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An Enhanced Learning Style Index: Implementation and Integration into an Intelligent and Adaptive e-Learning System

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ABSTRACT

Advances and accessibility of Internet services around the world have transformed the traditional classroom learning into web-based e-learning systems. In recent years, designing adaptive e-learning systems has become one of striking topic of discussions in the literature. Additionally, integrating such systems with intelligent and adaptive systems that can measure the learning preferences of the user can enable learners to obtain the most suitable learning objects that might be matched with their learning styles. Moreover, even in the classroom teaching, knowing the learning styles of students can also help teachers to adopt appropriate learning materials for efficient learning. This paper is concerned with the study, implementation, and application of a web-based learning style index. The paper also described a case study on the integration of the learning style index into an adaptive and intelligent e-learning system.

Keywords: intelligent learning, adaptive learning, learning style index, learning preferences, learning technology

INTRODUCTION

Recent development of the Internet has changed the way people interact and exchange useful information. This has also influenced the traditional educational systems and transformed them into e-learning based education systems. Interestingly, it makes learning easier and improved the learning outcomes of the students (Yeh, 2014). Intelligent and adaptive systems have established a long tradition in technology-enhanced systems for improving the learning process of an individual learner (Hamada M. , 2008). To utilize such systems efficiently during the learning process, learners have to be aware of their learning preferences. A learning style index can help learners to identify their learning preferences. It also supports to adopt suitable learning materials to enhance learner's learning process.

On the other hand, teachers can gain by knowing their students' learning preferences. From the teacher's point of view, if they figure out their students' learning preferences, they can adjust their teaching style and adopt suitable materials to best fit with the students' preferences.

If there is a mismatch between a learner's learning style and the way learning materials are presented, students are more likely to lose motivation to study.

Integration of learning style into learning systems can lead to an intelligent and adaptive learning system that can adjust the content in order to ensure faster and better performance in the learning process.

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State of the literature

- Traditionally, students attend classes and receive lectures in a group irrespective of their individual differences.
- Over many years, most of the research in the literature focused on how e-learning changes the traditional method of teaching and analysing its impact on the performance of students.
- Several works on learning style has been done using different methods of modelling and predicting the learning preferences of a learner.
- Integrating the e-learning systems with systems that can measure the learning preferences of a learner in order to (intelligently) provide efficient learning environment is one of the current trends in technology enhanced learning.

Contribution of this paper to the literature

- This paper introduces an extended version of learning systems that measures the learning preferences of a learner. The paper also described a case study on the integration of the new learning style index into an adaptive and smart e-learning system that can intelligently provide web-based learning based on the learning preferences of a learner. As indicated above, the contribution of this paper can be summarized in the following four items.
    1. Introducing an enhanced learning style index.
    2. Implementation of a web-based learning style index.
    3. Application of the implemented system to various groups of students.
    4. Integration of the learning style index into an intelligent and adaptive e-learning system.

So far, many learning models have been proposed recently (e.g. (Chang, 2016; Alias, 2014; Yang, 2016) to mention few) for the realization of the learning preferences of learners. Most of these models followed (Felder R. M., 1988) because of its simplicity and easy to implement through a Web-based quiz system (Felder R. a., 1997). The model classifies learners into four axes: active versus reflective, sensing versus intuitive, visual versus verbal, and sequential versus global.

Active learners gain information through a learning-by-doing style, while reflective learners gain information by thinking about it. Sensing learners tend to learn facts through their senses, while intuitive learners prefer discovering possibilities and relationships. Visual learners prefer images, diagrams, tables, movies, and demos, while verbal learners prefer written and spoken words. Sequential learners gain understanding from details and logical sequential steps, while global learners tend to learn a whole concept in large jumps.

While the Felder-Silverman learning model was developed mainly for engineering students, we think that with some modification, it can be adopted and used by junior learners at schools.

In fact, if learners become aware of their learning style, it is not always true that their grades will improve. However, knowing their learning style can help learners continue to study. If learners can continue to learn something for a long time, gradually a gap widens between the learners who study based on their learning style and the others.

We found that the quiz system in Felder-Silverman "Learning Style Index" (LSI) allows students to choose between only two alternatives.

However, in real life, not everything is black or white. Hence freedom has to be given to learners to choose among several alternatives in a fuzzy-like system. Therefore, we extended the Felder-Silverman LSI system to allow students to choose among five options.

Our *Enhanced Learning Style Index* (ELSI) is implemented in Java as an applet and integrated into a web-based system. The web-based system is connected to an SQL database using the Java Database Connector (JDBC).

Using a database system is essential to analyze the ELSI for a group of learners and help teachers to obtain a wider view of the learning preferences of their students.

To test and analyze our ELSI system, we applied the system with junior high school-students and analysed their learning preferences. Our system also distinguishes between male and female learners. This allows us to obtain a deeper understanding of the effect of gender differences on the learning process.

E-learning systems are widely used and rapidly increasing. The integration of a learning style index into an intelligent and adaptive e-learning system is useful to help e-learners to navigate through different available learning materials. As a case study we show the integration of our ELSI system into an intelligent and adaptive e-learning system for automata and theory of computation.

The rest of the paper is organized as follows. Section two presents a brief review of the relevant literature. Section three covers background in learning systems, our studies on the learning style index, and the extension of existing systems. Section four covers our web-based implementation of the ELSI. In section five, we apply our enhanced implemented system to students from different high schools and junior high schools. Then we analysed this result and report our observations. Section six describes the integration of our implemented ELSI into an e-learning system for the theory of computation topics. We conclude the paper in section seven.

LITERATURE REVIEW

Intelligent and adaptive e-learning systems are characterized by providing personalized educational resources dynamically to individual students who might match their learning requirements (Santos, 2002). Integrating intelligent adaptive e-learning systems with a system that can model the behaviour and profile of a learner is among the key outstanding research works that attracts attentions of researchers in this domain (Wang, 2013). One study by (Alias, 2014) that evaluated students' performance based on active learning style has shown the usefulness learning based on the learning preferences of a learner. Learning style index is a system designed to promote effective learning (Ozerem, 2015).

Over the past few decades, most research in computer science and education raised various concerns related to adaptive learning systems and learning style index (Tseng, 2008). Consequently, several learning systems have been proposed, and difference design and implementation models have been followed to measure the learning preferences of students to assist teachers in determining preferable ways that their students could learn efficiently. Snow and Farr have published an article (Snow, 1987) in which they described learning theories as unrealistic and incomplete without considering preferences of the learners, which indicates that no learning can be successful if the needs of individual students are given considerable attentions. Moreover, (Russell, 1997) also encouraged educational institutions to acknowledge the individual differences between learners and use relevant materials and available technology to teach them accordingly. Many other studies (Hassan M. a., 2015; Barbe, 1979; Waite, 2007; Coffield, 2004; Montgomery, 1995; Keefe, Learning style: Cognitive and thinking skills. Reston, VA, 1991; Yazici, 2016; Kazemi, 2016; Hamada M. a., 2017) have pointed evidently pointed out the roles of cognitive and learning styles on the learning outcomes and the relationships that exist between students in a specific subject matter and the learning styles of the learners.

Furthermore, the existence of educational technologies has enabled people to find the best lectures that are even better than the classroom teaching (Chengjie, 2015). One of the platforms that provide those interesting online lectures is MOOC, which stands for Massive Open Online Course (Pappano, 2012; Hsieh, 2016). A number of educational institutions and software vendors have argued that most of the today's educational challenges and the special needs of the students can be addressed using one-to-one tutoring systems (Johnson, 2016; Hamada M. &., 2016), and adaptive tutoring systems have the potential to provide such services. In a study set out to determine the methods and techniques of improving students' performance, (Brusilovsky, 1998) has made an extensive finding that recommended the use of adaptive learning systems to support efficient learning (Hassan M. &., 2016; Hassan M. a., 2016). More recently, Hou and Fidopiastis (Hou, 2017) have emphasized the applications of intelligent adaptive learning systems that effectively help in overcoming several educational challenges, and they also outlined several guidelines and methodologies on how to design adaptive, yet intelligent learning systems. The

Table 1. Learning and teaching styles

Learning Style		Teaching Style	
Process	Active	Student participation	Active
	Reflective		Passive
Perception	Sensory	Content	Concrete
	Intuitive		Abstract
Input	Visual	Presentation	Visual
	Verbal		Verbal
Understanding	Sequential	Understanding	Sequential
	Global		Global

general idea behind adaptive learning systems is the adjustment of course contents for individual learner based on some certain conditions, which includes the learner's profile and his particular learning styles (Brusilovsky, 1998). Therefore, considering learning preferences in building such systems to detect learning attitudes of the learner for adapting the course contents to meet his or her particular requirement is worth studying. The study of learning styles have started a long time ago (Keefe, . Learning style: An overview, 1979; Kolb, 1993) and the evidence of its existences has been proved prior to the age of developing and analysing the learning styles of learners (Tallmadge, 1969).

LEARNING STYLE INDEX

Among the existing learning systems we chose Felder-Silverman model for the following reasons:

- It is widely known and applicable,
- It can describe learning styles in more detail than other models,
- Its reliability and validity have already been tested.

The Felder-Silverman LSI model classifies learners according to a scale of four dimensions: processing, perception, input, and understanding, as it is set in **Table 1**. Each of these dimensions consists of contrastive attributes listed in **Table 1**.

The Learning Style Index (LSI), based on the Felder-Silverman model, is an outline questionnaire for identifying learning styles. The LSI consists of 44 questions for the afore-mentioned four dimensions, where each dimension has 11 questions. These preferences are expressed with values between +11 to -11 and each problem has 1 or -1 (minus 1). For example, if you answer a question related to "active/reflective" attributes and your answer has an active preference, +1 is added to the score; whereas 1 is subtracted from the score if you answer the question with a reflective preference. That is, the degree of preference for each of dimension is just the algebraic sum of all values of the answers to the eleven questions, as it is shown in the following equation:

$$i_{DIM} = \sum_{i=1}^{11} q_i^{DIM}$$

Where, DIM is the set of dimensions that embraces four pairs of dimensions: {A/R, S/I, V/V, S/G} is the set of four dimensions, whose initial means: A/R for Active/Reflective; S/I for Sensory/Intuitive; V/V for Visual/Verbal; S/G for Sequential/Global. *I* is the vector of indexes composed by {$i_{A/R}$, $i_{S/I}$, $i_{V/V}$, $i_{S/G}$}. *I* describe attributes in each dimension. *Q* is the sum of questions belonging to each dimension, thus *Q* ={q1, q2,…, q11}, and each q_i indicates the contribution given by the *i-th* question within the eleven questions for each DIM to detect whether preference 1 or -1 is substituted into q_i.

The results are divided into three groups, according to points shown in **Figure 1**. If the score is between 3 and -3, the learner is categorized into "well balanced". If the score is between -5 and -7, or between 5 and 7, the

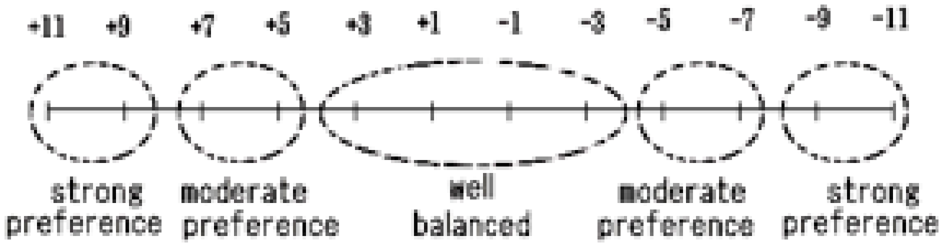

Figure 1. Learning style index

learner is classified into "moderate preference". If the score is between -9 and -11 or between 9 and 11, the learner grouped into "strong preference".

The reliability of LSI system was established in western style educational institutes because the western style culture allows clear-cut "yes/no" answers for queries. On the contrary, the reliability of LSI is not clear in Asian educational institutes because Asian culture (especially Japanese) tends to permit unclear fuzzy answers for queries. Hence, in order to be able to study the reliability of LSI in Asian educational institutes, it is necessary to extend the traditional "yes/no" style for answers to a new fuzzy-like system with an index of five levels. This extension will be explained in the next section.

Enhanced Learning Style

Our *Enhanced Learning Style Index* (ELSI) model extends the Felder-Silverman LSI model in two ways: a fuzzy-like evaluation system and a social/emotional dimension are introduced.

Fuzzy-like evaluation system

Our model is based on answers of an ascending risk scale of 1 to 5 (see **Figure 2**). The assessment system extends the Felder-Silverman model as shown in the following equation:

$$i_{DIM} = \sum_{i=1}^{11} q_i^{DIM-} - \sum_{i=1}^{11} q_i^{DIM+}$$

DIM, *Q* and *I* are the same sets explained previously set in section 2, while q_i^{DIM+} and q_i^{DIM-} are attributes to represent the contrast of each dimension. The Felder-Silverman model only assigns *one* value 1 or -1 to each dimension when the learner answers a question. Our new model has *five* different values assigned for each question. Depending on the choice of the learner from the 5 scale values of the question's answer, q_i^{DIM+} and q_i^{DIM-} take one of the next positive or negative values: 1, 0.75, 0.5, 0.25, or 0, based on the next instances of selections made by the learner:

S/he clicks 1st option in q_i, the value +1.0 is set to q_i^{DIM+} and 0 to q_i^{DIM-},

S/he clicks 2nd option in q_i, the value 0.75 is set to q_i^{DIM+} and 0.25 to q_i^{DIM-},

S/he clicks 3rd option in q_i, the value 0.5 is set to q_i^{DIM+} and 0.5 to q_i^{DIM-},

S/he clicks 4th option in q_i, the value 0.25 is set to q_i^{DIM+} and 0.75 to q_i^{DIM-},

S/he clicks 5th option in q_i, the value 0 is set to q_i^{DIM+} and 1.0 to q_i^{DIM-},

At the values assigned to the attribute q_i^{DIM+} and q_i^{DIM-} are accumulated. Then a subtraction between the two calculated values of the couple of attributes will be the result of learner's learning preference.

For example, suppose that the first choice is closest to "active" and fifth choice is closest to "reflective." If learner chooses the first option in this question, +1 point is added to the attribute of "active'. If learner selects the

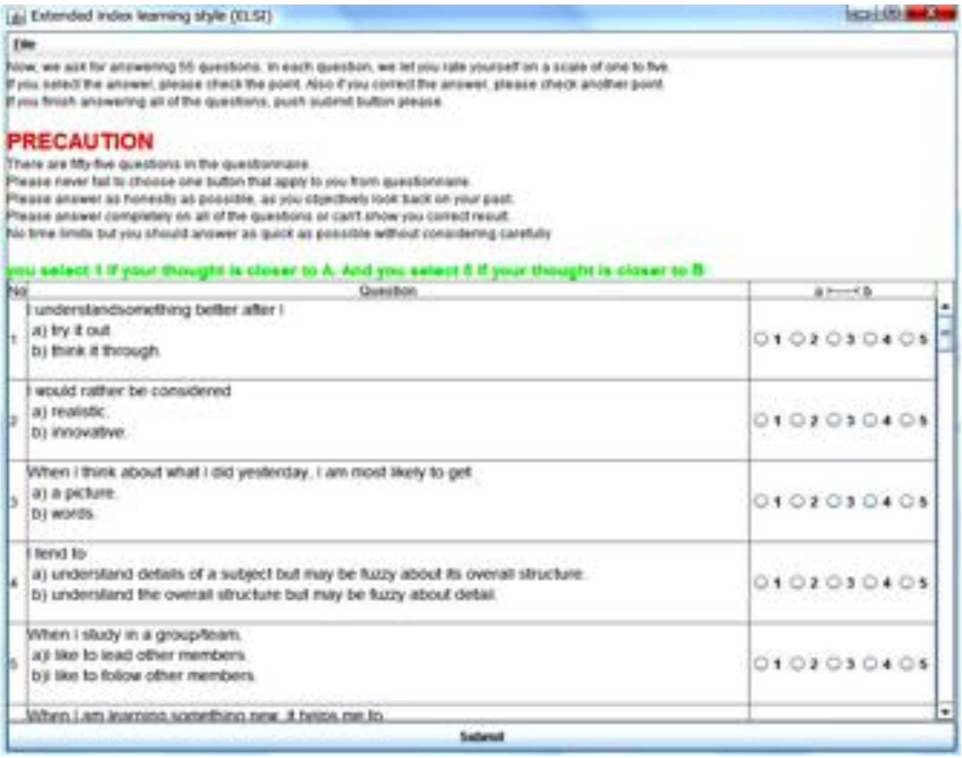

Figure 2. Learning style index questionnaire

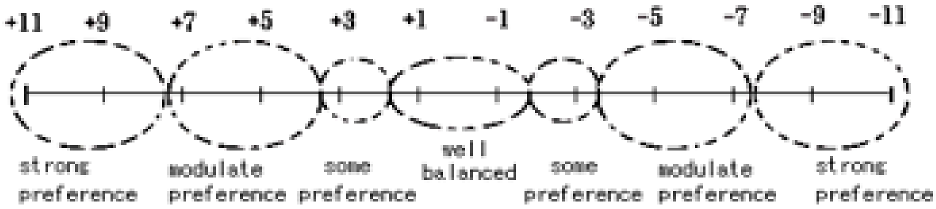

Figure 3. Extended learning style index

second option, +0.75 is added to the attribute of "active" and also +0.25 is added to the attribute of “reflective.” Likewise, if learner picks the third option, +0.5 is added to "active" and +0.5 to “reflective” and so on. Then the result of the learning preference in the active/reflective dimension is calculated by subtracting the total value assigned to “reflective" from that assigned to "active".

After the change in the point allocation system, we changed the degrees of preference (**Figure 3**). If the learner’s score is between 11 and 7.5, or between -11 and -7.5, it is categorized into “strong preference.” If learner’s score is between 7.5 and 3.5, or between -7.5 and -3.5, it is classified into "moderate preference." If learner’s score is between 3.5 and 2, or between -3.5 and -2, it is grouped into “some preference.” If learner’s score is between -2 and 2, it is stated into "well balanced".

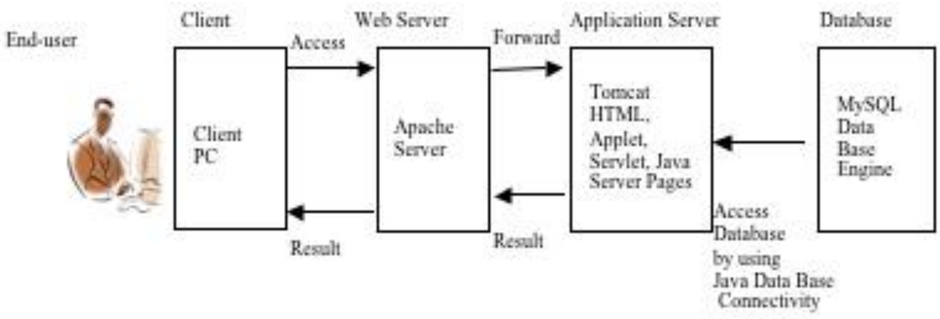

Figure 4. General implementation overview

Social/Emotional dimension

Social/emotional learning (SEL) is a process for helping people to develop the fundamental skills for achieving an effective life. SEL teaches the skills we all need to handle our relationships, our work, and ourselves effectively and ethically. SEL holds the next five keys:

Self-awareness: Assessing self-feelings, interests, values, and strengths

Self-management: Regulating self-emotions to handle stress, control impulses, and persevere in overcoming obstacles,

Social awareness: The ability of been aware of how others are feeling through their actions

Relationship skills: Establishing and maintaining healthy and rewarding relationships based on cooperation

Responsible decision-making: Making decisions based on consideration of ethical standards, safety concerns, appropriate social norms, respect for others, and likely consequences of various actions.

These skills include recognizing and managing emotions, developing caring and concern for others, establishing positive relationships, making responsible decisions, and handling challenging situations constructively and ethically. SEL is a framework for school improvement.

Teaching SEL skills help to create and maintain safe, caring learning environments. Social and emotional skills are implemented in a coordinated manner, school wide, from preschool through high school. Lessons are reinforced in the classroom, during out-of-school activities, and at home. Educators receive on going professional development in SEL. Families and schools work together to promote students' social, emotional, and academic success.

We extended the Felder-Silverman LSI model by adding a new "realistic" dimension that concerns with the effect of emotion and social learning styles. To this extent, we added a new set of eleven questions to the quiz system of LSI for assessing the level of social/emotional preference of the users. In designing these new eleven questions we referred to the Temperament and Character Inventory (TCI) model shown in **Figure 4** (Kumiko, 2009).

Table 2 summarizes the new realistic (social/emotional) dimension, where the main attributes for both categories are the following:

Social learners prefer reading books, discussions, social interaction, recognized and valued, and they may need repetition for detail

Emotional learners are affected by their emotion. **Table 3** (Kort, 2001) represents a continuum of emotions ranging from positive to negative and their effect on learning. The emotions listed on the continuum can either affect learning in a positively or in a negative way.

Table 2. Realistic (social/emotional) dimension

Realistic Learner	
Social	**Emotional**
Social learners are more interested in concepts than details. They are motivated by relationships and care in a great deal about what others think of them. They make more effort to attract people's attention. As a result, they are vulnerable to criticism. They also prefer cooperation rather than completion.	Emotions can affect the learning process, in both a positive and negative way. When a learner experiences positive emotions, the learning process can be enhanced. When a learner experiences negative emotions, the learning process can be persuaded.

Table 3. Emotion sets possibly relevant to learning

Axis	-1.0	-0.5	0		0.5	1.0
Anxiety-Confidence	Anxiety	Worry	Discomfort	Comfort	Hopeful	Confident
Boredom-Fascination	Ennui	Boredom	Indifference	Interest	Curiosity	Intrigue
Frustration-Euphoria	Frustration	Puzzlement	Confusion	Insight	Enlightenment	Epiphany
Dispirited-Encouraged	Dispirited	Disappointed	Dissatisfied	Satisfied	Thrilled	Enthusiastic
Terror-Enchantment	Terror	Dread	Apprehension	Calm	Anticipatory	Excited

IMPLEMENTATION

We built a web-based approach that embraces a web server, an application server and a database with the aim to analyze the learning styles. Some advantages of our model are outlined next.

1. Easy to use through its user-friendly interface
2. Easy to integrate into E-learning systems. As we will be explained in Section 5
3. Easy to find and analyze the learning style of a group of learners. This enables the teachers to have a bird's view of the learning preferences of all students in the class
4. Easy to access and use anytime anywhere.

The overview of our system is shown in **Figure 5**. The system consists of the following components: a user-friendly graphical interface, a web-server, an application server, and a database module.

The learning preference computational module of our system resides in the application server. It uses the new calculation model described in subsection 2.1.1. Such a model provides detailed information about the learning style of a learner.

The learner can access the system through the user interface. The system loads a java applet to run on a web browser (**Figures 2** and **6**). The learner then fills in all the answers of the quiz system and submits the answers to the Apache (ASF, 2008) web server through the client PC. The web server passes it to the Tomcat (Tomcat, 2010) application server.

The application server runs the computational module of the system to estimate the learning preferences of the user. The application server sends the result back to the learner through the Apache web server and the Client PC. A copy of the result is also stored in the MySql database, which is connected to the application server through the "Java Database Connector" (DBC). JDBC provides methods for querying and updating data in a database.

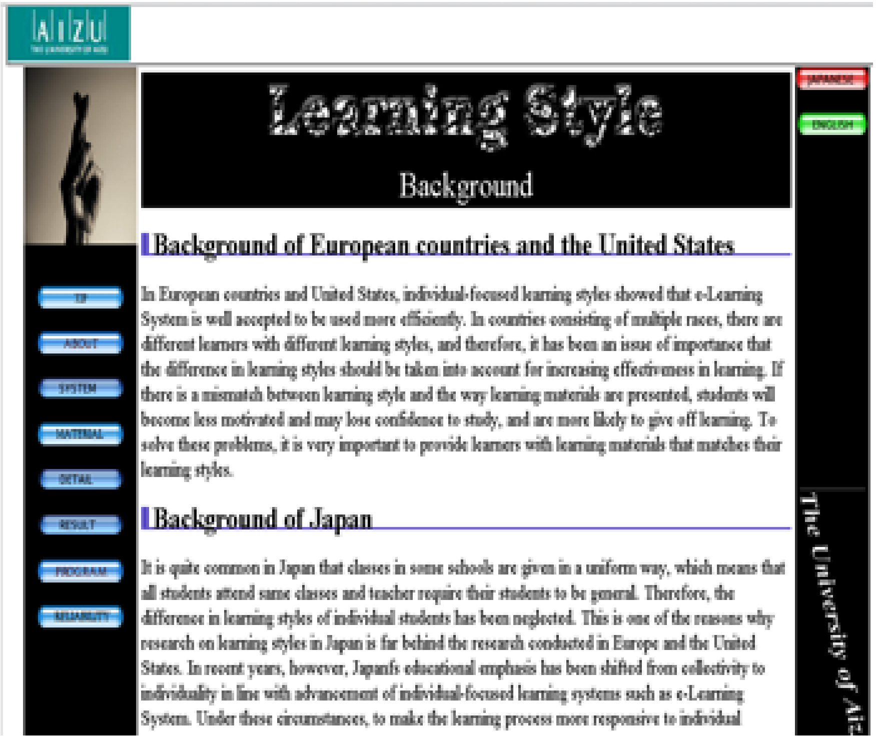

Figure 5. Implementation overview

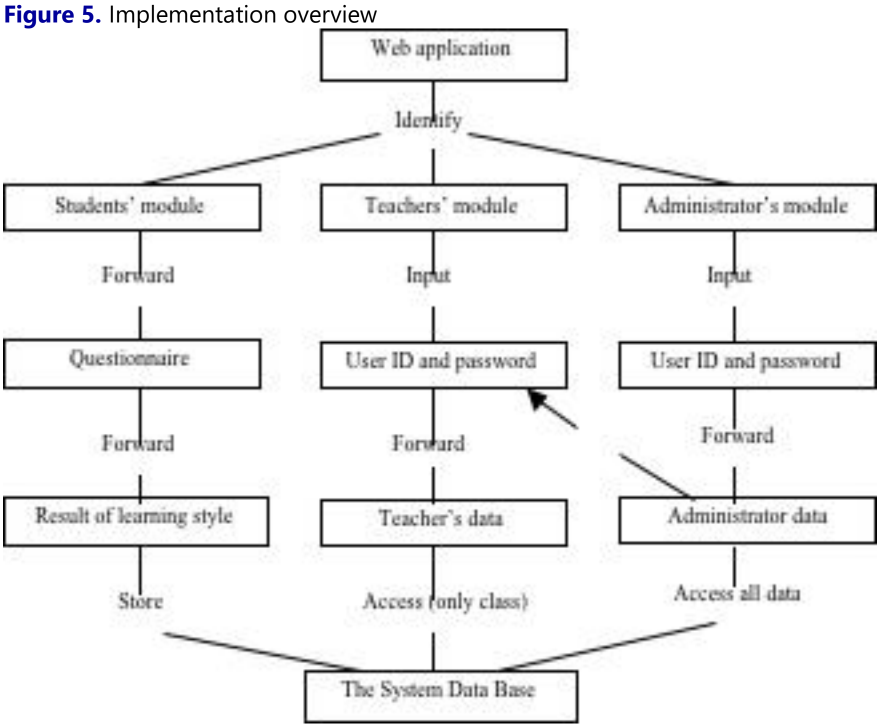

Figure 6. Detailed implementation overview

Figure 7. System login view

The system provides functions to maintain statistics with the learner gender distinguished. This helps educators to analyse the learning styles of their group of students, even concerning the gender, and then prepare suitable teaching materials to adapt their teaching style accordingly.

Web application

The proposed web-based approach is designed according to the modular structure outlined in **Figure 7**, where three main modules provide the basic functionality to different kinds of users as follows:

The students' module enables an individual student to analyze his/her learning preferences and/or send them to his/her teachers

The teachers' module enables teachers to access and analyze their students learning preferences individually or in groups, male or female sets, and get a graphical representation of their students learning preferences

The administrator module maintains the system and the database

Students' module

An individual student can access the system through the interface shown in **Figure 8**. Then the student can answer the questions and have her or his learning preferences analyzed automatically by the system. If the student provides her or his "Student ID", the system will store her/his learning preferences in her/his teachers' database.

Teachers' module

Teachers have their passwords provided by the system administrator in order to use the system and access the database. Teachers can log into the system using their passwords and IDs and have access to their students' learning preferences data.

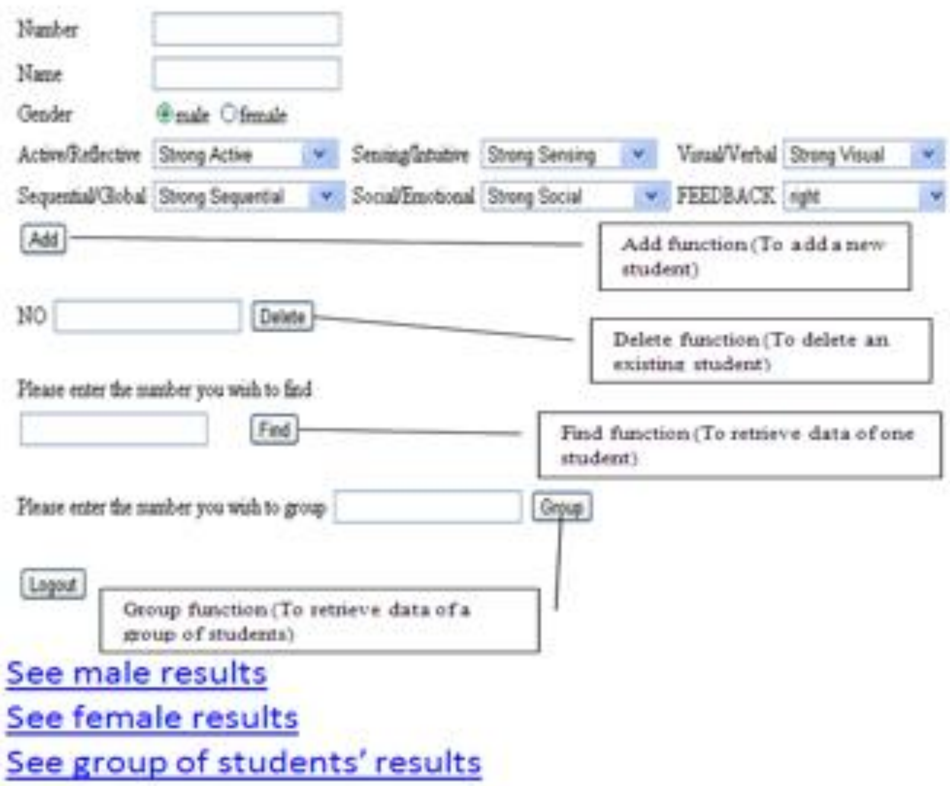

Figure 8. User view

An example of the use of our approach by a sample of volunteers is shown in **Table 4** and **Figure 9**. Then teachers can access the learning preferences of a single student, a group of students, all students, male students, and female students only.

The system also has a function to graphically analyse and presents the result for each dimension as it is shown in **Figure 10**. The collective result is also displayed graphically as it is illustrated in **Figure 11**. The system reliability can also be checked through the students' feedback. This reliability is represented graphically and displayed as illustrated in **Figure 12**.

Administrator's module

The system administrator may maintain the entire system, where he could create new or delete existing users (teachers), create or change passwords, and access/maintain the whole database. The administrator user interface sketched in **Figure 13**.

Support for intelligent and adaptive learning systems

Although they have different purposes to support the learning process, intelligent and adaptive systems are both model-based systems. An intelligent tutoring system (ITS) aims to provide learner-tailored support during a problem-solving process, as a human tutor would do. To achieve this, ITS designers apply techniques from the artificial intelligence and implement extensive modeling of the problem-solving process in the specific domain of application (Magnisalis, 2011).

Table 4. Registered students' information

Id	Name	Gender	ACT/REF	SNS/INT	VIS/VRB	SEQ/GLB	SOC/EMO	Feedback
01	Std01	Male	Some Active	Moderate Sensing	Well Balanced	Moderate Sequential	Well Balanced	Right
02	Std02	Male	Some Active	Moderate Sensing	Moderate Visual	Some Sequential	Some Social	Moderately right
03	Std03	Male	Well Balanced	Moderate Sensing	Some Visual	Well Balanced	Well Balanced	Right
04	Std04	Male	Moderate Active	Well Balanced	Some Visual	Some Sequential	Moderate Social	Right
05	Std05	Male	Well Balanced	Well Balanced	Some Visual	Well Balanced	Moderate Social	Moderately right
06	Std06	Male	Well Balanced	Well Balanced	Moderate Visual	Some Sequential	Moderate Social	Right
07	Std07	Female	Well Balanced	Moderate Sensing	Well Balanced	Some Sequential	Some Social	Right
08	Std08	Female	Well Balanced	Well Balanced	Moderate Visual	Some Sequential	Well Balanced	Moderately right
09	Std09	Female	Well Balanced	Well Balanced	Well Balanced	Some Sequential	Some Social	Moderately wrong
10	Std10	Female	Well Balanced	Well Balanced	Well Balanced	Moderate Sequential	Moderate Social	Moderately wrong
11	Std11	Male	Moderate Active	Moderate Sensing	Moderate Visual	Well Balanced	Strong Social	Moderately right
12	Std12	Female	Moderate Active	Some Sensing	Moderate Visual	Moderate Sequential	Moderate Social	Moderately right
13	Std13	Male	Some Active	Some Intuitive	Well Balanced	Well Balanced	Moderate Social	Moderately right
14	Std14	Female	Well Balanced	Moderate Sensing	Some Verbal	Moderate Global	Moderate Social	Right
15	Std15	Female	Well Balanced	Well Balanced	Moderate Visual	Well Balanced	Some Social	Right
16	Std16	Male	Some Active	Well Balanced	Some Visual	Well Balanced	Moderate Social	Moderately wrong
17	Std17	Female	Some Active	Well Balanced	Well Balanced	Well Balanced	Moderate Social	Moderately wrong
18	Std18	Female	Well Balanced	Well Balanced	Well Balanced	Well Balanced	Moderate Social	Right
19	Std19	Male	Well Balanced	Moderate Sensing	Moderate Visual	Moderate Sequent.	Moderate Social	Right
20	Std20	Female	Well Balanced	Well Balanced	Moderate Visual	Well Balanced	Some Social	Right
21	Std21	Male	Some Active	Well Balanced	Some Visual	Well Balanced	Moderate Social	Moderately wrong
22	Std22	Female	Some Active	Well Balanced	Well Balanced	Well Balanced	Moderate Social	Moderately wrong
23	Std23	Female	Well Balanced	Well Balanced	Well Balanced	Well Balanced	Moderate Social	Right
24	Std24	Male	Well Balanced	Moderate Sensing	Moderate Visual	Moderate Sequent.	Moderate Social	Right
...	...	...	...	...	...	...	...	...

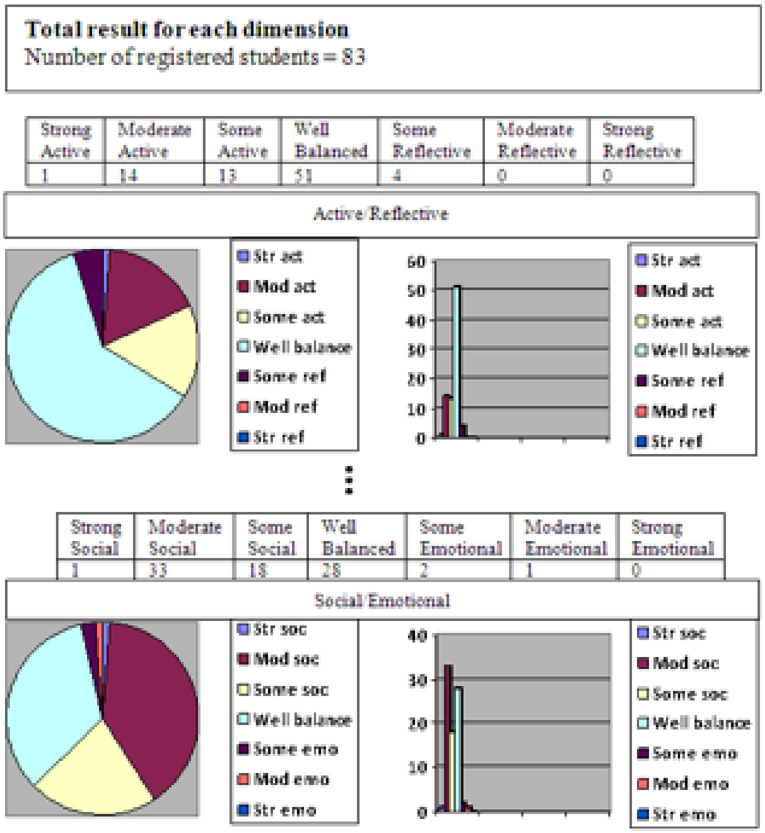

Figure 9. Result classification

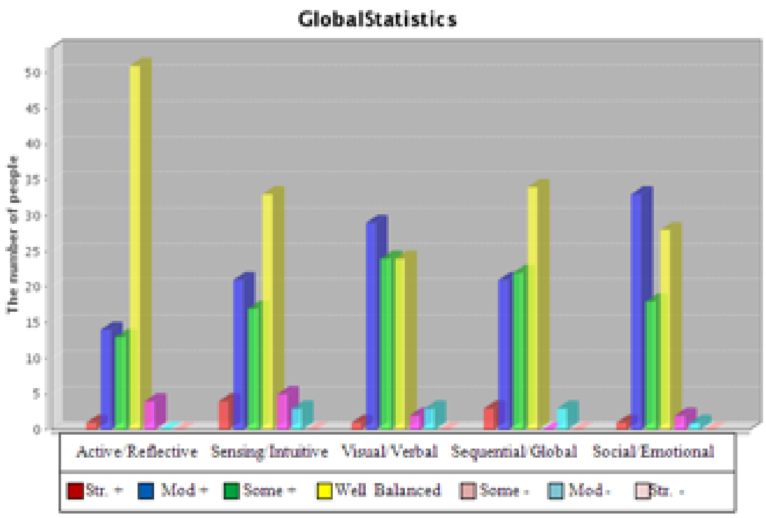

Figure 10. Global statistics overview

On the other hand, the main aim of an adaptive learning system is to adopt some of its key functional characteristics to the learners' needs and preferences, such as content presentation and/or navigation support. Thus an adaptive system operates differently for different learners exactly the way our system behaves.

The proposed LSI system could easily be integrated into intelligent and adaptive learning systems as outlined in Section 5.

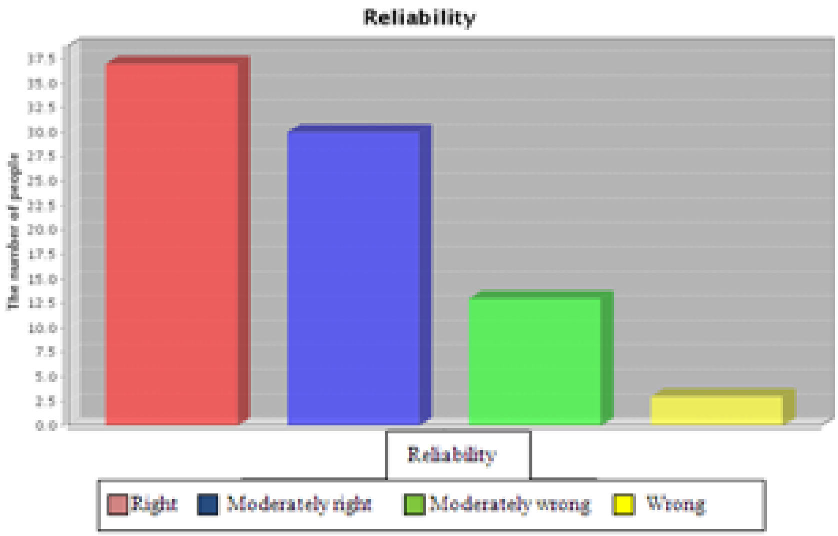

Figure 11. Reliability

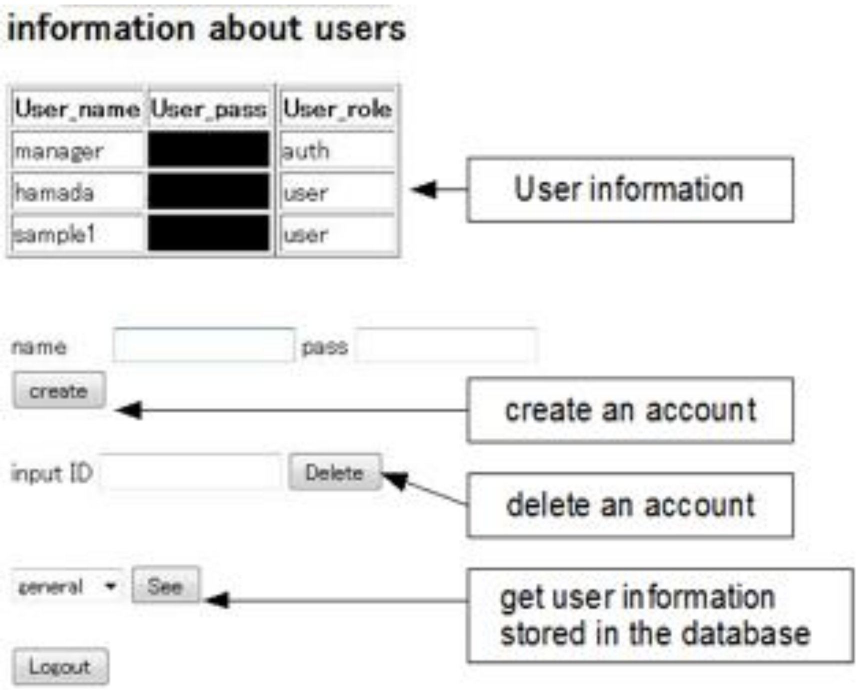

Figure 12. User information

APPLICATION

In western style of education, individual-based learning is well accepted and the uses of LSI and e-learning systems have been greatly adopted. However, in Asian countries (especially in Japan) the use of LSI is not so common. It is quite typical in Japanese schools that classes are given in a traditional lecture-driven style, which means that the differences in learning styles of individual students have been neglected.

Figure 13. Automata e-learning system

Table 5. Active-Reflective learners' distribution

Set	Strong preference for Active	Moderate preference for Active	Some preference for Active	Balance Active-Reflective	Some preference for Reflective	Moderate preference for Reflective	Moderate preference for Reflective
Boys	4% (1)	15% (4)	46% (12)	15% (4)	4% (1)	12% (3)	0
Girls	3% (2)	23% (13)	44% (25)	11% (6)	3% (2)	12% (7)	0
Total	5% (3)	21% (17)	45% (57)	12% (10)	5% (3)	12% (10)	0

Table 6. Sensory-Intuitive learners' distribution

Set	Strong preference for Sensory	Moderate preference for Sensory	Some preference for Sensory	Balance Sensory – Intuitive	Some preference for Intuitive	Moderate preference for Intuitive	Moderate preference for Intuitive
Boys	0	12% (5)	4% (1)	42% (1)	19% (5)	19% (5)	4% (1)
Girls	0	9% (5)	9% (5)	58% (3)	15% (9)	9% (5)	0%
Total	0	10% (8)	7% (6)	53% (4)	17% (14)	12% (10)	1% (1)

In recent years Japan's educational system has shifted from "collectivity" to "individuality" in line with the advancement of individual-focused learning such as e-learning systems. Under these circumstances, it is more suitable to make the learning process more responsive to individual learners. In this section, we introduce the use of our enhanced ELSI for junior high-school students.

Our sample consists of 83 students: 26 boys and 57 girls. All of them were second-year junior high-school students. The result of the questionnaire is listed in Tables 5 to 9.

Table 7. Visual-Verbal learners' distribution

Set	Strong preference for Visual	Moderate preference for Visual	Some preference for Visual	Balance Visual - Verbal	Some preference for Verbal	Moderate preference for Verbal	Moderate preference for Verbal
Boys	8%(2)	19% (5)	2% (6)	42% (11)	8% (2)	0%	0
Girls	0%	21% (12)	21% (12)	43 %(24)	12% (7)	3%(2)	0
Total	2%(2)	21% (17)	22% (18)	42% (55)	11% (9)	2%(2)	0

Table 8. Sequential-global learners' distribution

Set	Strong preference for Sequential	Moderate preference for Sequential	Some preference for Sequential	Balance Sequential -Global	Some preference for Global	Moderate preference for Global	Moderate preference for Global
Boys	4%(1)	12%(3)	12%(2)	52% (14)	8%(2)	12% (5)	0
Girls	0%	2%(5)	8%(4)	77% (42)	8%(5)	4%(6)	0
Total	1%(1)	6%(5)	8%(7)	71% (56)	7%(5)	7%(9)	0

Table 9. Social-emotional learners' distribution

Set	Strong preference for Social	Moderate preference for Social	Some preference for Social	Balance Social – Emotional	Some preference for Emotional	Moderate preference for Emotional	Moderate preference for Emotional
Boys	0	15%(4)	5%(1)	56% (14)	13% (3)	5% (1)	0
Girls	0	7%(4)	11%(6)	47% (42)	24% (14)	16% (9)	0
Total	0	11%(8)	8%(7)	51% (56)	19% (17)	11% (10)	0

Active/Reflective

The responses of boys were normally distributed, but girls showed some preference for *active*. Because second-year junior high school students were surveyed in this questionnaire, and since females tend to mature earlier than boys, both physically and socially, girls may tend to prefer active learning. Therefore, teachers should try to increase opportunities for group discussion and for experimental and practical lessons. This finding may raise learning efficiency.

Sensory/Intuitive

Both boys and girls display some preference for intuitive learning. 19 percent of boys have a little-to-moderate intuitive preference. Boys are more *intuitive* than girls. Intuitive learners tend to be better at grasping new concepts and are often more comfortable than sensors with abstractions and mathematical formulations. Intuitive learners have more interest in studying science. This may explain why in Japan most of the science and engineering students are boys. Therefore, teachers should try to explain interpretations or theories that link the facts or connections.

Visual/Verbal

Half of the students tend to be visual. We can tell that both boys and girls show a high visual preference. Visual learners remember best what they see. They like to see pictures and diagrams, and they are willing to make concept maps or mind maps. Such kinds of graphical and mental representations are the most appropriate ways to learn for students having this preference. In summary, it may be better for junior high-school students to assimilate

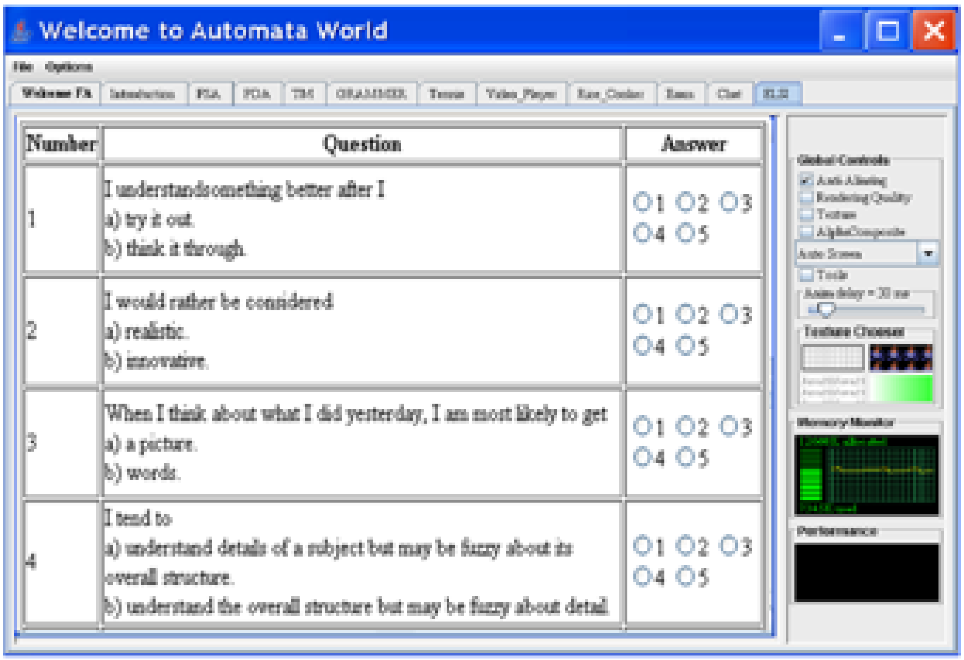

Figure 14. Integration of LSI into automata e-learning system

knowledge directly. The students who interpret knowledge are decreasing. Therefore, teachers should try to use visual material in class, which may also raise learning efficiency for this group.

Sequential/Global

Neither boys nor girls show a bias toward sequential or global orientation. Sequential and global distribution is fairly distributed. Teachers should try to be concise regarding two dimension's poles because most of the students are balanced on sequential and global. At the beginning of each lesson, teachers should explain the outline of the topic in a logical order and how it relates to real-life subjects and facts.

Social/Emotional

The respondents tend to concentrate centrally on this dimension. However, a greater percentage of boys display a preference for social learning than girls. On the other hand, girls indicate a higher preference for emotional learning than boys. This result is perhaps not surprising if we consider the possible gender-biasing effects of Japanese culture on the social behavior of people.

In conclusion, our survey revealed that most of the students in the sample tend to have "well balanced" learning preferences. However, a considerable number of them tend to have "visual" learning preferences.

INTEGRATION INTO INTELLIGENT AND ADAPTIVE E-LEARNING SYSTEM

Compared to traditional learning systems, e-learning provides a more comfortable learning environment, where learners can learn at their convenience. E-learning systems are widely used and rapidly increasing (Anshari, 2015).

Hamada (Hamada M. , 2008) built an e-learning system for automata theory and theory of computation based on Java2D technology (Microsystems, 2006). Such a system is illustrated in Figure 14. Hamada's e-learning system is an intelligent and adaptive learning system that embraces the next components:

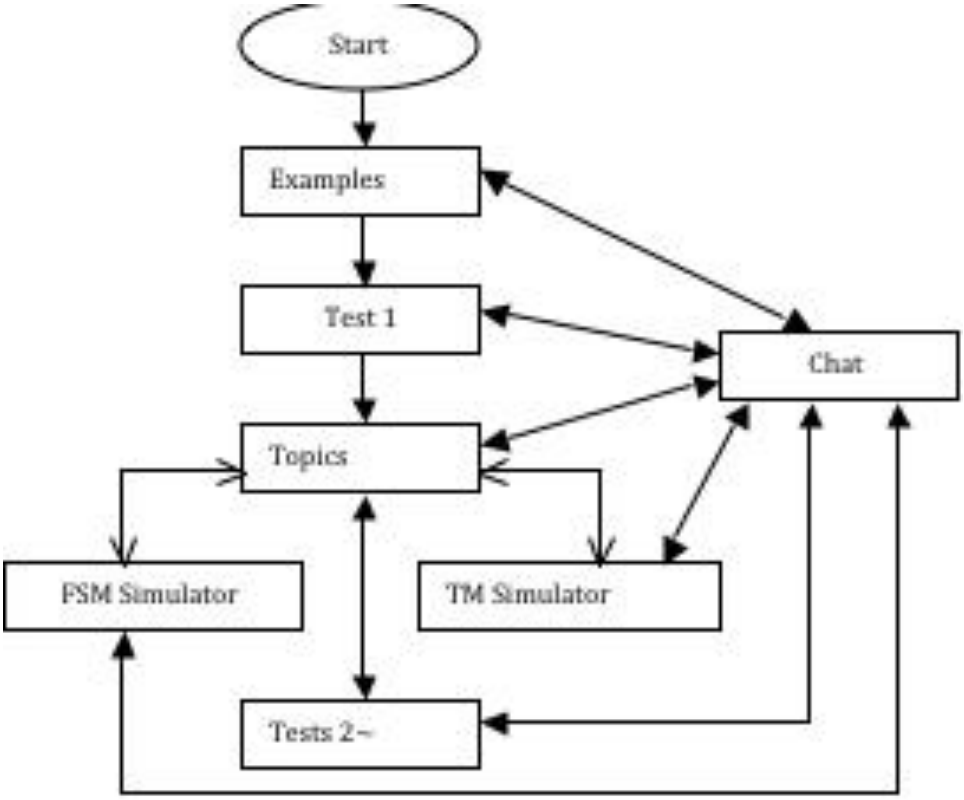

Figure 15. Recommended learning path 1

- Animated (movie-like) welcome component
- Hypertext introduction to some topics in theory of computations
- Finite state machine (FSM) simulator
- Turing machine (TM) simulator
- Self-assessment component,
- Chatting component for supporting online collaborative learning
- Other components showing visual automata examples such as a video player, rice cooker, and tennis game.

Novice automata learners find it difficult to grasp these comprehensive materials that were designed to meet all kinds of learning preferences. Learners do not know where they should start. In order to overcome such an issue, we extend Hamada's e-learning system by introducing an additional component to the learning style. This new component, shown in **Figure 15**, enables the user to find his or her learning preferences and hence to choose suitable components from the rich automata e-learning system.

The integration of our enhanced learning-style system into Hamada's automata e-learning system requires getting access to the source code. Fortunately, since both systems are written in Java, there was no compatibility problem in the integration process.

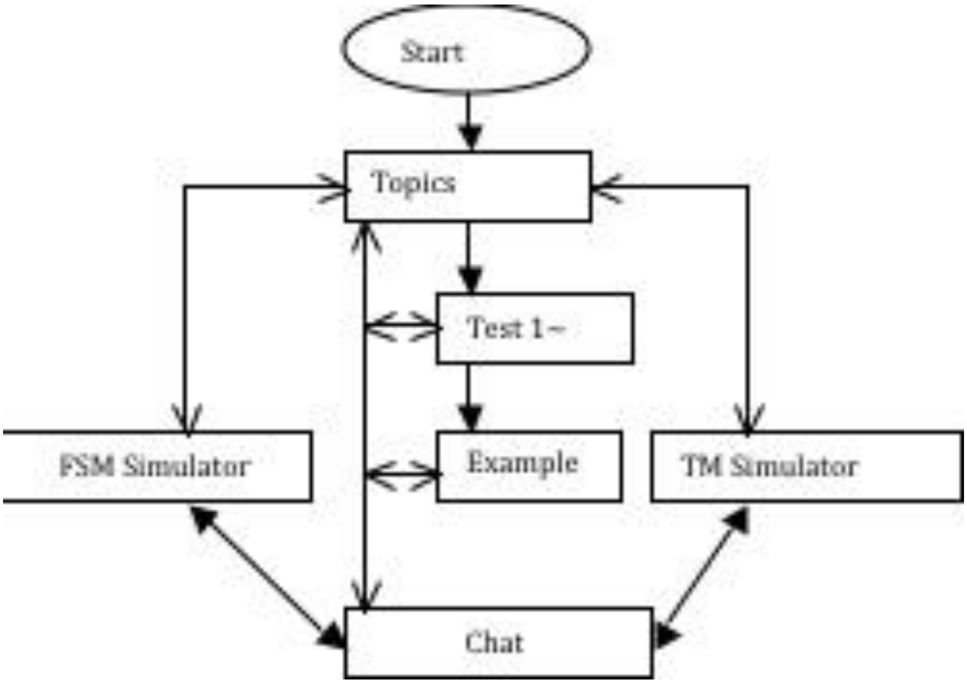

Figure 16. Recommended learning path 2

Learning Activities

When using the ELSI component of the Automata learning system, the user gets a set of recommendations to start studying automata based on her/his learning preferences. For example, a visual learner is recommended to select the following set of activities, which learners can consider when using the environment:

1. Start using the environment by playing with the visual examples. This does not need any special knowledge or background regarding the topics. It also will attract the learners' attention to the relevance of the topics. Learners' attention and topic relevance are basic to Keller's ARCS motivation model (Keller, 1987).
2. Take the first simple general test. By answering the easy and general questions in this test the learner gains familiarity and self-confidence which is an important factor of learners' motivation in ARCS motivational model (Keller, 1987). At this stage, learners are ready to start reading the theoretical concepts in the topics object.
3. Navigating the concepts in the topics' object provides the learners with the necessary theoretical background for the subject.
4. Start using the FSM and the TM simulators. Switching between reading the topics and using the simulators is recommended. After reading a certain topic, the learner can switch to the simulator and try to build a model for that topic and test the model with different inputs. This can help in deepening the learners' knowledge and can enhance the learning process.
5. While reading the topics and using the simulators, learners are recommended to try the corresponding test (in the test object) for self-assessment and to gain more confidence about their learning progress.
6. At any stage of the learning process, on-line learners can chat with each other through the chatting object. This enables learners to exchange ideas and help each other to understand the topics and answer the test questions in a collaborative way.

The environment objects and the workflow of the learning activities for visual learners are shown in **Figure 16**, whereas, reflective learners get a different set of recommended activities as the following:

1. Start by giving the concepts of related objects in the topics. This will provide the necessary theoretical background for the subject to the learners.
2. Try the corresponding tests starting from test number 1.
3. Play with the visual examples.
4. Use the FSM and the TM simulators. Switching between reading the topics and using the simulators is recommended,
5. At any stage of the learning process, on-line learners chat with each other by the chatting object. This enables learners to exchange ideas, help each other to understand the topics and answer the test questions in a collaborative way.

The environment objects and the workflow of the learning activities for reflective learners are shown in **Figure 17**. This process can be applied to other intelligent and adaptive e-learning systems such as (Violante, 2014) (Floyde, 2013)

DISCUSSION AND CONCLUSION

In this research, we developed an enhanced version of a learning style index that can be integrated into intelligent and adaptive learning systems. Our enhanced learning style index (ELSI) extends Felder-Silverman learning style index (LSI) in two ways: a new fuzzy-like evaluation system and a new social/emotional dimension. We implemented our model in a way that allows learners to check their learning preferences easily. Moreover, teachers can have a wider perspective on their students' learning preferences. To this extent, our implementation utilizes several important tools such as: web-based interface, java applets, Apache web server, Tomcat application server, MySQL database, and JDBC connector. Our implementation can produce graphical representations of the learning styles of a group of students, which is very useful for teachers to get a bird-view of the learning preferences of all students in their class.

We tested our system on a sample of 83 junior high-school students. We inferred their learning preferences as individuals and as groups. Then we analysed the result and reported our recommendations to their teachers who appreciated the work. However, we have not carried out a follow-up study of the recommendations. This issue will be considered in future work.

To show the flexibility and usefulness of our enhanced system, we integrated it into an intelligent and adaptive e-learning system that is based on Java2D technology and contains an intensive set of learning materials to support all kinds of learners. Thus, learners with different preferences will get different sets of learning activities. For example, active learners will be recommended to use relevant materials that matched their preferences. With this integration, the automata e-learning system should be more effective since learners can more easily explore and understand the rich set of materials in the system. However, this is just a starting point, and a follow-up and evaluation of the integration are necessary. This is what we intend to investigate in our future research.

REFERENCES

Alias, N. (2014). An evaluation of gas law WebQuest based on active learning style in a secondary school in Malaysia. *Eurasia Journal of Mathematics, Science & Technology Education, 10*(3), 175--184.

Anshari, M. (2015). Pervasive Knowledge, Social Networks, and Cloud Computing: E-Learning 2.0. *Eurasia Journal of Mathematics, Science & Technology Education, 11*(5), 909--921.

ASF. (2008, 9 1). *Apache Software Foundation*. Retrieved 2016 from http://www.apache.org

Barbe, W. (1979). *Teaching through modality strengths: Concepts and practices. Columbus, OH: Zaner-Bloser.* New York: Inc.

Brusilovsky, P. (1998). Methods and techniques of adaptive hypermedia. In P. a. Brusilovsky, *Adaptive hypertext and hypermedia* (pp. 1--43). Springer.

Chang, Y.-H. a.-Y.-S.-T.-J. (2016). Yet another adaptive learning management system based on Felder and Silverman's learning styles and Mashup. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(5), 1273--1285.

Chengjie, Y. (2015). Challenges and changes of MOOC to traditional classroom teaching mode. *Canadian Social Science, 11*(1), 135.

Coffield, F. (2004). *Learning styles and pedagogy in post-16 learning: A systematic and critical review.* Learning and Skills Research Centre London.

Felder, R. (1997). Index of learning style questionnaire. A*vailable online at in: http://www2. ncsu. edu/unity/lockers/users/f/felder/public/ILSdir/ilsweb. html* .

Felder, R. M. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674-681.

Floyde, A. A. (2013). The design and implementation of knowledge management systems and e-learning for improved occupational health and safety in small to medium sized enterprises. *Safety science, 60*, 69--76.

Hamada, M. (2016). A multimedia learning environment for information theory. *Teaching, Assessment, and Learning for Engineering (TALE), 2016 IEEE International Conference on* (pp. 55--61). IEEE.

Hamada, M. (2017). An Interactive Learning Environment for Information and Communication Theory. *Eurasia Journal of Mathematics, Science & Technology Education, 13*(1), 35--59.

Hamada, M. (2008). An integrated virtual environment for active and collaborative e-learning in theory of computation. *IEEE Transaction on Learning Technologies, 1*(2).

Hassan, M. (2016). Recommending Learning Peers for Collaborative Learning Through Social Network Sites. *7th International Conference on Intelligent Systems, Modelling and Simulation* (pp. 60--63). IEEE.

Hassan, M. (2016). Enhancing learning objects recommendation using multi-criteria recommender systems. *Teaching, Assessment, and Learning for Engineering (TALE), 2016 IEEE International Conference on* (pp. 62--64). IEEE.

Hassan, M. (2015). Learning system and analysis of learning styles for African and Asian students. *Teaching, Assessment, and Learning for Engineering (TALE)* (pp. 83--87). IEEE.

Hou, M. (2017). A generic framework of intelligent adaptive learning systems: from learning effectiveness to training transfer. *Theoretical Issues in Ergonomics Science, 18*(2), 167--183.

Hsieh, M.-Y. (2016). Online Learning Era: Exploring the Most Decisive Determinants of MOOCs in Taiwanese Higher Education. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(5), 1163--1188.

Johnson, D. (2016). The Potential Transformation of Higher Education Through Computer-Based Adaptive Learning Systems. *Global Education Journal, 2016*(1).

Kazemi, A. (2016). The Role of Cognitive and Learning Style in Second Language Learning. *Modern Journal of Language Teaching Methods, 6*(2), 527--534.

Keefe, J. W. (1979). Learning style: An overview. *Student learning styles: Diagnosing and prescribing programs, 1*, 1-17.

Keefe, J. W. (1991). Learning style: Cognitive and thinking skills. Reston, VA.

Keller, J. M. (1987). Development and use of the ARCS model of instructional design. *Journal of instructional development, 10*(3), 2-10.

Kolb, D. A. (1993). *Learning-style inventory: Self-scoring inventory and interpretation booklet: Revised scoring.* TRG, Hay/McBer.

Kort, B. (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion. *International Conference on Advanced Learning Technologies* (pp. 43--46). IEEE.

Kumiko, F. M. (2009). Cloninger's temperament dimensions, emotional experiences and emotional regulation, (In Japanese). *Education Science, 14*(4), 387--397.

Magnisalis, I. (2011). Adaptive and intelligent systems for collaborative learning support: A review of the field. *IEEE Transactions on Learning Technologies, 4*(1), 5--20.

Microsystems, S. (2006). Retrieved 3 11, 2010 from Java2D: www.sun.com

Montgomery, S. M. (1995). Addressing diverse learning styles through the use of multimedia. *Frontiers in Education Conference, 1995. Proceedings, 1995.1*, pp. 3a2--13. IEEE.

Ozerem, A. (2015). Learning Environments Designed According to Learning Styles and Its Effects on Mathematics Achievement. *Eurasian Journal of Educational Research, 61*, 61--80.

Pappano, L. (2012). The Year of the MOOC. *The New York Times, 2*(12), 2012.

Russell, T. L. (1997). Technology Wars: Winners and Losers-The No Significant Difference phenomenon. *Educom Review, 32*, 44--47.

Santos, J. (2002). On the Application of the semantic Web Concepts to Adaptive E-learning. *EurAsia-ICT 2002: Information and Communication Technology*, 536--543.

Snow, R. (1987). Cognitiveconafive-affective processes in aptitude, learning, and instruction: An introduction. *Conative and Affective Process Analysis. Hillsdale, New Jersey: Erlbaum, 3*, 1--10.

Tallmadge, G. K. (1969). Relationships among learning styles, instructional methods, and the nature of learning experiences. *Journal of Educational Psychology, 60*(3), 222.

Tomcat. (2010, 12). *Apache Tomcat*. Retrieved 2010 from http://tomcat.apche.org

Tseng, J. C.-C.-J.-C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers & Education, 5*(2), 776--786.

Violante, M. G. (2014). Implementing a new approach for the design of an e-learning platform in engineering education. *Computer Applications in Engineering Education, 22*(4), 708--727.

Waite, S. (2007). Our flexible friend: The implications of individual differences for information technology teaching. *Computers & Education, 48*(1), 80--99.

Wang, T.-S. (2013). Design and assessment of joyful mobile navigation systems based on TAM and integrating learning models applied on ecological teaching activity. *Eurasia Journal of Mathematics, Science & Technology Education, 9*(2), 201--212.

Yang, J. a. (2016). The Learning Preferences of Digital Learners in K-12 Schools in China. *Eurasia Journal of Mathematics, Science & Technology Education, 12*(4), 1047--1064.

Yazici, H. J. (2016). Role of learning style preferences and interactive response systems on student learning outcomes. *International Journal of Information and Operations Management Education, 6*(2), 109--134.

Yeh, S.-P. a.-W. (2014). Effects of Cooperative E-Learning on Learning Outcomes. *Eurasia Journal of Mathematics, Science & Technology Education, 10*(6), 531--536.

http://www.ejmste.com