Tuning Primary Learning Style for Children with Secondary Behavioral Patterns

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Abstract

Personalization is one of the most expected features in the current educational systems. User modeling is supposed to be the first stage of this process, which may incorporate learning style as an important part of the model. Learning style, which is a non-stable characteristic in the case of children, differentiates students in learning preferences. This paper identifies a new hybrid method to initiate and update the information of children's learning style in an educational system. At the start-up phase, children's learning style information is gathered through the modified Murphy-Meisgeier Type Indicator for Children (MMTIC) questionnaire, which is based on the well-known Myers-Briggs Type Indicator (MBTI). This primary information will be tuned by tracking children's behaviors during the learning process. Analytical data mining helped us to cluster these behaviors and find their patterns. The proposed method was applied on 81 fourth grade children in elementary school. Delivering results suggest that this method provides a good precision in recognizing children learning style and may be an appropriate solution for non-stability problems in their preferences.

Keywords: Automatic detection, children learning style, hybrid method, MBTI, personality type

Introduction

Rapid development of technology has made it a necessity to provide people life-long learning facilities. Life-long learning is the "life-long, voluntary, and self-motivated" pursuit of knowledge for either personal or professional reasons (Department of Education and Science, 2000). Although eLearning systems are identified as promoters of this term in the world of education, these systems do not consider children as one important category of users. In this regard much research has been done about cognitive traits, thinking and learning process, student modeling, and personalization in eLearning systems, but in most cases, college or high school students are considered (Gong, 2014; Romero & Ventura, 2010; Truong, 2016). It seems that identification of children's modeling methods is an obvious gap in the field of eLearning.

Learning style, defined as "a description of the attitudes and behaviors which determine an individual's preferred way of learning" (Honey & Mumford, 1992, p. 1), is considered as an essential factor in the learning process and forms a part of the student model. Many educational theorists and researchers agree that in-

corporating learning style in education has potential to make learning easier for students (Ghazali, Noor, & Saad, 2015; Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011). They believe that if student learning style is not supported by teaching environments, learners with strong preferences for a specific learning style might have difficulties in learning (Felder & Silverman, 1988).

Psychologist's opinions about learning style are different and affected by several aspects. According to research conducted in 2004, 71 models of learning styles are identified and the major models based on theoretical importance and widespread uses are considered (Coffield, Moseley, Hall, & Ecclestone, 2004). Kolb's learning style model, as the most widely used learning style model, has been used frequently in psychological and educational research (Kolb, 1984). The Felder-Silverman learning style, as the second model, has a special place in engineering research (Felder & Silverman, 1988). The Myers-Briggs Type Indicator (MBTI) is one of the most applicable learning style models, which investigates learners from the cognitive perspectives (Myers & McCaulley, 1998). Since MBTI models personal characteristics of people context independently, and includes important aspects of learning, it has been used as one of the most popular learning style models.

Children's experiences of learning are too little to determine their learning style, so most of the learning style models are not applicable for them. Murphy-Meisgeier Type Indicator for Children (MMTIC) is a modified version of MBTI questionnaire introduced for children (Potts Gilbert, 1990). Unlike MBTI, there are few studies about MMTIC. One of the reasons of this issue could be related to frequent changes in children's personality, which leads to non-accurate information about their learning style after a short time. It seems that if learning management systems (LMSs) are equipped with techniques to update children's style automatically this problem could be solved.

In this paper we propose a new approach to modeling children's style statically based on a modified version of the MMTIC questionnaire. We automatically update children's profiles using behavioral logs of their interaction to eLearning system.

The paper is organized as follows. The next section starts with a brief overview on learning style modeling and introduces MBTI. The third section presents our proposed method to determine children's learning style in a LMS and tune their information automatically. Describing the provided child-specific LMS and presenting our experimental results are accomplished in the fourth section, and the final section concludes the paper and outlines future research.

Background

Personalized systems have many goals, which guide the methods of user modeling and adaptation as the two key processes of these systems. In this respect, numerous articles address the problem of student modeling in personalized learning systems (Gong, 2014). These studies can be classified according to contents of model, types of modeling process, representing model, and retrieving model (García, Amandi, Schiaffino, & Campo, 2007). In a comprehensive study, Brusilovsky (2001) proposed several attributes to apply in user models of adaptive eLearning systems. Kim, Lee, and Ryu (2013) extended these attributes as shown in Figure 1. Learning style is a component of student preferences and MBTI is one of the most used models.
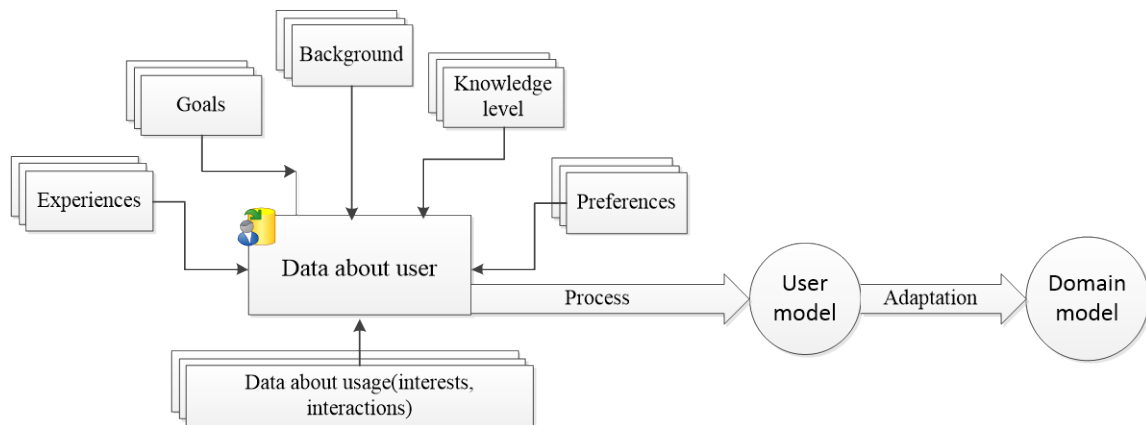
Figure 1. Elements of user model in an adaptive eLearning system, extended from (Brusilovsky, 2001; Kim et al., 2013)

Learning Style Modeling

Initiating and updating learning style information in a student model can be distinguished in two different ways (Brusilovsky, 1996): collaborative and automatic. In the collaborative approach, students provide explicit feedback, which can be used to initiate or update their information, while in the automatic one, the system uses learners' behaviors and actions. Applying a questionnaire is the easiest and common way for the first approach, whereas for the second several methods such as data mining algorithms are applied.

According to some theorists' opinions, learning styles are "flexibly stable" characteristics. In these approaches, learning styles of students are formed by their previous learning experiences and other environmental factors. Other researchers strongly relate learning styles to cognitive styles and abilities. They argue that learning styles remain stable over a long period of time. However, with respect to the life-long learning approach in eLearning systems, student learning styles are changed over time. In younger students, changes in their preferences occur with more frequency. In this respect, some researchers categorized all types of student modeling in two classes as statically or dynamically. The static student modeling refers to an approach where the student model is initialized only once. In contrast, the dynamic approaches frequently update the information of the student model (Graf, 2007).

Usually dynamic and automatic detection of learning style is based on system logs, so data mining methods play a key role in this work. For example, Özpolat and Akar (2009) use NBTree classification algorithm in conjunction with Binary Relevance classifier, which are applied on learning objects selected by students to recognize their learning style. In Chang, Kao, Chu, and Chiu (2009), a combined mechanism based on K-Nearest Neighbor classification and Genetic algorithm is proposed to classify students learning style. Dorça, Lima, Fernandes, and Lopes (2012) compare the Genetic Algorithm and Hidden Markov Model to determine and precisely adjust students' learning style automatically. They find the Markov based approach leads to more fine-tuned results than the Genetic Algorithm. Latham, Crockett, McLean, and Edmonds (2012) predict students' learning style through natural language dialogue. In this respect, they analyze the learning style models for language traits and conversational structure and adapt the generic logic rules to predict learning styles. Basheer, Ahmad, and Tang (2013) apply Multi-Agent System with the help of Ant Colony Optimization and Fuzzy Logic Search Algorithm as tools to detecting learning styles.

Myers-Briggs Learning Style

In the early l940s, Isabel Briggs Myers and her mother, Katherine Briggs developed MBTI as a test to be used for personnel selection. Myers believed that "different occupations favored different personality orientations, and that Jung's theory provided a theoretical link between personality and job performance" (Pittenger, 1993, p. 3). Consulting Psychologists Press acquired the right to sell the MBTI in 1975, and since then, the test has been successfully marketed to an extremely wide audience. Using mental habits, methods of understanding new information, and judging styles, the MBTI distinguishes a person's type according to four dichotomies, including (O'brien, Bernold, & Akroyd, 1998):

- Most natural energy orientation and direction of focus: Extroversion (E)/ Introversion (I)
- Perceiving function and ways of taking in information: Sensing (S)/ Intuition (N)
- Decision making and ways of coming to conclusion: Thinking (T)/ Feeling (F)
- Orientation to outer life and attitude toward the external world: Judging (J)/ Perceiving (P)

Table 1. Characteristic of MBTI personality dimensions

Dimension	Personality characteristics		Dimension
Extroversion	Thinks out loud (by talking)	Thinks privately	**Introversion**
	Being around people brings renewal and energy	Having time alone to think replenishes his energy	
	Is relaxed and confident	Is intense, bottling up emotions	
	Dislikes complicated procedures and gets impatient with slow jobs	Works on one thing for a long time	
	Is enthusiastic about activities involving action	Is hard to understand, quiet, and shy; seems deep	
Sensing	Sees the trees in the forest	Sees the forest (more global thinker)	**Intuitive**
	Handles details easily	Sees possibilities and details that others miss	
	Uses the five senses to perceive life	Uses meaning and possibility to perceive life	
	Learns best from an orderly sequence of details	Likes to have and do things differently from others	
	Is aware of environment and changes moods as physical surroundings change	Is an initiator, promoter, and inventor of ideas	
Thinking	Looks at data to decide	Decides based on personal feelings	**Feeling**
	Doesn't need harmony, but needs fairness	Values harmony	
	Is more truthful than tactful, if forced to choose	Is more tactful than truthful, if forced to choose	
	Is brief and businesslike	Finds it difficult to be brief and businesslike	
	Finds ideas and things more interesting than people	Is more interested in people than things or ideas	
	Holds firmly to a policy or conviction	Arouses enthusiasm	

Judging	Works first, then feels a freedom to play	Plays first, then works	Perceiving
	Prefers predictability in schedule	Likes dealing with events as they come	
	Likes things to be decided	Likes things to remain open	
	Is structured	Is flexible	
	Has settled opinions	Has trouble making decisions	

All possible combinations of these dichotomies can occur, which result in a total number of 16 types. Table 1 describes a brief explanation of the characteristics and preferences that MBTI has identified (Behaz & Djoudi, 2012; Brightman, 2007; O'brien, et al., 1998).

Despite the numerous studies which have been done on MBTI in learning and training process, investigating MBTI as learning style in eLearning systems starts from 2000 (Dewar & Whittington, 2000). Afterwards, some research shows students with different learning styles behave dissimilarly in learning environments and with respect to learning objects (Kim et al., 2013).

The MBTI indicates not only the learners' preferences, but also clearly expresses the preferences for particular poles over their opposite. For example, Figure 2 is a summarization of typical report from Consulting Psychologists Press, the MBTI authority organization (Choi, Deek, & Im, 2008). In this example, E is showing a greater presence on a moderate level, over its counterpart, I. Similarly, in other dimensions dominant preferences are shown.
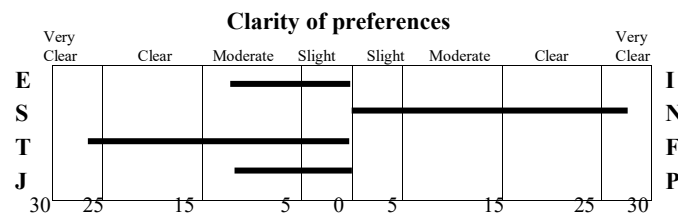

Figure 2. The strengths of MBTI type preferences

Although several versions of MBTI questionnaire are designed, they are all validated for people who are over 18 years old (Myers & McCaulley, 1998). The MMTIC is a self-report instrument designed for personality and psychological type assessment in youth aged 7-18 (Center for Application of Psychological Type, 2012). Children's lack of experience in learning activities and their learning styles non-stability have caused this questionnaire be mostly applied in learning activities instead of other domains. The dynamics of the MMTIC dimensions refer to how these four preferences interact in each individual. Like the MBTI, this questionnaire measures personality preferences on the same four sets. Both the MBTI and the MMTIC are multiple choice tests.

Incorporating Learning Style into a Child-Specific LMS

The aim of this study is investigating how learning styles can be incorporated in LMSs. Answering a psychological questionnaire is a common way for statically determining learning style. Although this method is easy and usual in learning environments, the static nature of the questionnaire makes it fault prone. Combining this static method with a dynamically driven one is the approach of this paper, which is applied to elementary school students. Receiving student's logs and pattern of their behavior, the system updates student profile information frequently.

The questionnaire describes the learning style of students at a specific point in time. Furthermore, some other problems such as misunderstanding of self-type can make the questionnaire results

not reliable. In general, the questionnaire has to deal with the problem that the given answers might not correspond to the real behaviors that the questions aim to investigate.

Therefore, using a questionnaire as an instrument for identifying learning styles is based on several assumptions. The first assumption is that students are motivated to fill out the questionnaire properly and to the best of their knowledge about their preferences. Secondly, filling out a questionnaire about the preferences requires that the students are aware of their preferred way of learning. Besides, children's learning styles have not yet stabilized and may change gradually (Warner, 2000). As soon as learning style changes, the results of the questionnaire are not valid anymore and a student would have to do it again. This approach would raise new issues, dealing with how to identify an occurring change in learning style and how to motivate students to fill out the questionnaire several times.

This problem can be solved through updating information of students' learning style based on their behavior and learning preferences. Table 2 is a summary of research conducted on learning preferences in MBTI dimensions (Dewar & Whittington, 2000; Lawrence, 1993). According to this table, some behaviors of students with different learning style are various. We use all the features mentioned in this table to extract students' learning preferences in online environments.

Table 2. Learning preferences associated with dimensions of MBTI

Dimension	Learning preferences		Dimension
Extroversion	Prefers action	Considers/thinks before acting	**Introversion**
	Plunges into new experiences	Holds back from new experiences	
	Has a relatively short attention span	Spends time in thought, before and after actions	
	Eagerly attends to interruptions	Dislikes interruptions	
	Likes to work by trial and error	Prefers setting his/her own standards when possible	
	Wants to experience things so as to understand them	Asks questions to allow understanding something before	
Sensing	Prefers facts and concrete information	Prefers abstract or theoretical information	**Intuitive**
	Is realistic and practical	Is imaginative and loves ideas and possibilities	
	Going step by step	Jumps to conclusions; makes factual errors	
	Prefers memorizing to finding reasons	Has intellectual interests	
	Likes to know the "right way" to solve problems	Likes problems that require new ways of being solved	
	Enjoys using skills already learned more than learning new ones	Seems to like something new all the time	
Thinking	Contributes intellectual criticism	Is motivated by others	**Feeling**
	Wants logical reasons before accepting new ideas	Permits feelings to override logic	
	Is objective	Is subjective	
Judging	Is more decisive than curious	Is more curious than decisive	**Perceiving**
	Likes assignments to be clear and definite	Is flexible, adaptable and tolerant	
	Tries to make situations conform to his or her own standards, "the way they ought to be"	Looks for new experiences, expects to be interested	
	Aims to be right	Aims to miss nothing	

We expect that the students' preferences in online learning environments to be same as the offline ones. So, we track behaviors of students in learning management systems and update their information models based on the extracted patterns that relate to learning style dimensions. But, for solving the cold start problem at the start-up phase of the system – not knowing the learner's profile – we use a personality indicator questionnaire. Figure 3 illustrates the process of our proposed method.
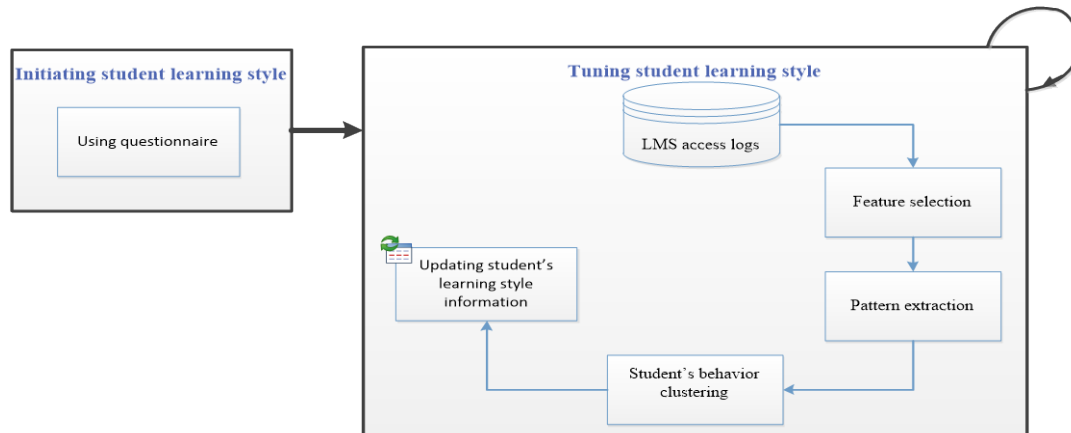

Figure 3. The process of tuning primary learning style with learner access logs

A. Initiating Student Learning Style: Static Determination

To identify the learning style of children at the starting-up of the system, we use the child personality indicator questionnaire. This questionnaire is a modified version of MMTIC that is translated to Persian language and localized based on some linguistic and cultural aspects. This test, which contains 70 questions about children preferences, is approved by a panel of psychology and pedagogy experts as discussed in a previous paper (Mosharraf, Taghiyareh, & Kharrat, 2013). The children personality indicator questionnaire is a self-reporting instrument in which a child is asked to choose between two preferences, neither of which is wrong. Same as MBTI and MMTIC, the four measured preferences in this test are E/I, S/N, T/F, and J/P. Test scores can range from one extreme to a contrasting extreme and each pole of the dimensions has different characteristics. Children scores can be any number in the spectrum of two poles.

B. Tuning Student Learning Style: Automatic Determination

As soon as a child's learning style changes, the results of the questionnaire may not be valid. To tune information of children's learning style, we use the new automatic method, which is based on tracking children's behaviors. In our proposed method, no additional effort is needed on the students' side in order to enable the system to get information about their learning styles. In this regard, students interact with the LMS only for learning activities, but the system monitors their behavior simultaneously. At arbitrary times, LMS administrators can check system access logs. If students' behaviors are recognized as contrary to the determined learning style stored in their model, information of student model should be revised. For this purpose, some data mining techniques are applied to students' access logs to extract behavioral patterns of each student.

In online environments, learning behaviors regarding the patterns are clustered based on selected features extracted from Graf (2007). Considering children limitations in the LMSs, these features include:
- Learning contents
- Outlines
- Examples

- Assessments
- Exercises

Regarding different features, the number of visits and the duration students spend on these objects are used as their behavioral patterns. Learning preferences, which are mentioned in Table 2, corroborate this claim. Occurrence frequency of learning patterns that is used in any learning style dimensions is context sensitive and affected by course subject. Therefore, we use the behavior of students to determine thresholds of each pattern. For this purpose, we cluster all the children's behaviors in three categories: low, middle, and high.

The category of learning patterns which is labeled "high" is matched to one style dimension. For example, sensing learners favor concrete materials like facts and data, so they prefer to learn from examples. Therefore, a high number of visited examples and time spent on them may be indicants of sensing style. On the other hand, intuitive learners prefer to learn from abstract materials such as theories and their underlying meaning, so they probably choose to learn from content objects. A high number of visited contents and time spending on them can be demonstrators of initiative style. Furthermore, sensing learners like to solve problems in accordance with a standard procedure, which can be indicated by a high interest in examples. In these students, multiple reviews in examples are done to see and learn existing approaches and a high number of assessments and exercises are conducted in order to check the acquired knowledge. Regarding Table 1 and Table 2, sensing learners are more patient with details and work carefully, but slowly. With respect to the preference for working slowly, the times taken for visiting examples, assessments, and exercises are considered as a pattern. However, intuitive learners tend to be more creative. Therefore, they are expected to be better in answering questions about developing new solutions, which requires the understanding of underlying theories and concepts. In contrast to sensing students, intuitive learners like challenges.

Research shows gender differences in feeling/ thinking dimension of MBTI and this issue has caused students' behaviors to become unpredictable in different contexts (Dewar & Whittington, 2000). In addition, both perceiving and judging types indicate an appreciation for online learning environments, but extracted patterns of them are not valid for children. According to O'brien et al., (1998) sensing/ intuitive dimension is proposed as the dimension with most differences in learning behaviors. Because of the importance of group learning, the introvert/ extravert dimension is also important. Therefore, we study only two dimensions in this paper: E/I and S/N. Kim et al. (2013) verified that E/I and S/N dimensions are the most dominant functions of the MBTI in learning behaviors. Table 3 summarizes all the selected features that are available in children learning behaviors.

Table 3. Selected features of learning behaviors related to learning style dimensions

Features	Pattern	Pattern Description	E/I	S/N
Outline	OutlineVisit	Number of visited outlines	U	N
	OutlineStay	Percentage of time spent on outlines	I	N
Content	ContentVisit	Number of visited content objects	I	N
	ContentStay	Percentage of time spent on content objects	I	N
Example	ExampleVisit	Number of visited examples	U	S
	ExampleStay	Percentage of time spent on examples	I	S
Assessment	AssessmentVisit	Number of performed self-assessment questions	E	S
	AssessmentStay	Percentage of time spent on self-assessment tests	I	S
	AssessmentRetry	Number of retry for assessment	E	S
Exercise	ExerciseVisit	Number of performed exercises	E	S
	ExerciseStay	Percentage of time spent on exercises	E	U

In the above table: "U" is the acronym of "Undefined".

In addition to the number of visits and duration students spend on learning objects, the pattern of navigation for each learning style dimension is different (Anohina, Vilkelis, & Lukasenko, 2009; Graf, 2007). For example, thinking students like to analyze and solve the practical exercises using course knowledge. So, the navigation plan of these students is usually the sequence of contents, examples, and then exercises. On the other hand, feeling students use practical exercises to be familiar with course subject; therefore, their navigation plan is exercises, examples, and contents (Bachari, Abdelwahed, & Adnani, 2010). Table 4 indicates the patterns of navigation in the E/I and S/N dimensions of learning style. All the patterns of student navigation, which are the sequential subset of any presented navigation in this table, can be applied to determine learning style.

Table 4. Navigation pattern related to learning style dimensions

Learning style dimension	Navigation pattern
I	Learning contents, Assessments, Exercise
E	Assessment, Exercise, Learning content, Example
S	Example, Learning content, Assessment, Exercise
N	Exercise, Learning content, Example

Although each dimension of learning style has specified patterns, some of them may yield conflicting results. As Table 3 shows, one relevant pattern of IN students is OutlineStay, but for IS students this object can be a contradiction. For solving this problem, we use students' scores in each dimension of learning style that are obtained by the questionnaire. Like frequency of learning behaviors, we divide the scores of each learning style dimension in three groups as weak, moderate, and strong (presented in Table 5). A weak style is considered as undefined. Considering dominant style, if the indicants of weak style in one dimension and strong style in the other are gathered in a child, we expect the strong style to dominate. In other cases, learning style is undefined. When conflict occurs in some features and learning style becomes undefined, the system uses other learning features to resolve this conflict. In the mentioned instance, OutlineVisit or ExampleVisit can be determiner of learning style.

Table 5. Segmentation of learning style scores

Score range	Learning style
0 – 30	Weak
30 – 70	Moderate
70– 100	Strong

Experimental Results

One of the main difficulties of research about children is encouraging them to effectively participate in all the research stages. In addition, children's education should be done in special environments. For example:

- Children's motivation for engaging in learning activities (Gagne & Deci, 2005);
- Effect of operative feedback and interactive learning environment (Mosharraf & Taghiyareh, 2012);
- Limited children's working memory and profitable user interface for system (Wang, Li, & Shi, 2007);
- Children's curiosity and fantasy-driven nature (Asgari & Kaufman, 2004).

Providing some arrangements to obtain these conditions was one of the first steps in this research. To this end, we implemented a learning management system for children (Mosharraf, Taghiyareh, & Nasirifard, 2013). The Child-specific LMS provides all the proposed features which are identi-

fied in Table 3. In order to investigate learners' behaviors, the learning materials are distinguished according to the proposed features. In addition, for some features, an additional description of the material is specified. For example, with the aim of distinguishing between contents and outlines, we extend our implemented LMS by including the possibility of using meta-data for teachers and course developers to specify information about the created learning materials.

A. Extensions Regarding Questionnaire Results

The proposed approach for defining children's learning style was examined on fourth-grade elementary school children. For this purpose, 81 students were asked to respond to the prepared questionnaire. This process was done when a student logged in to the system for the first time. Table 6 shows the results of children styles obtained by the questionnaire.

Table 6. Questionnaire result of learning style

Learning style dimension	Min	Max	Median	Std Deviation
E/I	22.2	88.9	44.4	17.1
J/P	-27.8	22	11	14.7
S/N	-77	66.7	-11	36.8
T/F	-25	25	0	19.9

We normalize all the children's scores in each dimension of learning preferences to (-100, 100) as E/I, J/P, S/N, and T/F. As Table 6 shows, all the examined children are extravert. This issue can be relevant to children's conditions at an early age and their tendency to be in a group of friends. The achieved scores for J/P and T/F dimensions are less than 30 for all of the students, which lead to weak preferences in these dimensions. One reason for this may be relevant to inappropriate perception of children from these dimensions of their personality. The recorded scores in the S/N dimension show high diversity of the examined children. Children's distribution is seen in all the three strong, moderate, and weak groups in intuition preferences. But, the sensing children are located in moderate and weak groups.

B. Extensions Regarding Behavioral Tracking

Tracking children behaviors in learning environments can help the system to respond to children's preferences when they change and always deliver personalized services to them. Students' access logs in LMS make it possible. The LMS logs of children's interactions in biology context and creatures' course was used for our research. Collected data set contain 169,908 records related to 23 days of student training.

The time-consuming step in detection of children's style was data cleaning and outlier removing. Using obtained data, we calculated the number of visited learning objects and the time spent on them for each child. After that, we applied K-Means algorithm on each of the learning features, which are mentioned in Table 3, separately and divided the children in three groups based on their behaviors. So, we used the information of this table to determine the expected style for all of the behaviors that are labeled "high".

In order to determine learning style of children based on their navigation pattern, we used AprioriAll algorithm (Agrawal & Srikant, 1995). This algorithm is applied on all the features of Table 4. But, the low support and confidence in the extracted sequences make these features to be not valid.

To evaluate the effectiveness of our hybrid method to detect the children's style, we compare the result of the proposed automatic method with questionnaire as a common approach in learning style modeling. We expect the results of both methods to be same after short time duration. Au-

tomatic detection of children's style was done 17 and 23 days after answering the questionnaire. Since these time durations are short, it is expected that the children's styles are not changed significantly. Therefore, calculating the precision of our method needs to use some measures. We define the precision of automatic method as:

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{\text{automatic}}, LS_{\text{questionnaire}})i}{n} \cdot 100, \quad (1)$$

Where LS $_{\text{automatic}}$ refers to the learning styles diagnosed by our automatic method. Also, LS $_{\text{questionnaire}}$ represents the learning styles indicated by the prepared questionnaire, and n is the number of all the students. The function Sim compares its two parameters LS $_{\text{automatic}}$ and LS $_{\text{questionnaire}}$ and returns 1 if both are equal. Table 7 shows the precision of the implemented system in automatic detection of children's style.

Table 7. System precision

Time duration	Extravert / Introvert (E/I)	Sensing / Intuitive (S/N)
17 days	56.79%	72.84%
23 days	69.14%	80.24%

The important restriction in our system evaluation is the low time interval between the static and automatic tests. Since the style of children can change repeatedly, the time interval between the two tests should be low. However, this short interval leads to few students' access logs which may be not enough for extracting their patterns. We hope that as time passes and more children's data is collected this will lead to detecting better patterns of their behaviors; the results of the system tend to the reality.

The proposed automatic detection of children's style is focused on only two dimensions of their learning style. According to the mentioned results in Table 7, this method has shown an acceptable similarity in the S/N dimension. Considering the problem of a questionnaire as a static method for determining children's learning style, our results in automatic method can be acceptable even in the E/I dimension. Due to our achievements, diagnosing the E/I dimension of learning style based on children's behavioral patterns in an online learning environment needs more access logs. However, we need to focus on learners' behaviors on the other dimensions and not rely only on the questionnaire results. It seems this method can accelerate learners' modeling process, which is a time-consuming procedure in adaptive learning processes.

In the automatic method, we assign all the learning preferences of children in the E/I and S/N dimensions to learning objects and find their appropriate behaviors. Accomplishing these assignments in the T/F and J/P dimensions needs more research on the children's preferences and learning behaviors. As shown in our study, perception of children in these dimensions is weak. So, investigating this issue can face many troubles.

Conclusion

In this paper we concentrated on learning styles of children considering the life-long learning approach. Since the learning experiences in children are too little to gain the accurate perception of their style, we used personality type instead. For initiating primary information of children's learning style, a modified version of the MMTIC questionnaire was used. The questionnaire results showed almost all of the children are extravert, but in absorbing information they can be sensing or intuitive. Also, it seems that children do not have any strong preferences in the perceiving/ judging and thinking/ feeling dimensions.

For solving the non-stability problem of children's learning style, we used access logs of the system in order to tune the children's model. In this regard, we applied clustering algorithm on ex-

tracted behavioral patterns of children. Regarding learning preferences which are compatible to each cluster, children's information can be tuned. Experimental results show this method has an acceptable precision in diagnosing children's learning style.

Although tuning the student models is done based on automatic approach, it does not work fully automatically. Pre-processing steps including data cleaning and outlier removing are case sensitive. In addition, some analyses are context based and need human opinions. Due to these restrictions, it would be very useful to improve eLearning systems with automatic data mining methods. In addition, the experimental results show children's navigation plan cannot be applicable in the case of learning style detection. However, this feature may be used in other age classes. Furthermore, there are two aspects of MBTI, perceiving/ judging and thinking/ feeling, which our results did not find good criteria for categorizing children at this age, but we believe they may be more effective in older students. All the findings and prototypes developed in this paper can be used as the basis for further research and developments regarding providing advanced adaptivity in LMSs.

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