

# A Fully Personalized Adaptive and Intelligent Educational Hypermedia System for Individual Mathematics Teaching-Learning

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**Abstract** – In this study, architecture and development process of UZWEBMAT, an adaptive and individualized environment based on learning styles and supported with expert system, are presented. UZWEBMAT was developed to teach probability unit of 11th grade mathematics course. Three different contents, which are appropriate to Visual-Auditory-Kinesthetic (VAK) learning styles, are presented to learners. Content of each sub-learning style is presented with expert system support. Thanks to this expert system, it is possible for learners with same learning style to take different contents. By this means, highest level of individualized learning environment was tried to be created via UZWEBMAT. Integration of UZWEBMAT to real classroom environment shall be made in future studies. Evaluation of UZWEBMAT and its impact on academic achievements of learners shall be researched.

**Keywords** – Individualized e-learning, individual learning differences, adaptive educational hypermedia and mathematics teaching-learning.

## 1. Introduction

Learning is a complicated and difficult process. Many parameters such as perception of information by the individual, his/her processing the information, general abilities, developmental characteristics and environmental factors play a part in this process. Undoubtedly, learning process, being influenced by this many and this much different factors, bears important differences for individuals. Taking into account these differences while designing learning environments shall increase the efficiency of learning activities [1-2]. Many parameters such as general abilities of individuals, their cognitive processes, emotions and tendencies, developmental characteristics, previous information and social environment around them influence their learning. Broadly, Learning Style (LS) can be defined as learning preferences and differences of an individual [3-4]. According to Babadoğan [5], learning processes of individuals shall be planned more easily providing that their learning styles are known. This will facilitate the selection and application of learning environment that will be prepared for

individuals. Previous researches indicate that organization of learning environments according to learning styles of learners increase the efficiency of learners' learning. Besides, these studies revealed that learning which takes place in environments that are appropriate for learning styles positively influence students in terms of remembering and using their knowledge and their attitudes regarding the subject [6-8]. Besides, previous studies indicate that organization of education according to learning styles has positive impacts on learning outputs [2, 6, 9-11].

Methods of comprehending the information by individuals can be divided into three categories which are visual, auditory and kinesthetic [1-2, 13-14]. The model that is accepted as learning style based on this fact, Visual-Auditory-Kinesthetic (VAK), was designed by Sarasin [15] and improved by Coffield et al. [13]. According to VAK learning style, learners who learn visually learn best by seeing. For these learners, pictures, flow diagrams and videos are the best learning instruments. Learners who learn audibly learn best by hearing. For these learners, audible lectures are the best learning instruments. Learners who learn kinesthetically learn best by doing-experiencing. For these learners, computer games, interactive animations are the best learning instruments.

### 1.1. Transition from traditional e-learning environments to individualized e-learning environments

In parallel with rapid development of informatics technologies, e-learning environments change and encounter with innovations as well. Traditional e-learning environment presents pre-fixed contents in the same sequence to all learners. Preliminary information, learning styles and individual differences of learners regarding the subject are not taken into account in these environments. This cannot be accepted in terms of individual learning. Individual differences, preliminary information and needs of learners can be different. These differences

may have an impact on their learning. Adaptive Educational Hypermedia System (AEHS) became alive in this phase and they were suggested as alternatives to traditional hypermedia developed according to “one-size-fit-all” approach [16-18].

AEHS creates a user model determining individual differences such as preliminary information regarding the subject, preferences and learning styles of each learner unlike traditional web based education systems [9, 18-20]. In this sense, learning styles come first among the concepts taken as basis for development of individualized and adaptive e-learning environments. Thus, it is possible to encounter with many adaptive e-learning studies based on learning styles in literature [9]. Major studies among these can be listed as follows. Triantafyllou, Pomportsis & Georgiadou [21] developed AES-CS. Witkin and Goodenough LS was employed in this system. Two different LSs which are field dependent and field independent are used in this system. A learning style from general to specific is employed for those who are field dependent while a learning style from specific to general is employed for those who are field independent. Arthur was designed and developed by Gilbert & Han [10]. System is based on VAK LS model and visual-interactive, audial-voiced and text-writing contents were prepared and presented to the learners. System was developed to teach C++ which is a computer programming language. CS383 was developed by Carver, Howard & Lane [22]. Felder-Silverman LS was employed in this system. The system was developed for “Computer Systems” course. Brown, Fisher & Brailsford [23] developed the system they called DEUS. This system is based on Felder-Silverman LS. The system was prepared at primary school level to teach life cycle and flowering plants subjects of biology course. eTeacher was developed by Schiaffino, Garcia & Amandi [24]. Felder-Silverman LS was employed in this system. The system was prepared to teach artificial intelligence course lectured in department of system engineering. iWeaver was developed by Wolf [14]. Dunn & Dunn LS was taken as basis in this system and an adaptive version of it was used. The system intended to teach Java programming course. It was enriched by style based media components and other learning instruments. Four different contents were prepared and presented according to perceptions of individuals. ILASH was developed by Bajraktarevic, Hall & Fullick [25]. Hsiao LS was employed in this system. This system was designed to teach “characteristics of waves” and “solar system” subjects of Physics course. INSPIRE was developed by Papanikolaou, Kornilakis & Magoulas [26]. Honey & Mumford LS was taken as basis in this

system. WHURLE-LS is a system built on WHURLE system developed by Moore, et. al [27]. Felder-Silverman LS was taken as basis in this system and visual/oral contents were presented to learners. The system was developed and applied to teach internet and www subjects in Department of Computer Sciences and IT in Nottingham University [1]. Mustafa & Sharif [28] developed AES-LS system which uses VARK LS. This system is intended to teach JavaScript.

This study concentrates on architecture and development of UZWEBMAT, a system designed to teach probability unit of 11th grade mathematics subjects. UZWEBMAT is individualized based on VAK learning style. It is designed as an adaptive and intelligent e-learning environment. Architecture of UZWEBMAT and its components are explained in detail in the next sections of this paper. UZWEBMAT is based on .net technology. The system was developed using C# language in Visual Studio 2010. Learning objects are used in UZWEBMAT were coded with Adobe Flash CS5 and ActionScript 3.0. SQL Server 2008 was used for database. The system developed can be reached via <http://www.uzwebmat.com>.

## **2. UZWEBMAT: A Fully Personalized Adaptive and Intelligent e-Learning Environment**

System architecture and details of the system called UZWEBMAT are concentrated on in this section. UZWEBMAT system can be analyzed under six categories. These categories can be listed as architecture, expert system supported content, personalized assessment module, learner module, teacher module and messaging module.

### **2.1. Architecture**

Architecture of UZWEBMAT is dealt with in detail in this section. Basic architecture of UZWEBMAT system is shown in Figure 1.

As it is seen in Figure 1, the learner who registers to the system takes Learning Style Inventory (LSI) firstly. LSI was used in order to determine the learning styles of learners. At the end of literature review, we encountered with many LSIs appropriate for VAK learning styles. Five point likert type scale developed by Gökdağ [29] was employed in the study and used in various studies. Cronbach Alpha reliability coefficient of the scale, which divides learners into three that are visual, auditory and kinesthetic, was found as 0.74. Credibility and reliability studies of the scale were conducted by Gökdağ [29].

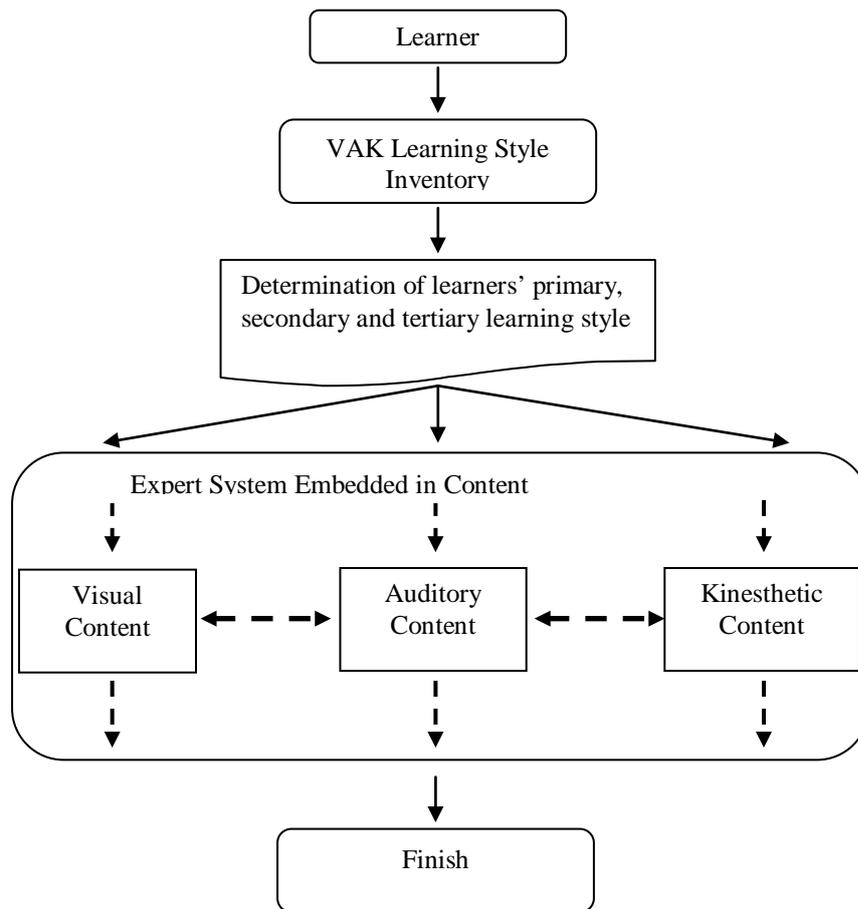


Figure 1. Architecture of UZWEBMAT

## 2.2. Expert system supported content

Probability unit of 11th grade mathematics curricula constitutes the content of UZWEBMAT. Sub-topics of probability unit are permutation, combination, binomial expansion and probability. Fifty-three learning object (LO) scenarios were prepared in total to teach these subjects. These scenarios are transferred to digital environment as different learning objects of each sub-style of VAK LS. Characteristics of each sub-learning style of VAK LS were taken into consideration while preparing these LOs. Thus, figures, pictures and animations are prominent for visual learners. Voiced instructions, warnings and feedbacks are prominent for auditory learners. Similarly, learning materials were prepared using interactive animations predominantly for kinesthetic learners and an environment enabling learners to learn by experience and practicing was created.

Table 1 shows distribution of fifty-three LOs prepared for each sub-learning style according to subjects.

Subject	LO's
Permutation	1-16
Combination	17 – 27
Binomial Expansion	28-31
Probability	32-53

Table 1. Distribution of 53 LOs according to subjects

One of the most important characteristics of UZWEBMAT is that content is presented with the support of expert system. An expert system was prepared while preparing the content and it was buried in the content. This expert system has two main duties. First of them is determining the questions and solution supports learners will take within LOs according to their answers. Second of them is to enable learners browse between primary, secondary and tertiary learning styles.

Primary duty of expert system within UZWEBMAT is to make directions in LOs and to present solution supports. In this sense, Fig. 2 shows presentation plan of a sample learning object used in UZWEBMAT. Figure 2 shows the presentation plan of 12th LO prepared to teach circular permutation.

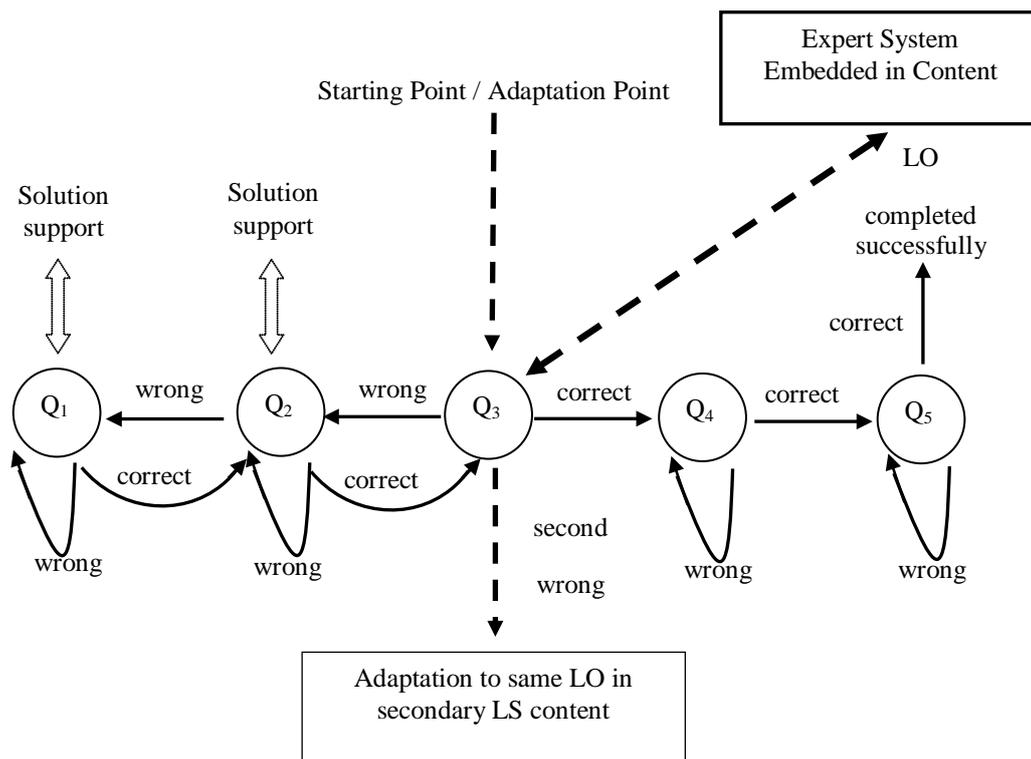


Figure 2. Expert system structure in a sample LO and its process

There are a total of five questions in this LO. The learner initially encounters with the third question in this LO. The learner correctly answering this question will successfully complete the LO on condition that s/he correctly answers the fourth and fifth questions respectively. In this case, s/he will be directed to the next LO. The learner failing in answering the third question for the first time will be directed to simpler second question. The learner correctly answering this question is directed to the first question. Solution support is provided to the learner failed in answering the second question by the system. Should the learner failed in answering this question again, s/he is directed to simpler first question. The learner who gets solution support for the first question will get enough solution support to correctly answer this question. The learner correctly answering this question will be directed to the second question with the same reason. The learner correctly answering the second question will be directed to the third question. Since introduction question of this LO is the third one, this question is considered as the direction point by the expert system. The learner who failed in answering the third question twice will automatically be directed to the same LO of his/her secondary learning style by the expert system.

As it can be seen from Figure 2, each learner does not take the same content in this LO. Solution supports the learner will take and his/her path of progress may change according to the learner

answers. All the possible paths in this LO are thus can be listed as below:

- First Path:*  $Q3 \rightarrow Q4 \rightarrow Q5 \rightarrow LO \text{ completed.}$
- Second Path:*  $Q3 \rightarrow Q2 \rightarrow Q3 \rightarrow Q4 \rightarrow Q5 \rightarrow LO \text{ completed.}$
- Third Path:*  $Q3 \rightarrow Q2 \rightarrow Q1 \rightarrow Q2 \rightarrow Q3 \rightarrow Q4 \rightarrow Q5 \rightarrow LO \text{ completed.}$

All the LOs constituting UZWEBMAT were prepared in this structure. In other words, there are graded questions, solution supports and direction points between styles in any of LOs. Expert system is activated according to learner performances and answers and it leads learners to the most appropriate path.

Second duty of expert system buried in content is to direct learners between styles. Fig. 3 shows architecture of a learner's direction to LOs of different styles by the system.

According to Figure 3, learner progressing in primary style of UZWEBMAT is directed to the same LO of secondary learning style at some specific points providing that s/he could not complete the activities of learning objects. Learner taking and successfully completing the LO of secondary learning style is directed to content primary learning style and continues this way. Learner not being able to complete the LO of secondary learning style successfully is directed to the same LO of tertiary

learning style. Learner taking LO of tertiary learning style shall be redirected to content of primary learning style should s/he successfully completes the LO and s/he continues with the next LO of primary style. Learner failing in LO of tertiary learning style is recorded and reported to the teacher. Learner whose situation is reported to teacher is redirected to the content of primary learning style and continues

with the next LO. Thus, UZWEBMAT does not present a fixed content to learners even with the same learning style. Learners with the same learning style may progress in different ways due to expert system buried in the content. This indicates that UZWEBMAT is individualized at the highest level.

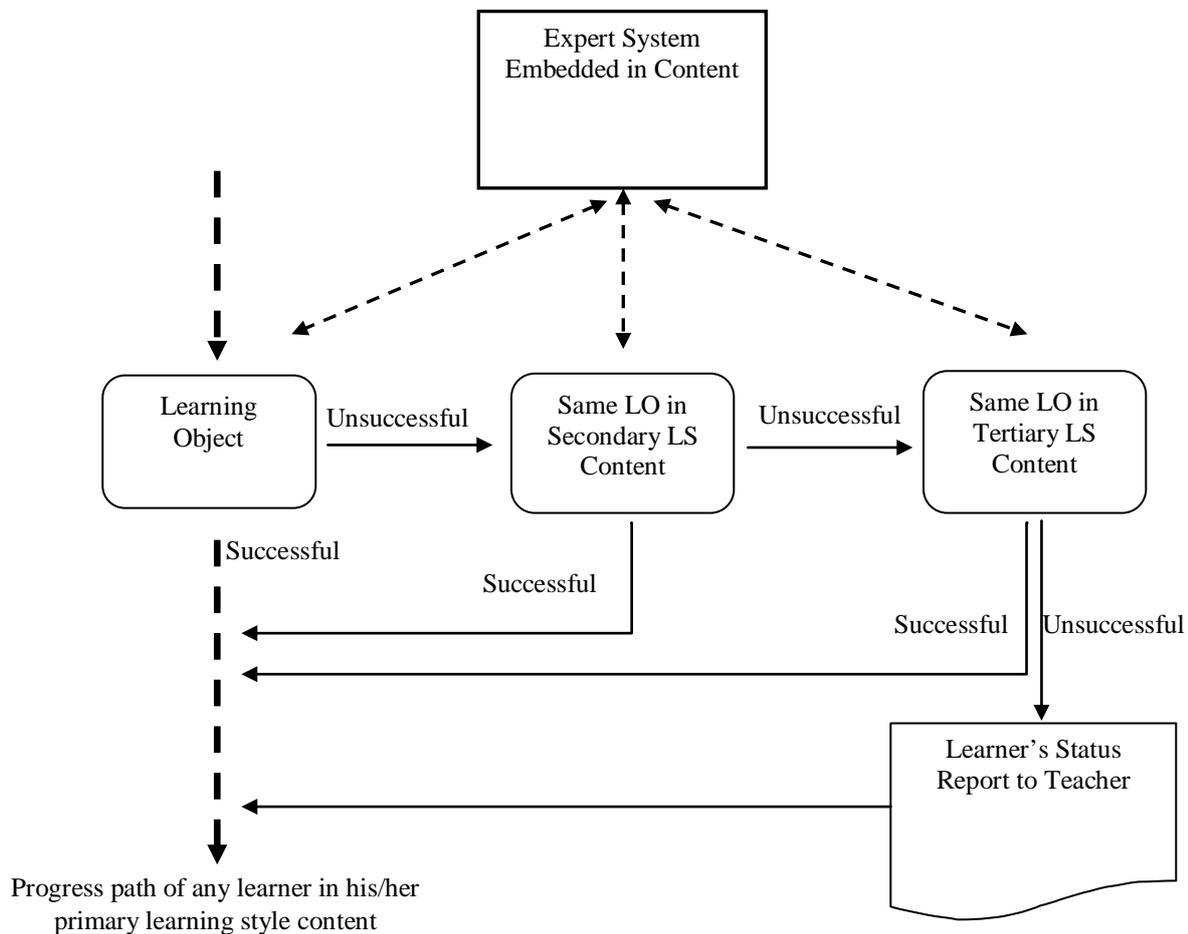


Figure 3. Architecture of expert system supported inter-style direction in UZWEBMAT

### 2.2.1. A sample LO scenario and screen shots

Screen shots from LOs of different styles constituting the content of UZWEBMAT are given in this section. Scenario and presentation plan of a random selected LO developed for teaching combination is displayed in Table 2.

As seen Table 2, This LO is one the LOs developed for teaching combination. There are two questions in LO. Learner takes the first question initially and the activity is done if his/her answer is right for the first question. The learner is directed to simpler second question if the answer is wrong. The learner is redirected to the first question if the answer is right for the second question and s/he is expected to solve the first problem with the same logic.

Learner failing in the second question is given solution support to solve the problem. Learner solves the problem and is redirected to the first question again. Learner's progress between questions and providing solution support are decided by expert system; it makes the necessary guidance. If learner fails in the first question again, expert system does its second duty which is guidance among learning styles. This expert system directs the learner to the same activity of secondary learning style automatically.

Elif, Hale, Pelin and Merve participated in basketball team auditions organized in the school annually. Team coach will choose 2 new players for basketball team this year.



1. How many different selections can be made with these four candidates?
2. How many selections would be made if two player were selected among Elif, Hale and Pelin?

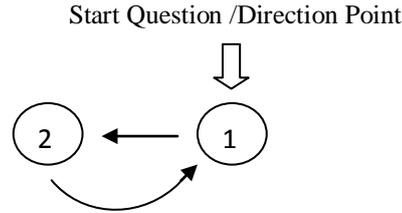


Table 2.A sample LO scenario developed for combination

Figure 4 and Figure 5 shows sample screen shots for visual and kinesthetic learning styles from this LO respectively. No screen shots can be used for audial content since all the feedbacks and solution supports of this LO are voiced commands.

be played gradually. Animation shows selection of two people out of three step by step to the learner. In this way, the learner will see how two people can be selected out of three and total number of selections as solution support.

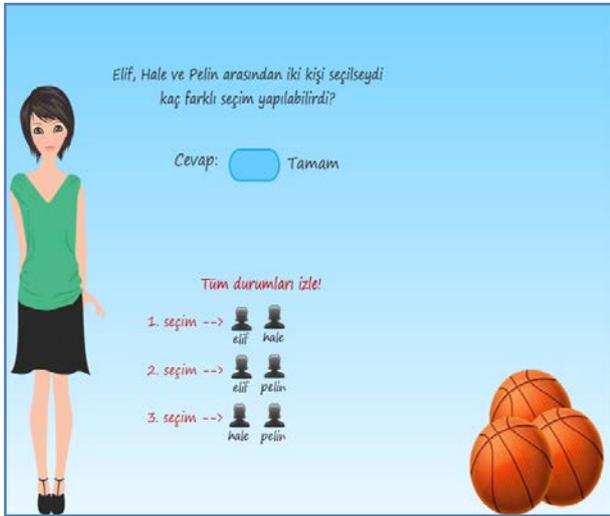


Figure 4. Screen shot of solution support given in case of failing in the second question of LO in visual LS

Figure 4 displays screen shot of solution support given in case of failing in the second question in LO. This question asks how many different couples can be made with two people out of three. If learners correctly answer this question, s/he will be redirected to the first question without any solution support. If learner cannot give two correct answers for the second question, animation in displayed in Fig. 4 will

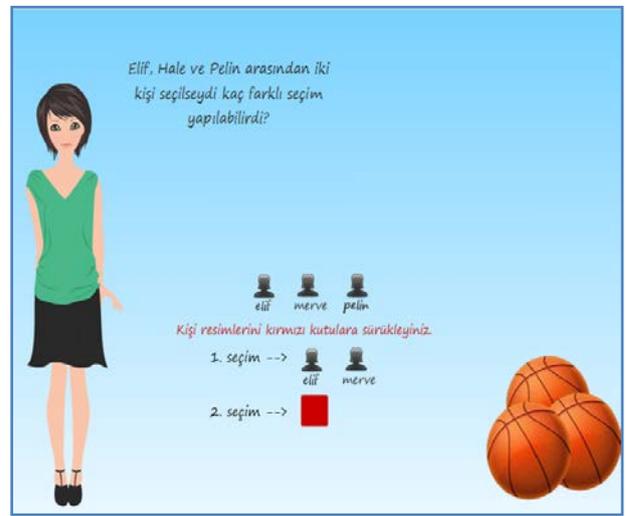


Figure 5. Screen shot of solution support in case of failing in the second question of LO in Kinesthetic LS

Fig. 5 shows screen shot of solution support in case of failing in the second question of LO. This question asks learners how many different selection of two peoples can be made with three people. If learner answers correctly, s/he will be redirected to the first question without getting any problem support and s/he will be expected to answer the question with the same logic. If learner fails for both questions asked in

the same question, animation in Fig. 5 will be played by the learner. By dragging the pictures of people seen on the screen on the boxes, the learner will see each selection. Fig. 5 shows the screen shot of the animation after some part of it was played. Main approach here is to enable learner learn as if playing a game using the animations which is learning by practice. In this way, the learner will see how many selections can be made with two people out of three by doing it himself.

Fig. 6 and Fig. 7 show the feedback given to learner who complete the LO successfully and directed to the next LO and feedback given to learner who failed in the first question which is the direction point and directed to the content of secondary LS respectively.



Fig. 6. Screen shot of feedback given to the learner who completed the LO successfully and directed to the next LO



Fig. 7. Screen shot of feedback given to the learner who is directed to the same LO of secondary LS on adaptivity point

## 2.3. Personalized Assessment Module

An individualized learning environment is presented to learners via UZWEBMAT. In this context, Item Response Theory (IRT) was employed instead of classical test theory as assessment module and Computerized Adaptive Test (CAT) was developed and integrated into UZWEBMAT using Item Response Theory. IRT is a mathematical model which takes into consideration a person's possibility of giving the right answer to each item and defines the participant independent from the participant and the test [30-31]. In this theory, even if two tests with different questions were to be applied on the same learner, estimated ability level would not be different. IRT uses various models to estimate ability. This estimate ability is known as  $\theta$ . It is a value between -3 and +3. On  $\theta$  scale, 0 represents average estimate ability, negative values represent estimate ability lower than average and positive values represent estimate ability higher than average estimate ability [30, 32-33]. IRT uses various models to estimate ability. These models vary from each other in terms of the number and variety of used parameters [31-32, 34-35]. The most common model is 1-parameter logistic model, 2-parameter logistic model and 3-parameter logistic model [30]. Which model will be used is decided by analyzing model-data adaptation in IRT analyses.

CAT systems provide an adaptive test to each participant adapted to his/her estimate ability. CAT systems are based on asking different questions by making adaption of item selection according to person's estimate ability instead of giving the same test for each user. Asking question which are not in compliance with estimate ability of a person may both make him or her bored and negatively influences his or her motivation [33, 36-38].

Success of any CAT system largely depends on a high quality item pool. Item production is the first and maybe the longest phase of development of a CAT system. Final item pool should contain 5 to 10 times more items considering the items to be presented to participants [33, 35]. Five tests in total were designed for the CAT system to be integrated into UZWEBMAT. Four of these tests were organized as subject tests for permutation, combination, binomial expansion and probability respectively. The numbers of questions in these tests are 20, 20, 15 and 20 respectively. As for the fifth test, it was prepared as end of unit test. Questions in this test were prepared taking into account that it will cover all subjects. Total number of questions in this test is 30. Total number of questions in CAT system was planned to be 105. An initial item response consisting 940 questions was prepared for the CAT system and these questions were applied in various

periods on eleven different high schools in city centre of Trabzon and various districts of Trabzon, Turkey during 6 months. MULTILOG 7.0 was used in this study to test model data adaptation and to decide which logistic model to use. According to results of analyses, majority of test items were in compliance with 3-parameter logistic model (3PL). Problematical items which are not in compliance with 3 parameter logistic model were not included in item pool. Parameters (a, b, c) in 3-parameter model were obtained via MULTILOG 7.0. A CAT application was developed using the remaining questions for the application and it was integrated into UZWEBMAT.

Possibility of giving correct answer for each ability level between -3 and +3 in 3PL was calculated using formula 1 [30]. These calculated values are recorded in database. The probability values were calculated for the entire pool of questions.

$$P(\theta) = c + (1 - c) \frac{e^{Da(\theta-b)}}{1+e^{Da(\theta-b)}} \quad (1)$$

a: item discrimination index  
 b: item difficulty parameter  
 c: guessing parameter  
 $\theta$ : ability level  
 D: scaling multiplier (1.7)  
 e: fixed (2.718)

$P(\theta)$ : Probability of giving correct answer of a person with  $\theta$  level of ability

The learner completing each sub-topic in UZWEBMAT is directed to the related end of subject test. Learner completing these subject tests takes the LOs for the next subject and takes the subject tests again when s/he reaches the end of subject tests. An end of unit test is prepared for a learner taking all the subjects. Incorrect answers of learners given to end of unit test is recorded and subjects in relation to these questions are marked as unperceived by UZWEBMAT. Related learner is redirected to these subjects automatically and s/he repeats these subjects. This is recorded and reported to teacher as well.

Maximum Likelihood Estimation (MLE) method was employed to estimate ability levels of learners taking CAT application. This method is commonly used for ability estimation. It finds the value of ability level making the answer set probability highest based on the answers given by participants. Maximum Information Selection (MIS) method was employed to select questions appropriate for ability level estimated from item pool. With this method, the

question providing the most extended information about the ability level of participant is selected. Introduction question is selected considering the fact that the participant has a middle level of knowledge [32]. In this study, introductory question for the first subject test of permutation was accepted as 0 which is middle level and the estimated ability level is accepted as 0 as well. The first question was asked from this ability level. In the later end of subject tests and end of unit tests, the ability level estimated in previous test is accepted as introductory level and the question is asked accordingly. System will ask the question which will provide the furthest information about ability levels of learners between -3 and +3 ability levels after selecting it. In this respect, the learner will take the most appropriate question according to his or her ability level. Since fixed number of questions is used in developed tests, fixed numbered stopping principle was based on at the end of the tests.

Learner answers were assessed by the system at the end of the tests and their scores are calculated according to IRT. Test score of learners in IRT are calculated according to formula 2 after determining ability level of learners [30].

$$TS_j = \sum_{i=1}^N P_i(\theta_j) \quad (2)$$

$TS_j$ : score of the test containing j number of questions

$\theta_j$ : ability level estimated at j number of item

$P_i(\theta_j)$ : Correct answer probability of i item which is correctly answered at the estimated ability level

This scoring system is different from classical test theory. Besides, it is a rather productive method for individual assessment. The learner answering the same number of questions may get different scores in IRT while they are given equal scores in classical test theory. Main reason of this is the questions answered by the learner and the fact that estimated level of ability may be different after completing the test. Learners taking the questions at end of subject test and architecture of ability level estimation are shown in Figure 8.

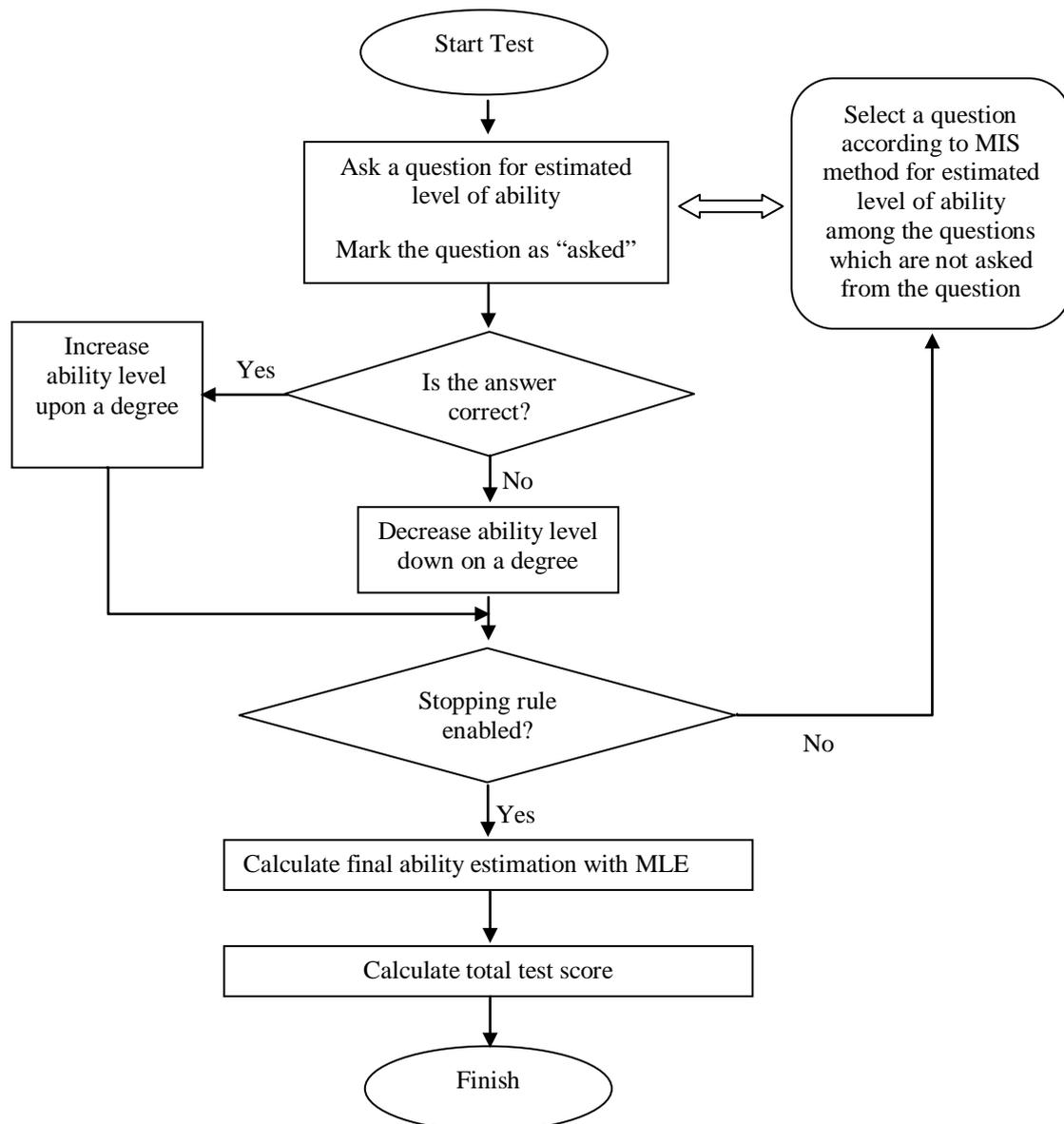


Figure 8. Architecture of question selection and ability estimation in UZWEBMAT and CAT

## 2.4. Learner Module

Learner module is one of the most important components of AEHS. Learner module in UZWEBMAT was designed as such: learner registers in to the system. Learner registering the system waits for the approval by the teacher. The learner whose registration is not approved by teacher can by no means use system. Learner whose registration is approved takes VAK LSI initially. Primary, secondary and tertiary learning styles of learners are determined and recorded in database. The learner is automatically directed to the content of his/her primary learning style. Learner taking the content of his/her primary style is supported by browsing support between styles when necessary thanks to expert system buried in content. This browsing between styles are recorded in database and reported

to the teacher. Teacher can observe the progress of the learner in the system thanks to this data.

The other information kept in learner module is the performance of student in personalized assessment module in UZWEBMAT. All end of subject and end of unit test performances of the student, ability levels and total scores are recorded in database.

## 2.5. Teacher Module

Teacher module of UZWEBMAT was developed for teachers to login to the system and follow learner activities. When students became a member of UZWEBMAT, they wait for the approval by teachers. Registration of the student which is not approved by the teacher is kept passively. Student whose registration is approved by the teacher can use the system actively.

All activities of the student registered in UZWEBMAT within the browsing between pages and learning styles and their performances in tests can be observed by teacher thanks to this module. In addition to performance of the student, system keeps information such as the times when student logs in and out and how much time s/he spends in one page. The teacher can access to the information of any student by clicking on it. In short, thanks to this module, teachers can follow the learners within UZWEBMAT. Therefore, it is possible for teachers to know his or her learners better individually.

## 2.6. Messaging Module of UZWEBMAT

This module was created in order to provide messaging between members of UZWEBMAT. All the learners and teachers registered in the system can send e-mails to each other. Thanks to this structure named as “UZWEBMAT e-mail” users can send e-mails to each other when they deem it necessary. Each user can view his or her inbox when they log in the system under this module. The module was designed as a real mail sending-receiving medium. Members can see their mails in the form of inbox, read them and delete them. Information about the inbox is given to the members who log in the system. In this way, members can see whether they have unread mails. Briefly, learner-learner; learner-teacher; teacher-learner interactions are provided thanks to this module.

## 3. Conclusion and Future Work

Education technology brings many changes and innovations each day. It also encounters you with many alterations. Traditional e-learning environments provide the same content to each student. Due to their aforementioned structures, traditional e-learning environments are especially criticized in terms of individual learning. These criticisms and innovative approaches led to traditional e-learning environments’ replacements by individualized and intelligent e-learning environments gradually. Thanks to these new approaches, e-learning environments taking individual differences of students such as learning styles, pre-information about subjects and needs into consideration are being developed and prevailed.

In this study, architecture and design of an individualized adaptive and intelligent e-learning environment named UZWEBMAT are focused on. UZWEBMAT was designed to teach sub-topics of probability unit of mathematics which are permutation, combination, binomial expansion and probability. UZWEBMAT is an individualized adaptive and intelligent e-learning environment

based on VAK LS. UZWEBMAT decides learning styles of students and presents the appropriate content to each student according to their own learning styles. Expert system buried in content of UZWEBMAT was used. Solution supports to be given students in LOs and inter-page browsing are decided using this expert system. Thanks to this expert system, different learners with the same learning style may be put subject to different instructions according to their performances and ability levels. Therefore, individual learning has become prominent instead of learners’ taking the same content in web mediums. Taking this structure into consideration, it is possible to say that UZWEBMAT is totally a learner centered system and it proposes choices to learners in each step according to their performances. Briefly, UZWEBMAT presents what learners need.

UZWEBMAT will be a beneficial instrument for teachers due to these characteristics. Hence, teachers can use this system in real class environments. From this aspect, this system can be used both for individual learning and formal learning in real class environments. In future studies, UZWEBMAT will be presented to the evaluation of teachers and students and effect of this system on academic achievements of students shall be searched. As a result of these studies, applicability of UZWEBMAT’s aforementioned frame for other subjects of mathematics and more broadly for different courses will be searched. As a result of these studies, use of adaptive and intelligent e-learning environments may be become widespread and related studies shall gain speed. Thus, it is thought that development and proliferation of this and similar systems will contribute much to the individualization of e-learning environment.

## Acknowledgement

This research is being supported by The Scientific and Technological Research Council of Turkey (TUBITAK), Social Sciences and Humanities Research Group (SOBAG), under Grant no. 109K543.

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