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# Development of Learning Style based Personalized e-Learning System

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**Abstract—***Personalized Learning Environment or Personalized e-learning emerges as new research area in the field of technology enabled education. Every learner can be thought of having his/her own learning style. In our research, we investigate use of learning style in Instructional Delivery mechanism. Every learner has different Learning Style (LS) and if we provide LS based e-content, then learner can experience easy and effective learning. We have developed and tested a system that delivers appropriate Learning Objects (LO) suitable to learner's LS.*
*In this paper, we present our Personalized e- Learning Architecture. We tested new architecture with data collected from 114 undergraduate students. The phase-wise description of three phases of the system namely Pre-Test( conducted to understand prior knowledge of learner about subject), Content Delivery( delivery of LOs according to LS of learner) and Post-Test( determine the effectiveness of learning). The result of investigation are positive and discussed in this paper in detail.*

**Keywords***: personalised learning environment, e-learning, learning style, cognitive traits, learning objects.*

## 1. INTRODUCTION

This paper describes technical and education as-pect of Ph.D. project. The main objective of this project is to study use of LS personalization. We also proposes Personalized e-learning architecture and further investigates its implementation. Nowadays many students learn using distance learning methods. There are multiple options avail-able like Computer Assisted Learning (CAL), On-Line Learning, e-Learning, Web-based Learning etc. Intelligent Tutoring System (ITS) provides cus-tomized instruction material to the student. This method of learning method is more suitable for those learners who want to learn by their own choice of time, choice of place and choice of content also. Every e-learning system has two parts 1. Instructions Creation 2. Instruction Delivery. Instruction Delivery (ID) planning plays important role in personalization of e-learning system Many e-Learning tools are available to deliver instructional content. Learning Management System (LMS) like Moodle are also used for Instructional Delivery. All these tools deliver same content to each user with respect to specific course or subject.

In learner centric approach, which is important in any distance learning methods, each learner has to get instruction content as per his/her own choice. This choice depends on learner's ability to under- stand that topic. This will be a personalized learning in true sense. Moreover, learners have their own learning style like learning by visuals or verbal, sequential or global etc. So the instructional de- livery should be based on the individual learning style of each learner. Lots of instructional content are available but its proper delivery should be as- sured. To propose an intelligent instruction delivery mechanism that particularly takes care of learner's

Learning style is the motivation of this project.

### 1.1 Related Work

Technology enabled learning can be traced back to 1960's when students of University of Illinois reported to access course information through com- puter terminal in class while listening lecture[1].

This process still continue with new way of e- learning Personalized e-learning in the form of Adaptive Educational Hypermedia System (AEHS).

CooTutor[2], INSPIRE[3], WELSA [4] are some examples of AEHS.

In this section we present a bird's eye view of ar-chitectures used in various Personalized e-Learning systems. Some researchers have analysed various architectures which uses LS as one of the attributes of Learner Model. Table V gives brief idea of vari-ous personalized architecture in tabular form. After analyzing nine different personalized e-learning ar-chitectures presented by researchers, we observed that,

- Many researchers build Learner Model based on the LS, cognitive traits, Learning behavior etc. after content delivery
- Very few adapted building of LM before content delivery and evolve after it.
- Many researchers had adopted course level content selection.

- Very few have partially used LO level learn-ing content selection.

However we have proposed to use Felder- Silverman Learning Style Model (FSLSM) with three dimensions - Active-Reflective, Visual-Verbal, Sequential-Global, to define our Learner Model. Learner Model (LM) of every learner has been iden- tified before delivering instructions. Each Learning Object has been selected based on LS dimensions.

## 2. PROPOSED MODEL

Development of Learner Model before content delivery and LO level content selection with deliv-ery are two main feature of our proposed Person-alized e-Learning Architecture as shown in fig. 1

This architecture has 3 module which interacts each other to deliver instruction to the learner

1) Learning Style Identification Module (LSIM): The process of identification of LS in FSLSM was done through ILS questionnaire. This questionnaire helps us to identify various dimensions of LS of the learner. The output of LSIM is the Learner Model (LM).

2) Learning Object Selection Mod-ule(LOSM): The selection of LOs from Learning Object Repository (LOR) has been done in accordance with LM. LOR contains LOs and its meta-data called LOM. LOM contains various characteristics and attributes of LOs in the form of elements.

3) Instructional Delivery Planning Module: This module delivers the LOs selected in LOSM. This delivery has been done through Learning environment.

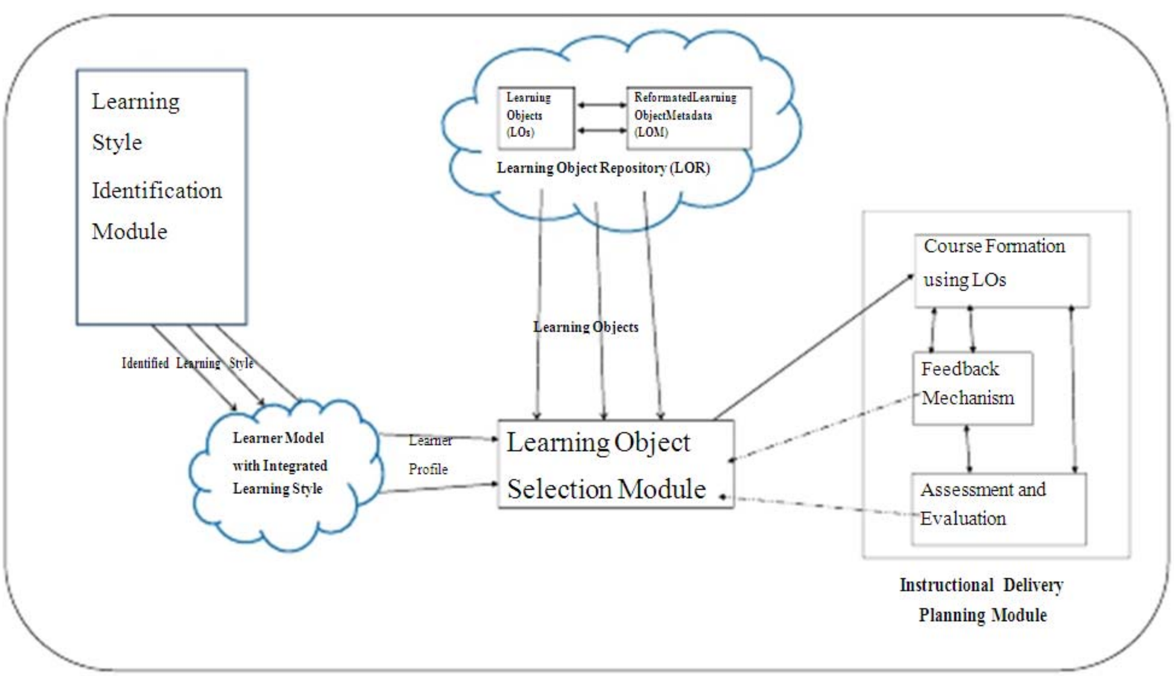
## 3. EXPERIMENTAL WORK

We had conducted two experiments. First exper- iments has been conducted for Automatic Classi- fication and second is for implementation of our Personalized e-learning architecture

### 3.1 Automatic Classification

This section describes how we conducted experiment to justify the use of LS in personalization and observations has been stated.

1) Methodology: Although the concept of LS has been proposed several years ago[5], it is not accepted unanimously. Several researchers claim its usefulness in Teaching Learning process [6] [7] [8] whereas some researchers claims that LS does not contribute in the TL process[9]. However, most of these claims by both the sides are based on experiments conducted in face-to-face – classroom environments. In order to verify whether LS really plays a vital role, we developed a computational automatic classification model. This model involves typical data mining classification algorithms. As mentioned earlier, we are experimenting with three dimensions of LS proposed by FSLSM namely Active/Reflective, Visual/verbal, and Sequential/Global. Apparently, we have developed




**Personalized e-Learning Architecture**

**Fig. 1: Personalized e-Learning Architecture**

eight distinct LOs that correspond to combination of these three dimensions as follows.

1) Active(0)/Reflective(1): Active learner who process information by doing activities based on the e-content. On the other hand Reflective learner only think about material and try to understand it.

2) Visual(0)/Verbal(1): Visual learner learns from what they see. They prefer more graph-ical, animated contents. They trust on “pic-tures speaks louder than words”. Verbal learner learns from words/text and/or oral explanation

3) Sequential(0)/Global(1): Sequential learner prefers learning in sequential manner with elaboration at every step, while Global learner prefers learning a concept as whole. They want “big picture” to be explained and details has been understood later by going through it.

These LOs are tagged with the corresponding LS as proposed by [10]. We ensured that these Los must be from varied domains of knowledge and most of our users (participants of the experiment) do not have prior knowledge of these topics. Some of these topics include “heart functioning”,“English grammer”,“origami” etc. More than 100 partici- pants were asked to interact with all the eight ex- plicitly developed LOs. Every participant has been asked to rank each LO on the scale of 5 to represent how well they understood the topic. And finally they have asked for one LO that they understand most.

2) Observation: A J48 classification algorithm on Weka platform revealed that participants LS and the tag of the most understood LO is matching for most of the participants. Some of the classification rules are as shown below.

**Table I: Classification Rule**

| Rule No. | Learner's LS | Matching LO | No. of Learners (in%) |
|---|---|---|---|
| 1 | 000 | 000 | 62% |
| 2 | 001 | 001 | 42% |
| 3 | 010 | 010 | 60% |
| 4 | 011 | 011 | 80% |
| 5 | 100 | 100 | 80% |
| 6 | 101 | 101 | 68% |
| 7 | 110 | 110 | 75% |
| 8 | 111 | 111 | 60% |

B. Personalized e-Learning

Our proposed architecture has been implemented in modular way. As explained in section III, we implemented 3 modules separately. The methodology used for implementation and the observations thereof are explained in this section

1) Methodology: Learning style is the way how learner understand. Many researchers have proposed methodologies to identify learning style.

In our proposed architecture as shown in fig. 1, we used Felder Silverman Learning Style Model (FSLSM).

For the experimentation, we selected 146 students studying in First Year of B.Sc.(CS), B.Sc.(IT) and BCA. These students do not have prior knowledge of subject - Data Structure. As per our architecture, we started process of Learning Style Identification Module.

1) Student has to create login by filling up necessary information.

2) After successful login, student attempts Felder Soloman Index of Learning Style (ILS) questionnaire, which comprises of 33 two choice questions.

3) Once student submits answers of all ques- tions, system identifies Learning Style of stu- dent and LM was created.

Out of 146 learners, 111 learners successfully completed first phase of experiment. These 111 learners has been distributed in 8 groups as shown in fig. 2.

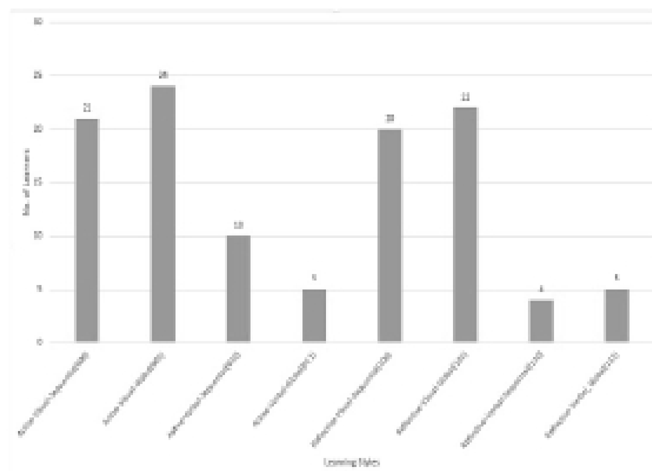


**Fig. 2: Distribution of learners in groups**

The delivery of Instruction or Learning Objects (LO) is the next step of the experiment. We had created Learning Object Repository (LOR). This repository is a collection of LOs with Learning Style tag. LS tagging depends on the suitability factor towards type of LS dimensions.

Learning Object Selection Module(LOSM) and its delivery to the learner was done using MOODLE - an open source Learning Content Management System. By using MOODLE, we delivered content to all 111 learners as per above mentioned groups.

Learner in each group first appeared for Pre- Test to investigate his/her prior knowledge and then content delivered as per Learner Model.

Every learner had gone through all content and at the end he/she attempted Post-Test. This Post-Test helps researcher to analyze performance of learner after instructional delivery

2) Observations: We had collected data of Pre-Test grading and Post-Test grading. Based on these data, performance improvement has been investigated. Fig. 3 shows LS wise distribution of learners who improves performance.

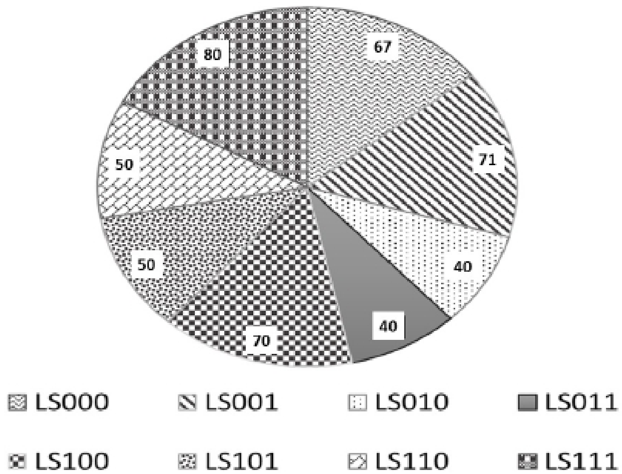



**Fig. 3: Improvement Chart - LS wise in %**

Fig. 3 shows that more than 50% learners in LS000, LS001, LS100, LS101, LS110 and LS111 groups improves their performance, but learner with Active-Verbal group not improved satisfactorily irrespective of third dimension Sequential/Global.

Data summarized in table II, IV, III revels following observations

1) 70% Learners whose LS matches with Los improves their performance.

2) 40% Learners whose LS does not matches LOs deteriorates their performance

3) Active Learners improves irrespective of A c- tive/ Reflective LOs delivered to them.

4) Visual Learners improves irrespective of Vi- sual/Verbal LOs delivered to them.

5) Sequential LOs improves performance of Se- quential as well as Global learners.

6) Visual/Verbal dimension has more impact on the improvements than other two dimensions.

**Table II: Improvement Index-Active-Reflective Learner**

| LS Dimensions | Active LO | | Reflective LO | | Total | |
|---|---|---|---|---|---|---|
| | Learners | Improvement | Learners | Improvement | Learners | Improvement |
| Active | 29 | 15 | 31 | 22 | 60 | 37 |
| Reflective | 26 | 16 | 25 | 14 | 51 | 30 |
| Total | 55 | 31 | 56 | 36 | | |

**Table III: Improvement Index-Visual-Verbal Learner**

| LS Dimensions | Visual LO | | Verbal LO | | Total | |
|---|---|---|---|---|---|---|
| | Learners | Improvement | Learners | Improvement | Learners | Improvement |
| Visual | 41 | 24 | 46 | 31 | 87 | 55 |
| Verbal | 10 | 05 | 14 | 07 | 24 | 12 |
| Total | 51 | 29 | 60 | 38 | | |

**Table IV: Improvement Index-Sequential-Global Learner**

| LS Dimensions | Sequential LO | | Global LO | | Total | |
|---|---|---|---|---|---|---|
| | Learners | Improvement | Learners | Improvement | Learner | Improvement |
| Sequential | 28 | 18 | 27 | 16 | 55 | 34 |
| Global | 28 | 20 | 28 | 13 | 56 | 33 |
| Total | 56 | 38 | 55 | 29 | | |

## 4. CONCLUSION

In this paper, we described the development of personalised e-learning architecture. We applied au- tomatic classification algorithm to justify that learn- ers prefer and understand the LOs matching to theirLS. Hence, we proposed LO level personalization while instruction delivery.

The proposed model is elaborated and result of improvement in performance among all learners after providing LOs that matches their LS is pre-sented.

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