Chapter 5
A Study of a Learning Style Index to Support an Intelligent and Adaptive Learning Systems

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Abstract. An intelligent and adaptive learning system should adjust the content in order to ensure a faster and better performance in the learning process. One way is to help the learners and teachers to discover the preferences of learners. A learning style index is a method to classify the learning preferences of learners. Learning preferences can then help learners to find their most effective way to learn. It can also help teachers to adopt suitable learning materials for an efficient learning. This chapter is concerned with the study, implementation, and application of a web-based learning style index. We also describe a case study on the integration of the learning style index into an adaptive and intelligent e-learning system.

5.1 Introduction

An Intelligent and adaptive systems have established a long tradition in technology systems for individual learning. To better utilize such systems in the learning process, learners have to be aware of their learning preferences. A learning style index can help the learners to identify their learning preferences. It also supports to adopt suitable learning materials to enhance the 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 their 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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So far, many learning models have been developed (e.g., Felder and Silver-man 1988, Herrmann 1990, Kolb 1984) for the realization of the learning preferences of learners. Among these models, the one made by Felder and Silverman 1988 is simple and easy to implement through a Web-based quiz system (Soloman and Felder 2009). Their 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 the 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 Felder-Silverman learning model was developed mainly for the engineering students, we think that with some modification, it can be adopted and used by junior learners at schools.

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

Our *Enhanced LSI* (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 the teachers to obtain a wider view of the learning preferences of their students.

To test and analyze our extended ELSI system, we applied the system with junior high school students and analyzed 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 LSI in an intelligent and adaptive e-learning system is useful to help e-learners to navigate through a different available learning materials. As a case study, we show the integration of our extended ELSI system into an intelligent and adaptive e-learning system for automata theory and theory of computation.

The rest of the chapter is organized as follows. Sect. 5.2 covers the background in learning systems, our study on the LSI, and the extension of existing systems. Sect. 5.3 covers our web-based implementation of the LSI. In Sect. 5.4 we apply our enhanced implemented system to the students from different high schools and junior high schools.

Then we analyze this result and report our observations. Sect. 5.5 describes the integration of our implemented LSI into an e-learning system for the theory of computation topics. We conclude this chapter in Sect. 5.6.

5.2 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 the 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 5.1. Each of these dimensions consists of a contrastive attributes listed below.

The Index of Learning Style (ILS), based on the Felder-Silverman LSI model, is an outline questionnaire for identifying learning styles. The ILS consists of 44 questions for the afore-mentioned four dimensions, where each dimension has 11 questions. These preferences are expressed with the 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 dimension is just the algebraic sum of all values of the answers to the eleven questions, as it is shown in Equation (5.1).

$$i_{DIM} = \sum_{i=1}^{11} q_i^{DIM} \tag{5.1}$$

Ta**ble 5.1** Learning and teaching styles

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

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 {iA/R, iS/I, iV/V, iS/G}. *I* describes the 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 Fig. 5.1. 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 learner is classified into "moderate preference". If the score is between -9 and -11 or between 9 and 11, the learner is grouped into "strong preference".

The reliability of LSI system was established in a 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 an Asian educational institutes because the Asian culture (especially Japanese) tend to permit unclear fuzzy answers for queries. Hence, in order to be able to study the reliability of LSI in an 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.

5.2.1 Enhanced Learning Style Index

Our ELSI model extends the Felder-Silverman LSI model in two ways: a fuzzy-like evaluation system and a social/emotional dimension are introduced.

5.2.1.1 Fuzzy-like Evaluation System

Our model is based on answers of an ascending risk scale of 1 to 5 (Fig. 5.2). The assessment system extends the Felder-Silverman model as shown in equation 5.2.

$$i_{DIM} = \sum_{i=1}^{11} q_i^{DIM-} - \sum_{i=1}^{11} q_i^{DIM+} \tag{5.2}$$

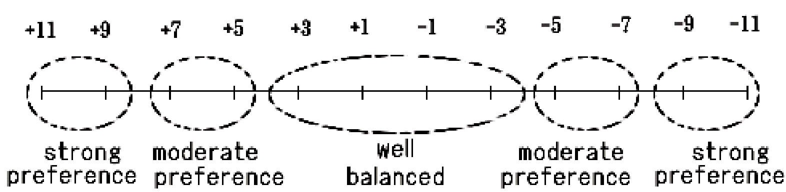


Fig. 5.1 ELSI evaluation system

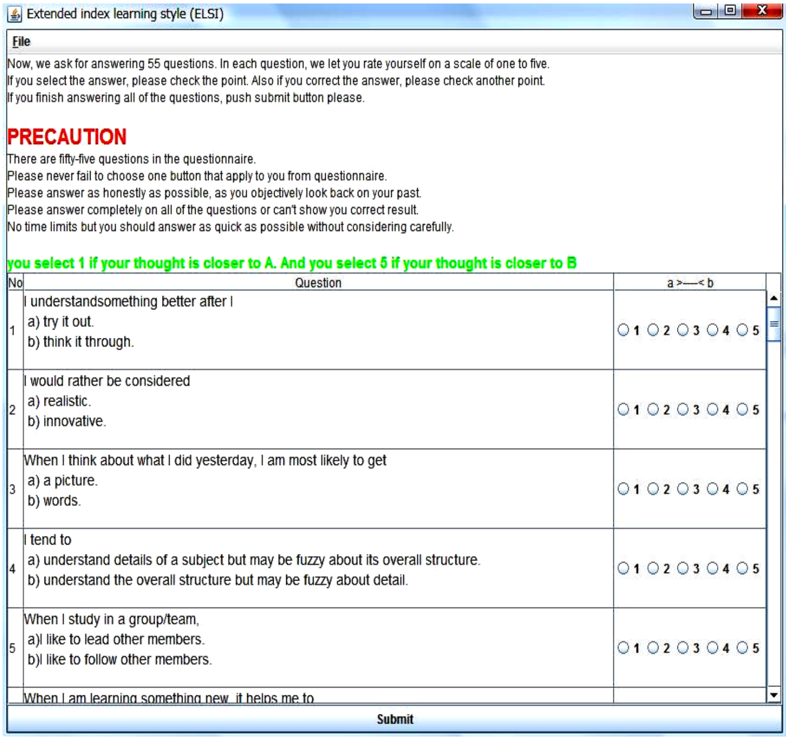


Fig. 5.2 ELSI five options system

DIM, *Q,* and *I* are the sets, previously set in section 5.2. 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 choses the first option in this question, +1 point is added to the attribute of "active'. If learner selects the 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 (Fig. 5.3). 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".

Several studies have been carried out to analyze the Felder-Silverman LSI model (Silvia et al. 2006, Silvia et al. 2007, Thomas et al. 2007), but none have considered the extension of the evaluation system in the way reported here.

5.2.1.2 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 ourselves, our relationships, and our work, effectively and ethically. SEL holds the next five key:

- Self-awareness: assessing one’s feelings, interests, values, and strengths,
- Self-management: regulating one’s emotions to handle stress, control impulses, and persevere to overcome obstacles,
- Social awareness: is able to take the perspective of and empathize with others,
- 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.

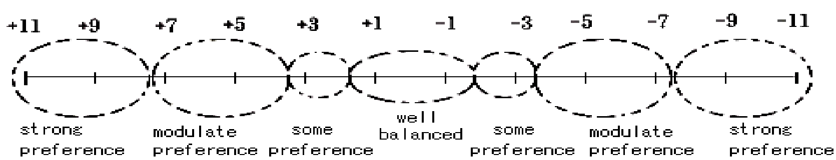


Fig. 5.3 Enhanced LSI evaluation system

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 helps to create and maintain safe, caring learning environment. 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 ongoing 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 this new dimension. In designing these new eleven questions we referred to the Temperament and Character Inventory (TCI) model (Kumiko and Mari 2009).

Table 5.2 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 5.3 (based on Kort et al. 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 positive (+) or negative (-) way.

5.3 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 explain in Sect. 5.5,
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 Fig. 5.4. The system consists of the following components: a user-friendly graphical interface, a web-server, an application server, and a database module.

Table 5.2 Realistic (social/emotional) dimension

Realistic Learner	
Social	Emotional
Social learners tend to be big picture people; concepts are more interesting than details. They are motivated by relationships and care 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 disabled.

Table 5.3 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

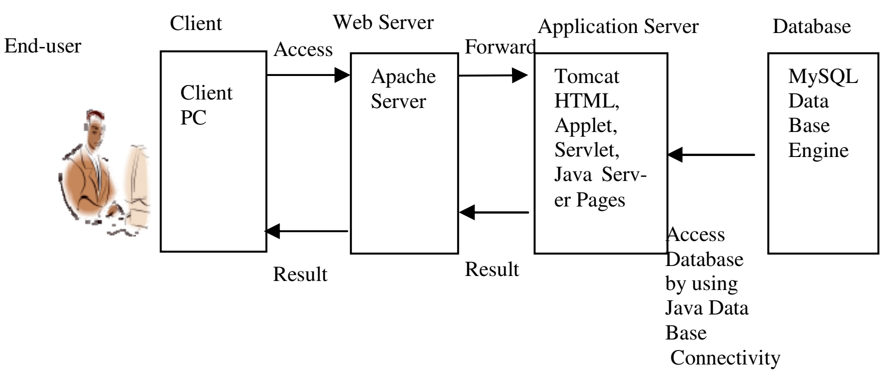


Fig. 5.4 Extended ILS system outline

The learning preferences computational module of our system resides in the application server. It uses the new calculation model described in subsect. 5.2.1. 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 5.2 and 5.5). The learner then fills in all the answers of the quiz system and then 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.

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

5.3.1 Web Application

Our web-based approach is designed according to the modular structure outlined in Fig. 5.6, 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 data base.

5.3.1.1 Students' Module

An individual student can access the system through the interface shown in Fig. 5.7. Then the student can answer the questioner and have her/his learning preferences analyzed automatically by the system. If the student provides her/his "Student ID", the system will store her/his learning preferences in her/his teachers' data base.

Fig. 5.5 Extended ILS web-based interface

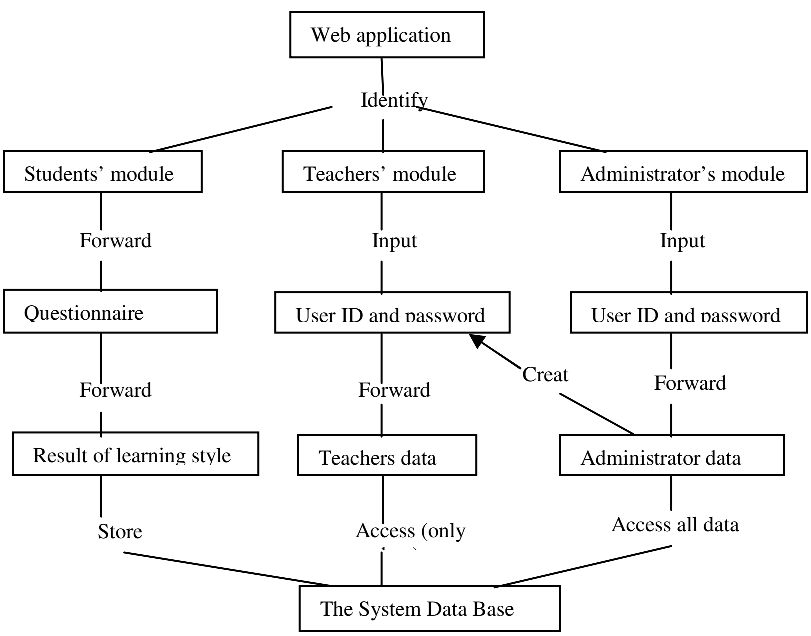


Fig. 5.6 The Web-based application architecture

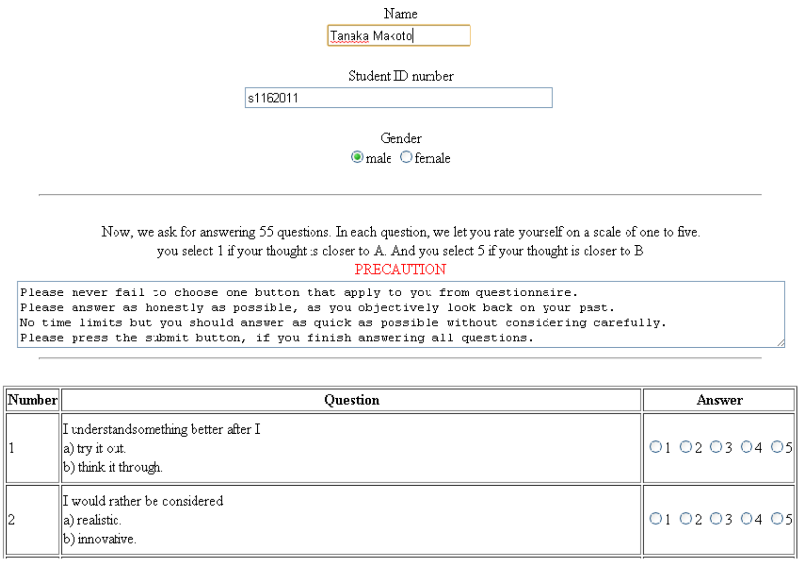


Fig. 5.7 Extended ILS web-based interface

5.3.1.2 Teachers' Module

Teachers have their passwords provided by the system administrator in order to use the system and access the data base. By means of the password they can login to the system and have access to their students' learning preferences data.

An example of the use of our approach by a sample of volunteers is shown in Table 5.4 and Fig. 5.8. Then teachers can access the learning preferences of a single student, a group of students, all students, male students only, and female students only.

The system also has a function to graphically analyze and represent the result for each dimension as it is pictured in Fig. 5.9. The collective result is also displayed graphically as it is illustrated in Fig. 5.10. The system reliability can also be checked through the students' feedback. This reliability is represented graphically and displayed as shown in the Fig. 5.11.

5.3.1.3 Administrator Module

The system administrator may maintain the whole system, create/delete new users (teachers), create or change passwords, and access/maintain the whole data base. The administrator user interface sketched in Fig. 5.12.

Table 5.4 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	Moderate-ly 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	Moderate-ly 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	Moderate-ly right
09	Std09	Female	Well Balanced	Well Balanced	Well Balanced	Some Sequential	Some Social	Moderate-ly wrong
10	Std10	Female	Well Balanced	Well Balanced	Well Balanced	Moderate Sequential	Moderate Social	Moderate-ly wrong
11	Std11	Male	Moderate Active	Moderate Sensing	Moderate Visual	Well Balanced	Strong Social	Moderate-ly right
12	Std12	Female	Moderate Active	Some Sensing	Moderate Visual	Moderate Sequential	Moderate Social	Moderate-ly right
13	Std13	Male	Some Active	Some Intuitive	Well Balanced	Well Balanced	Moderate Social	Moderate-ly 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	Moderate-ly wrong
17	Std17	Female	Some Active	Well Balanced	Well Balanced	Well Balanced	Moderate Social	Moderate-ly 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
...	...	...	...	...	...	...	...	...

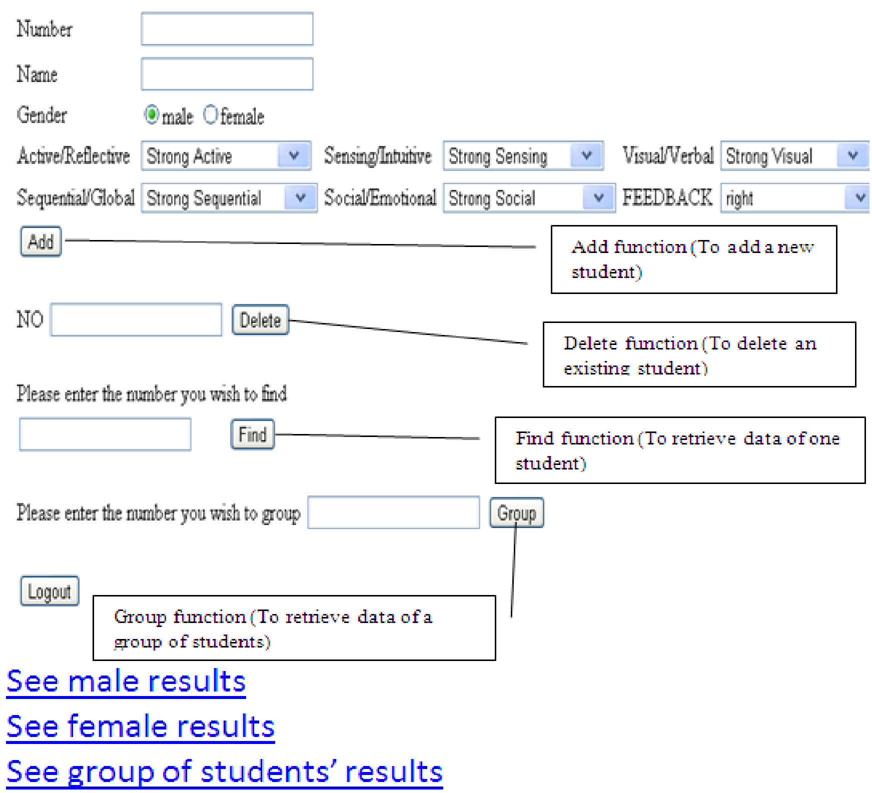


Fig. 5.8 Teacher's module interface

5.3.2 Support for Intelligent and Adaptive Learning Systems

An Intelligent and adaptive systems are both model-based systems although they have different purposes to support the learning process. An intelligent tutoring system (ITS) aims to provide the 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 et al. 2011).

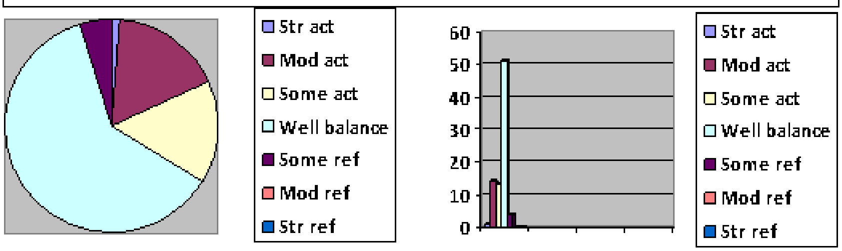
On the other hand, the main aim of an adaptive learning system is to adopt some of its key functional characteristics to the learner needs and preferences. For example, content presentation and/or navigation support. Thus an adaptive system operates differently for different learners exactly the way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

Our learning style index system can easily be integrated into intelligent and adaptive learning systems as we outline in Sect. 5.5.

Total result for each dimension
Number of registered students = 83

Strong Active	Moderate Active	Some Active	Well Balanced	Some Reflective	Moderate Reflective	Strong Reflective
1	14	13	51	4	0	0

Active/Reflective



Strong Social	Moderate Social	Some Social	Well Balanced	Some Emotional	Moderate Emotional	Strong Emotional
1	33	18	28	2	1	0

Social/Emotional

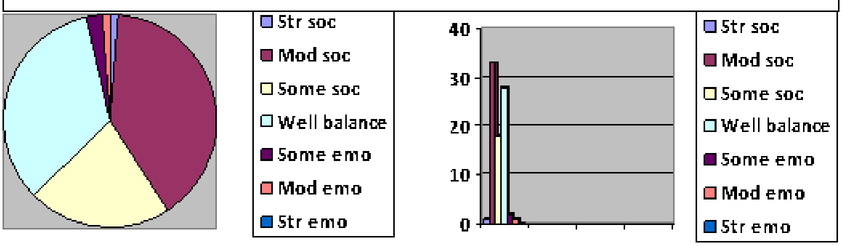


Fig. 5.9 An example of graphical representation of the learning preferences for each dimension

5.4 Application

In the western style education, individual-focused learning is well accepted and the use of LSI and e-learning systems is more efficient. However, in Japan the use of LSI is not so common. It is quite typical in Japanese schools, the classes are given in a traditional lecture-driven style, which means that the difference in learning styles of an individual student has been neglected.

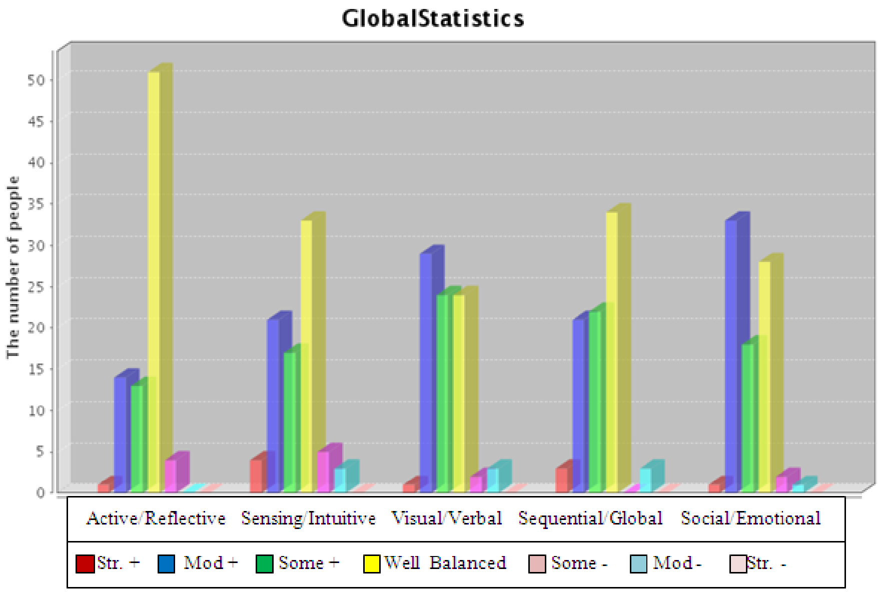


Fig. 5.10 Graphical representation of the collective learning preferences for a group of students

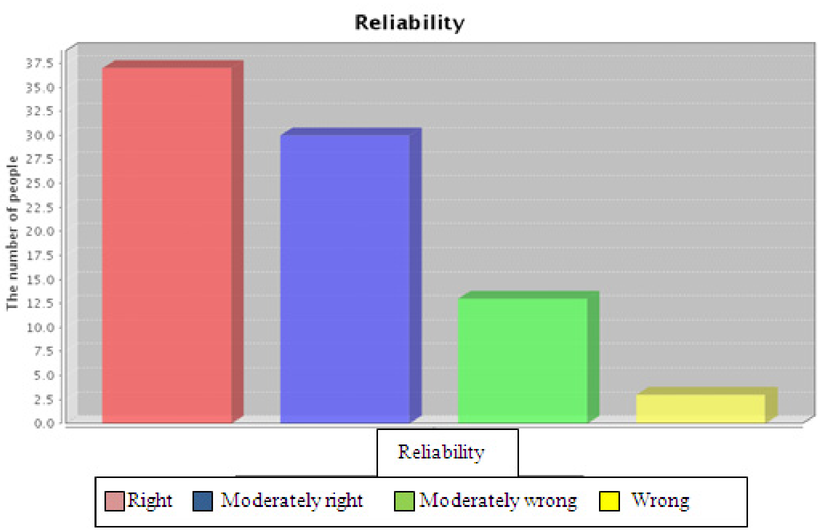


Fig. 5.11 Graphical representation of the system reliability

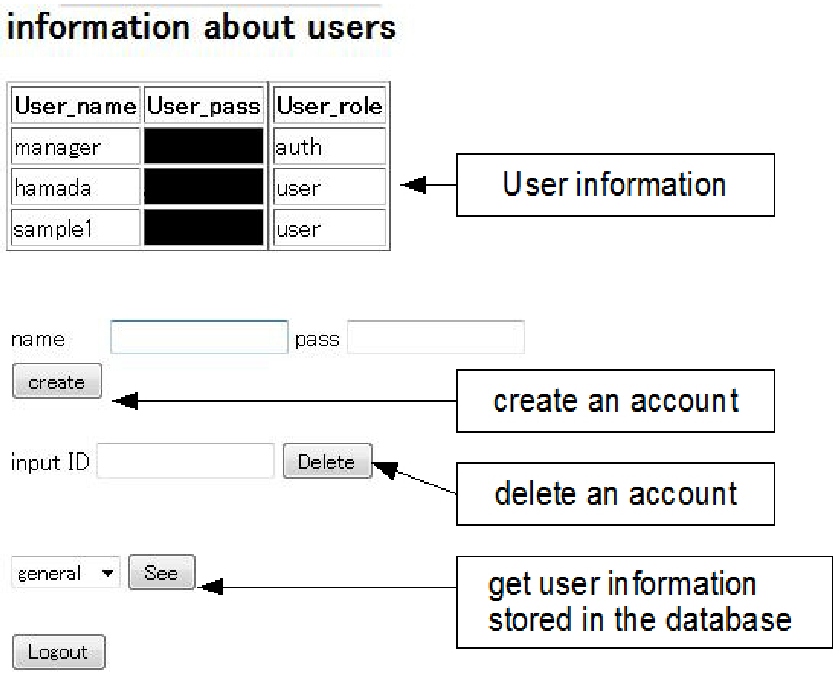


Fig. 5.12 Administrator’s module interface

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 are second-year junior high school students. The result of the questionnaire is listed in Tables 5.5 to 5.9.

Table 5.5 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 5.6 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)

Table 5.7 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 5.8 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 5.9 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

5.4.1 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.

5.4.2 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.

5.4.3 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 kind 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 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.

5.4.4 Sequential/Global

Neither boys nor girls show a bias towards sequential or global orientation. Sequential and global distribution are 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 logical order and how it relates to the real life subjects and facts.

5.4.5 Social/Emotional

The respondents tends 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 greater 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.

5.5 Integration into Intelligent and Adaptive E-Learning System

Compared to traditional learning systems, e-learning (Advanced Distance Learning Group, ADL 2007) provides a more comfortable learning environment, where learners can learn at their convenience. E-learning systems are widely used and rapidly increasing.

Hamada 2008 built an e-learning system for automata theory and theory of computation based on Java2D technology (Sun Microsystems 2006). Such a system is illustrated in Fig. 5.13. Hamada's e-learning system is an intelligent and adaptive learning system that embraces the next components:

- Animated (movie-like) welcome component,
- Hypertext introduction to the theory of computation topics,
- 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 adding a new component for learning style. This new component, sketched in Fig. 5.14, enables the user to find his/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.

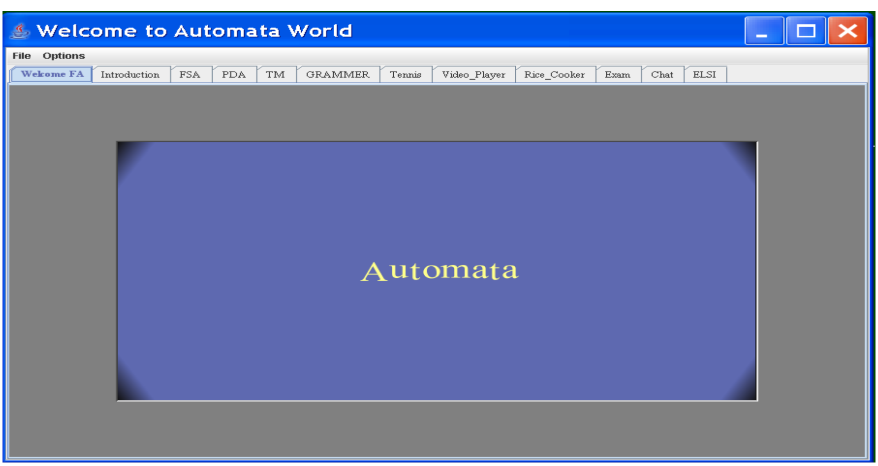


Fig. 5.13 Automata e-learning system interface

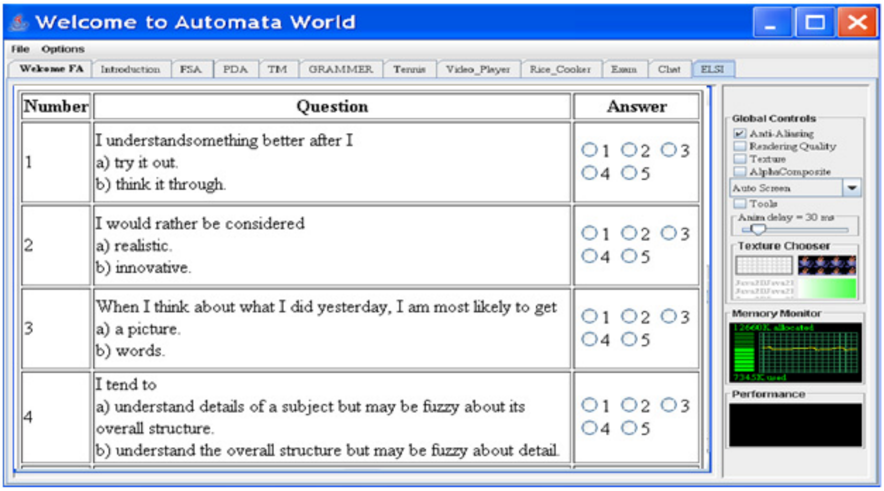


Fig. 5.14 EILS integrated into Hamada's automata e-learning system

5.5.1 Learning Activities

When using the EILS 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 the basics 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 for 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 are 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 Fig. 5.15. Whereas, reflective learners get a different set of recommended activities as the following:

1. Start by navigating the concepts in the topics object. This will provide the learners with the necessary theoretical background for the subject,
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 are 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 Fig. 5.16.

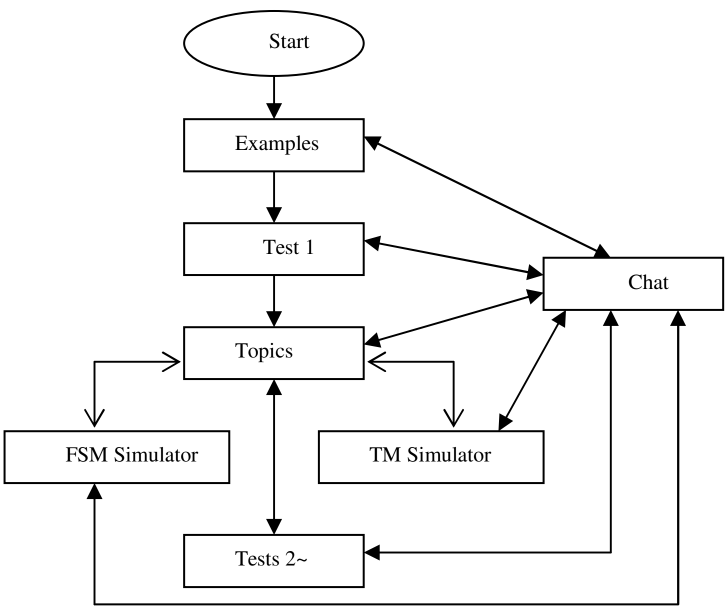


Fig. 5.15 Workflow of learning activities for visual learners

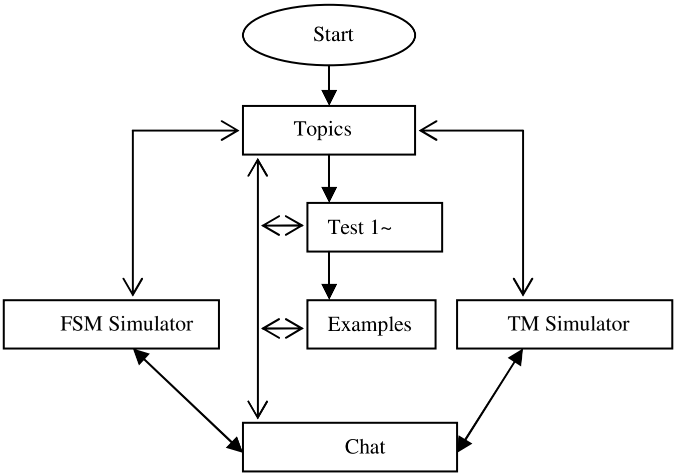


Fig. 5.16 Workflow of learning activities for reflective learners

5.6 Conclusion

In this research, we developed an enhanced version of a LSI that can be integrated into intelligent and adaptive learning systems. We implemented our model in a way that allows learners to easily check their learning preferences.

Moreover, teachers can have a wider perspective on their students' learning preferences. To this extent, our implementation utilizes several useful tools such as: web-based interface, java applets, Apache web server, Tomcat application server, MySQL database, and JDBC connector.

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 analyzed 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 implemented 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 kind 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 match 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.

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Abbreviations

ADL	Advanced Distance Learning
A/R	Active/Reflective
ARCS	Attention – Relevance – Confidence – Satisfaction model
ASF	Apache Software Foundation
DIM	Dimension
ELSI	Enhanced Learning Style Index
FSM	Finite State Machine
ILS	Index of Learning Style (see also LSI)
ITS	Intelligent Tutoring System
Java2D	Java 2 Dimension

JDBC	Java DataBase Connect
LSI	Learning Style Index (see also ILS)
MySql	My SQL (see SQL)
PC	Personal Computer
SEL	Social Emotional Learning
S/G	Sequential/Global
S/I	Sensory/Intuitive
SQL	Structured Query Language
TCI	Temperament and Character Inventory
TM	Turing Machine
V/V	Visual/Verbal