Workshop Proceedings of International Conference on E-Learning and Games, April 17-19, 2006, Hangzhou, China

# An Adaptive Learning System with Learning Style Diagnosis based on Interface Behaviors

Hyun Jin Cha, Yong Se Kim, Jee Hyong Lee, and Tae Bok Yoon

**Abstract** — *Each learner has different preferences and needs. Therefore, it is very crucial to provide the different styles of learners with different learning environments that are more preferred and more efficient to them. This paper reports a study of the intelligent learning environment where the learner's preferences are diagnosed, and then user interfaces are customized in an adaptive manner to accommodate the preferences. A learning system with a specific interface has been devised based on the learning-style model by Felder & Silverman, so that different learner preferences are revealed through user interactions with the sys-tem. Using this interface, learning styles are diagnosed from learner behavior patterns on the interface using Decision Tree approach*[1].

**Index Terms — Adaptive Learning System. Adaptive User Interface. Learner Modeling.**

## I. Introduction

THE computer mediated education in the 21st century knowledge-based society calls for an intelligent learning environment that is adaptive to learner's various needs and changing situations in a learning process. Such intelligent a learning environment can be embodied by having intelligent features such that the user interfaces are adaptive to user's learning styles and other behaviors. In other words, interfaces that support customization and can adapt to each individual's specific preferences may be more effective than ones designed to be "one size fits all" [1]. In this context, it seems to be meaningful to explore the system that can intelligently recognize the individual's learning styles through learner's behavior patterns for the user interface, and customize its user interface to fit the individual's specific preferences and styles. Felder & Silverman [2] have already performed research on classification of students, development of tutoring strategies, and the evaluation of learning strategies. By using the learning-style model by Felder & Silverman, this study demonstrated a case of the learning environment where the learning styles are diagnosed using learner models, the learner's behaviors are recognized, and customized user interfaces can be, finally, reconfigured in an adaptive manner to accommodate the learning styles.

[1] This work was supported by the Korean Ministry of Science & Technology through the Creative Research Initiative Program.

H. J. Cha is with Creative Design & Intelligent Tutoring Systems Research Center, Sungkyunkwan Univ., Suwon, Korea (e-mail: lois6934@skku.edu).

Y. S. Kim is with Creative Design & Intelligent Tutoring Systems Research Center, Sungkyunkwan Univ., Suwon, Korea (e-mail: yskim@skku.edu).

J. H. Lee is with School of Information & Communication Engineering, Sungkyunkwan Univ., Suwon, Korea (e-mail: john@skku.edu).

T. B. Yoon is with Creative Design & Intelligent Tutoring Systems Research Center, Sungkyunkwan Univ., Suwon, Korea (e-mail: tbyoon@skku.edu).

is work was supported in part by the U.S. Department of Commerce under Grant No. BS123456 (sponsor acknowledgment goes here).

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F. A. Author is with the National Institute of Standards and Technology, Boulder, CO 80305 USA (e-mail: author@ boulder.nist.gov).

S. B. Author, Jr., was with Rice University, Houston, TX 77005 USA. He is now with the Department of Physics, Colorado State University, Ft. Collins, CO 80523 USA (e-mail: author@lamar. colostate.edu).

T. C. Author is with the Electrical Engineering Department, University of Colorado, Boulder, CO 80309 USA, on leave from the National Research Institute for Metals, Tsukuba, Japan (e-mail: author@nrim.go.jp).

## II. Learner Model

Chen and Mizoguchi [3] emphasize that a learning system is considered to be "intelligent" if it can adapt its tasks to the learning content based on a learner model, so the learner model is a very important part in intelligent learning systems. Learner model is to be updated according to the analysis in a dynamic manner to provide an adaptive learning environment tailored to each learner. In this research, learner model has been designed: (i) it can provide the tutoring system with all relevant learner information, (ii) it will help in designing a tutoring system which can respond to the learner's various activities and situations, and (iii) for learning interface adaptation, which is the focus of this paper, it provides a capability to look through the learner's information and activities, and then extract the most appropriate learner aspects for designing the behavior-based user interface customization.

### Adaptive Customization of Learning Interface

The *Index of Learning Style* (ILS) in a learning-style model by Felder & Silverman was adopted in this research as an appropriate category for designing the behavior-based learner diagnosis in that each learning style can be classified into two distinctive preferences [4]. The ILS has four dimensions; Global (G) vs. Sequential (Q) in terms of understanding process of information, Visual (V) vs. Auditory (A) in terms of information input, Sensory (S) vs. Intuitive (N) in terms of information perception, and Active (C) vs. Reflective (R) in terms of information processing.

The distinctive characteristics in each dimension suggested by Felder & Silverman are described in Table I. Among them, by using some of the characteristics which can be reflected on

TABLE I
CHARACTERISTICS OF ILS

| Global | Sequential |
|---|---|
| Jumping directly [G1] | Steady progression [Q1] |
| Intuitive leaps, Divergent thinking and synthesis | As presented, Convergent thinking and analysis |
| Big picture [G2] | Partial materials [Q2] |
| **Visual** | **Auditory** |
| Pictures & Demonstrations [V1] | Words & Explanation [A1] |
| **Sensing** | **Intuitive** |
| Senses, facts and experimentation | Perception, principles and theories |
| Patient with details, Careful but may be slow [S1] | Bored by details, Quick but may be careless [N1] |
| By standard methods, empirical experimentation | Innovation, Logical inference, Dislike repetition |
| **Active** | **Reflective** |
| Work in groups [C1] | Work alone [R1] |
| Brief discussion or problem-solving activities, Practical [C2] | Occasional pauses for thought, Fundamental [R2] |
| Experimentalists | Theoreticians |

([ ] IS THE CHARACTERISTICS INCORPORATED FOR THIS RESEARCH)

user interfaces, learner behavior patterns on learning interfaces were hypothesized for this research. The rest of the characteristics are not incorporated due to the difficulties in being externally observed as user behaviors on user interface. A specific learning system has been designed so that learning activities can be flexibly occur reflecting learning preferences of each learner for the domain of architectural history.

### A. Global vs. Sequential (G vs. S)

The ILS work states that the instructor should offer "the big picture of a lesson (G2)" before presenting the learning steps.

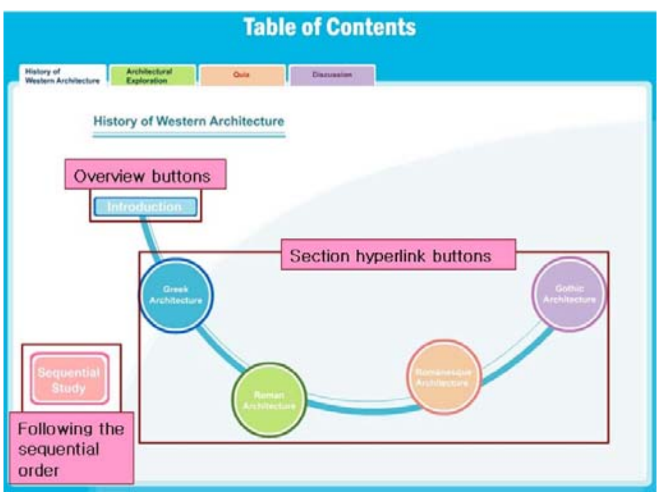


**Fig. 1. Interface Layout for Table of Contents**

From this viewpoint, if a learner wants to look through the overview of the contents, they may be Global learners. Thus, the overview buttons are located on the table of content screen for learners themselves to determine to look over the big picture (Fig. 1). Furthermore, Global learners may want to jump to the section (G1) they are interested in by clicking the section hyperlinks rather than following the sequential order (Q1) that may be preferred by Sequential learners. Furthermore, on the content screen, Sequential style learners may study in a steady order by clicking the arrow buttons, while Global learners may jump to select the content that they want by choosing the section name buttons directly shown in Fig. 2.

Visual vs. Auditory (V vs. A)

Felder & Silverman discuss that Visual style learners may prefer images (V1), while Auditory learners may prefer written texts (A1). Thus, the second interface layout in Fig. 2 has content areas configured by both images and text. The learners can choose either picture-driven or text-driven areas. In the picture-driven area, the detailed explanations are mainly led by images in order to help the learners establish an understanding of the learning contents. On the other hand, the text-driven area is led by written texts.

Sensing vs . Intuitive (S vs. N)

ILS regards Sensory learners as having attentiveness to details (S1) and Intuitive learners as being bored by details (N1) and an interface design has been devised to determine whether Sensory learners are patient with the additional materials when additional contents or examples are given as references. If students are interested in additional materials, they may click the button for additional materials on the interface (Fig. 2). Furthermore, a quiz section was designed as a problem solving situation where learners have to select and insert a correct piece into a correct place on the problem. This has been suggested in that Felder & Silverman mention that while Sensory type learners are careful but may be slow (S1),

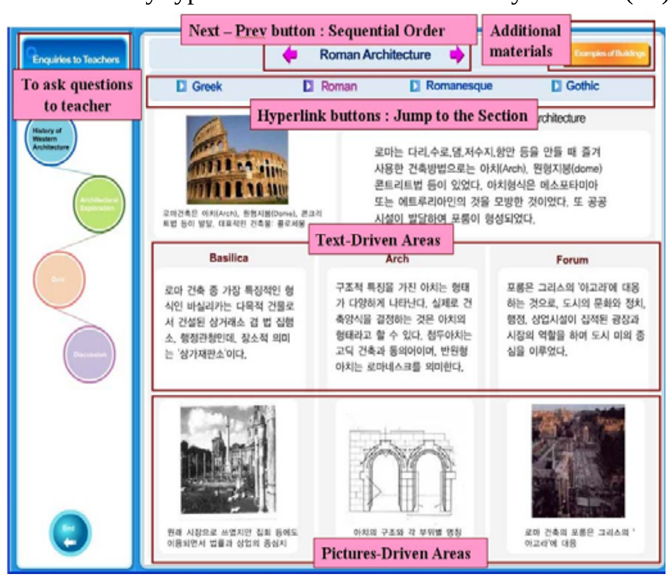


**Fig. 2. Interface Layout for Main Learning Contents**

Intuitive learners are quick but may be careless (N1). The user

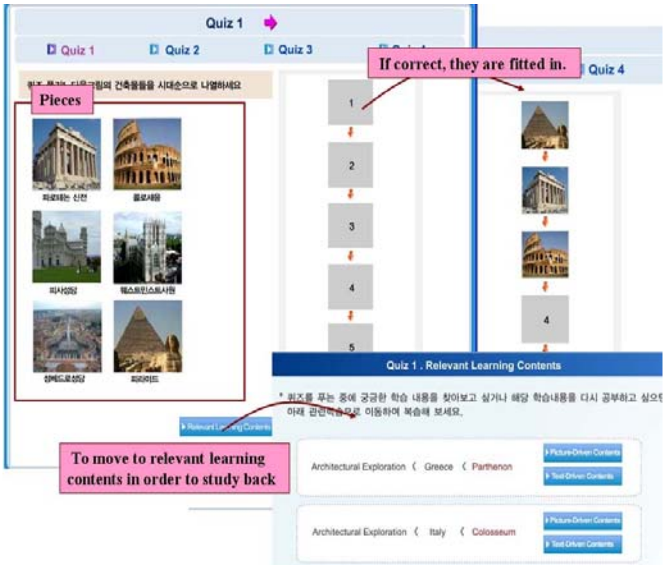


**Fig. 3. Interface Layout for Problem Solving Situation**

interface in Fig. 3 works in the way that as soon as the students drag and drop a piece on the answer section, if correct, the piece is fitted in, but if wrong, it goes back to the original place. If student are careful to choose the answer, they may have low trials and high completion, but if they try it out carelessly, they may have high trials and low completion.

Active vs .Reflective (C vs. R)

Felder & Silverman point out that an Active learner is someone who feels more comfortable with active experimentation (C2). Conversely, Reflective learners process information reflectively (R2) and tend to think about what others have told. From this viewpoint, if Active learners have arguments, they may expose their opinions freely to friends, but Reflective learners may have a time to think about it at first. The Active and Reflective learners may reveal differences between behaviors in situations that they can voluntarily participate in.

## IV. BEHAVIOR PATTERN EXTRACTION

The first step in providing adaptive learning interface customization is to find the adaptation strategy as a decision making process [5]. In the context of this paper, it is possible by monitoring the learner's behaviors collected from the user interface, and trying to extract hidden predictive information from the data collection. For the data mining, the *decision tree* (DT) approach was used in this study. It can be not only easy to use, but the rules of the classification are also visible and easy to understand as a data mining technique for the pattern recognition and classification [6].

Fig. 4 shows the detailed approach of this study in order to extract learner's hidden behavior patterns on the hypothesized user interface and derive a classification of the learning styles for each learner from them. First of all, the data was collected from the experiment where the learners with different learning styles studied the learning content designed in the architecture domain with the hypothesized interfaces, and the actions and events on the learning content were recorded in XML files. Secondly, a procedure of Preprocessing of the data based on the XML files was needed in order to make the data easier to mine and more useful [6]. Thirdly, a DT algorithm was applied to construct decision

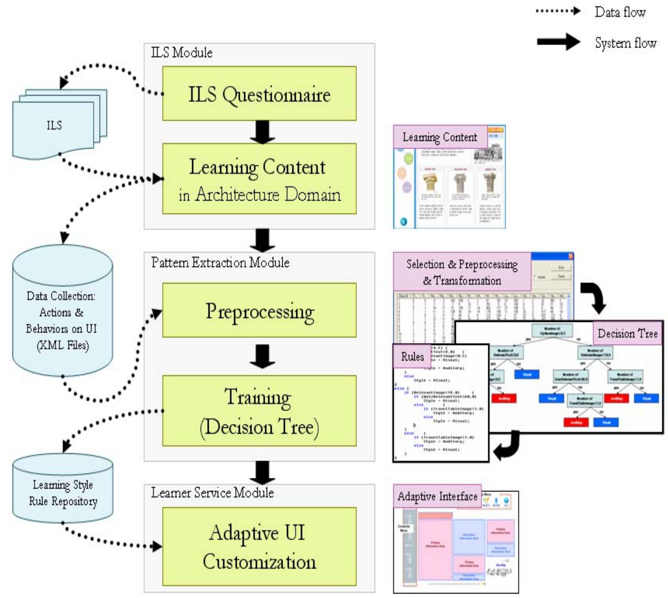


**Fig. 4. Workflow for Adaptive User Interface Customization**

trees using training data. The DTs also generated rules which reflect the learner's behavior patterns in each learning style and help to map undefined learners into predicted learning styles. The rules play a pivotal role in providing the customization of the adaptive learning interfaces.

### A. *Experiment*

The classification algorithms require the characteristics of data already known to belong to the defined classes prior to the data mining [6]. For this, an experiment was conducted with 70 university students in this study. In the experiment, subject's learning styles were figured out by conducting the ILS questionnaire by Felder & Silverman at first, and then they studied the learning content in the architecture domain designed based on the hypothesized interfaces in order to collect the behavior characteristics that can be predefined responding to the learning styles in training data. All of their events and actions on the hypothesized user interface were recorded as XML files.

### B. *Preprocessing*

The XML data was parsed, and attributes that may represent characteristics of the defined classes were selected according to each learning style dimension. Furthermore, anomalous and erroneous data was removed as a process of Preprocessing and some data was encoded or transformed into more usable format. For instance, same types of actions (e.g. chatting with friends and asking to teachers) are combined into an instance, and durations in same properties of events (e.g. time spent on picture-driven contents) are added and put into an instance. In addition to these, as other examples, it was taken into consideration how correct the students solved the quiz or how careful they tried to solve it. The attributes that were purified through the procedure of preprocessing usually consisted of the number of button clicks, the durations of some activities, the correctness of solving quizzes, the number of opinions that they wrote or read, the trial rate of the quiz, and so on.

### *C. Attributes*

A total of 58 attributes as shown in Table II has been devised so that DT based diagnosis can be constructed. For example, “GQ_MainCntsGlobal” in the G vs. Q dimension, represents the number of clicks for contents selection through hyperlink buttons as in Fig. 2. A global learner would move to other content with the hyperlink (MainCntsGlobal) button rather than moving in a sequential order. The attribute, “VA_OptionalImg” in the V vs. A dimension, represents the number of image-driven content selection when image/text options are available.

In the S vs. N dimension, “SN_AddMaterial” is an attribute gained by counting how many times the students clicks the button for the additional contents shown on the top right in Fig. 2. Lastly, in the C vs. R dimension, “CR_OpinionUpload” is the button for writing the learner’s opinions and “CR_Readopinion” for reading others opinions. The attributes record the number of the button clicks.

**TABLE II**
**DIAGNOSIS ATTRIBUTES FOR DTS**

| Learning Style | Attribute Lists | |
|---|---|---|
| G vs. Q | GQ_TableofCntMenuClick<br>GQ_TableofCntTabClick<br>GQ_TableofCntSeqClick<br>GQ_TableofCntMenuFirst<br>GQ_MainMenuSymbolFst<br>GQ_MainCntsSequence | GQ_MainCntsGlobal<br>GQ_MainScreenMove<br>GQ_DetailGlobal<br>GQ_DetailSequence<br>GQ_SubCntsGlobal<br>GQ_SubCntsSequence |
| V vs. A | VA_TravelTableofCtImg<br>VA_TravelTableofCtTxt<br>VA_RelevantImg<br>VA_RelevantTxt<br>VA_RelevantImgTime<br>VA_RelevantTxtTime<br>VA_MainImg<br>VA_MainTxt<br>VA_MainImgTime<br>VA_MainTxtTime<br>VA_LargeImg | VA_LargeImgTime<br>VA_OptionalImg<br>VA_OptionalTxt<br>VA_OptionalImgTime<br>VA_OptionalTxtTime<br>VA_AddtionalImg<br>VA_AddtionalTxt<br>VA_QuizReturnImg<br>VA_QuizReturnTxt<br>VA_AllImgViewTime<br>VA_AllTxtViewTime |
| S vs. N | SN_MenuDetail<br>SN_AddMaterial<br>SN_AddDetail<br>SN_Q1Trial<br>SN_Q2Trial<br>SN_Q3Trial | SN_Q4Trial<br>SN_Q1Yes<br>SN_Q2Yes<br>SN_Q3Yes<br>SN_Q4Yes<br>SN_ReturningtoEdu |
| C vs. R | CR_OpinionUpload<br>CR_ReadOpinions<br>CR_ProfessOpinionRead<br>CR_ChatButton<br>CR_ReadRealTitle<br>CR_QuizTime | CR_ThinkShareTime<br>CR_LearningTime<br>CR_LearningEtcTime<br>CR_ReturningQuizFirst<br>CR_RealOpinionTime<br>CR_ProOpinionTime |

### *D. Decision Tree*

In machine learning, a decision tree describes a tree structure of which leaves represent classes and branches represent conjunctions of features that lead to those classes. A decision tree can be generated by splitting the data set into subsets based on the information gain.

The set of attributes (e.g. the button for studying in picture-driven content areas) explained above and their values (e.g. the number of the button click) derived from the experiment were used as instances for the DT algorithm [7]. Among 70 student's data sets, some of the data were utilized for training data sets and rests of them were used for validation sets. Fig. 5 is an example of final decision trees learned by the DT algorithm from 45 training examples in the Visual vs. Auditory dimension. Moreover, from the decision trees, sets of if-then rules could also be inferred so as to help classify undefined learners into 4 dimensions of the learning styles.

The decision tree in the example (Fig. 5) illustrates that the root classifier is the number of optional button click for choosing whether they want to study either in picture-driven contents or in text-driven contents. If the learner clicks optional buttons for picture-driven areas more than 8.3 times, the next step is to count how many times the learner click the optional buttons for text-driven contents. If the learner clicks them less than a time, they may check whether the learner tends to click image menu buttons for moving to the learning contents in table of contents. If the learner prefer using the image menu button and click the button more than a time, the decision tree will determine them to be a Visual learner, which was one of the hypothesized behaviors from the user interface. This decision tree was validated with the 25 data sets in order to test the accuracy of the trees and rules, and the error rate is 16% in the decision tree (Fig. 5). As shown in the decision trees, some of the rules verified the hypothesized behavior patterns on the user interface even if all of the rules are not matched with the hypothesized patterns. The decision tress in

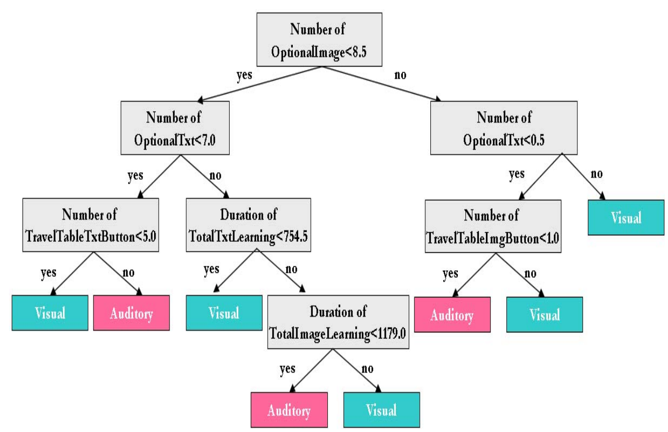

**Fig. 5. An Example of Final Decision Trees**

Sensing vs. Intuitive (SN) and Global vs. Sequential dimensions (GS) were also analyzed in the same way, and validated with quite low error rates (SN: 23%, GS: 36.6%), but Active vs. Reflective dimension had a quite high error rate (43.3%).

## V. ADAPTIVE INTERFACE

The DTs and the sets of rules can be applied to generate adaptation strategies for the customization of user interfaces in intelligent learning systems. The DTs and set of rules make it possible to determine intelligently the learning styles of undefined learners who study the learning content for ILS module. It means that individual learning styles can be recognized based on the user interface-based behavior patterns. Therefore, it is also possible to develop an intelligent tutoring system that is adaptive to the learning styles and preferences. In this CREDITS research center, a prototype of an intelligent learning environment that is adaptive to learning styles and situations has been developed on the subject of heritage alive of an old temple [8].

To illustrate, Fig. 6 illustrates a basic screen layout to reflect the suggested design guidelines and implement adaptive user interface features. Based on multimedia information guidelines [9, 10], the screen is subdivided into three pairs of widget placeholders. Each pair consists of primary and secondary information area. Emphasis on certain information is manipulated by swapping these two areas in a pair. For example, image data widget is located at the left-side position (primary information area) with larger portion of area compared with the right-side text data widget when the interface is customized for the Visual learning style (Fig. 6). On the other hand, left side widget is replaced by text data widget in case an Auditory style learner is using it. In case of Sensory and Intuitive styles, video and audio data widgets are customized to give a contrast to each other. As shown in Fig.

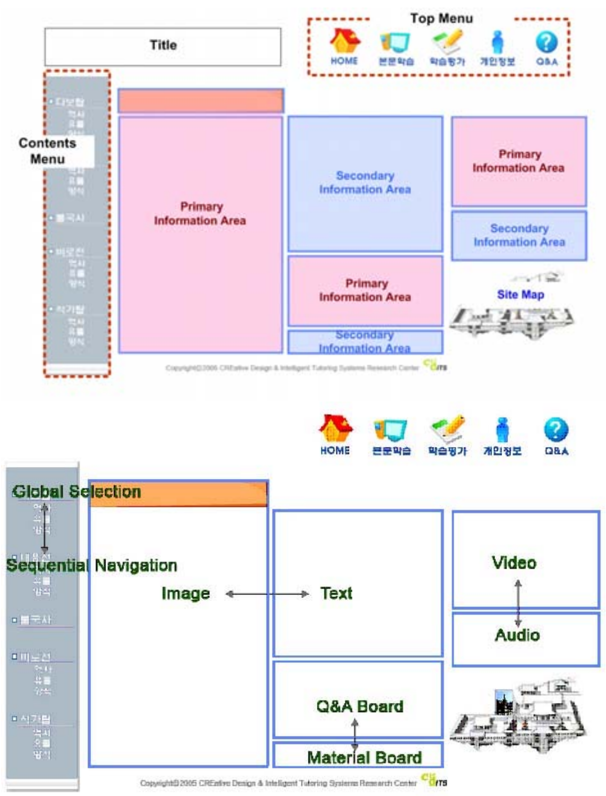


**Fig. 6. Screen Layout Guidelines and Interface Adaptation**

6, positions of video and audio data widgets are swapped according to the style change. Swapping the positions of Q&A Board and Bulletin Board is to reflect the difference between Active and Reflective styles.

## VI. Conclusion

The learning environment demonstrated in this paper aims toward extracting learner's behavior patterns for user interfaces, and developing an intelligent learning system which can enhance learning efficiency and experiences by providing effective user interfaces and learning contents depending on the learner's preferences. To achieve the aim, first of all, some behavior patterns in different learning style dimensions were diagnosed by conducting the experiment with a learning content built based on the ILS theory by Felder & Silverman and then finding the attributes and rules of classification in each learning style. Then, finally, this study also exemplified how the different learning styles can be adapted to the user interface layout in learning environments in order to support their interests and preferences. This approach and methodology could be extended to other aspects of learning strategies in the learner model.

## Acknowledgment

This research was supported by the Korean Ministry of Science & Technology through the Creative Research Initiative Program.

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[3]It is recommended that footnotes be avoided. Instead, try to integrate the footnote information into the text wherevepo

**Hyun Jin Cha** received the M.S. degree in Human Computer Interaction with Ergonomics from University College London, the U.K., in 2005.

She is currently a researcher with Creative Design & Intelligent Tutoring System (CREIDTS) research center at Sungkyunkwan University in Korea. Her research interests include adaptive learning interaction and intelligent tutoring system, broadly incorporating Human Computer Interaction.

**Yong Se Kim** received the Ph.D. degree in Mechanical Engineering from Stanford University, the U.S., in 1990.

He is currently a director at Creative Design & Intelligent Tutoring System (CREIDTS) research center, and Professor with School of Mechanical Engineering, at Sungkyunkwan University in Korea.

His current research goals are to investigate the fundamental processes in creative design & learning, and to provide computer-based aid to design learning including visual and geometric reasoning, and integrated product development processes.

**Jee Hyong Lee** received the Ph.D. degree in Department of Computer Science from Korea Advanced Institute of Science and Technology (KAIST), Korea, in 1999.

He is currently an associate Professor with School of Information and Communication Engineering, at Sungkyunkwan University, Korea.

His research interests include data mining, fuzzy theory and application, neural network, and ubiquitous computing.

**Tae Bok Yoon** received the M.S. degree in Computer Engineering from Sungkyunkwan University, Korea, in 2005.

He is pursuing Ph.D degree in Computer Engineering and involved in Creative Design & Intelligent Tutoring System (CREIDTS) research center, at Sungkyunkwan University, Korea. His research interests include data mining, user modeling, learning, and game AI.