps in scores.

Range (%)	Number of level to be increased or decreased
21-40	+2

Table 5. Zoom in Range for +(21-40)

The score difference that the learner had obtained for this scenario is shows at Table 5. The difficulty level for the next assessment will be set to level (9+2) = 11 for that learner. From the test-bed result at Table 3, the learner will be given 1 easy question, 5 moderate questions and 9 hard questions in the next assessment.

In the revised version, the learner latest difficulty level will only set to level (7+2) = 9 instead of level 11. The learner will still need to retake the assessment until his/her difficulty level reaches level 10 or higher before proceeding to the next assessment. The reason for revising this rule is to ensure that the learner must meet at least the expected level (level 10) which has been set by the tester (instructor or the learner him/herself).

In Scenario 3 [8, 13], the learner has obtained a previous score of 95% and the learner's difficulty level is at level 11. If the learner manages to get 95% for the next assessment, there will be no increment or decrement of the level of difficulty according to the IDR Table. Therefore, the next assessment level of difficulty for that learner will be remained at level (11+0) = 11.

However, the maximum and minimum levels of difficulty for the Difficulty Level Model are only up to level 11 and level 1 respectively. If the learner manages to get 100% instead of 95% in the previous example, the range differences that the learner obtained is (100-95) = +5%, which means that the difficulty level for the learner in the next assessment will still automatically set at the saturated level which is level 11. This is due to the fact that any level which higher than level 11 is a veto for the model.

However in the revised version, the learner can proceed to the next assessment once the learner has achieved the expected level (level 10). The Scenario 3 ruling is still applicable to the learner if the difficulty level is preset to level 11.

From the above scenarios, it can be concluded that the personalized learning assessment module is deft to decrease and increase the difficulty level to the correspondent learner when the learner fails an assessment or the performance of the learner in the current assessment is improved. Besides, the personalized learning assessment module will automatically imply that there will be no decrement or increment of level if the level of difficulty has reached the saturated level. With this features, a learner can self improve until the expected level for a particular assessment.

According to [8, 13] in scenario 4, 5, 6 and 7, the personalized learning assessment module has been proven and verified of being able to perform well although the passing marks for all the assessments have been up graded or down graded.

In the revised version, the difficulty level can also be augmented and reduced.

In scenario 8 of [8, 13], it demonstrated that the personalized learning assessment module is able to increase the level of difficult by 1 level until a saturated level although a learner manages to obtain perfect scoring in all the assessments including the initial stage.

Range (%)	Number of level to be increased or decreased
(1-20)	+1

Table 6. Zoom in Range for +(1-20)

As an example, assume that a learner does not have any previous result and the learner's current difficulty level is at level 6 and the passing marks for all the assessments are set to 90%. If in the current assessment, the learner manages to get 100%, the difficulty level for the learner in the next assessment will be set to (6+1) = 7 (1 level increment based on Table 6.). If in the next assessment, the learner still manages to get 100%, the next assessment level of difficulty for the learner will auto increment by 1 although the differences between the previous score and current score = 0%. The process of auto increment by 1 will be repeating if the learner obtains 100% for his/her current assessment again until the difficulty level reaches the saturated level.

In the revised version, the process of auto increment by 1 will be repeating if the learner obtains 100% for his/her current assessment again until the difficulty level reaches the expected level.

5. Conclusion and Future Work

This paper has presented the IDD Personalizing Framework which uses the co residential of IDR Table and Difficulty Level Model which we believe is the strength and winning edge over other e-learning systems. With the control of preset difficulty level and scoring, a learner can probably self improve him/herself until the expected level for a particular assessment. For future work, reviewing and revising the categorical and normalizing methods which is used in the question ranking will be our main focus besides the method of co residential of Difficulty Level Model and IDR Table. Anyhow, we still strongly believe that the IDD Personalizing Framework which has been developed will become a value added component for other e-learning systems in future.

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