Use of Learning Style Based Approach in Instructional Delivery

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Abstract Technology Enabled Learning (TEL) has started journey from off-line, non-interactive content available on storage media, and now current destination of that journey is personalised e-learning. Instructional Delivery is an important phase in e-learning environment. In our Personalised e-learning model, we have used Learning Style as deciding factor in Instructional Delivery mechanism. We tested our model on 111 learners. Our result shows that Learning style based learning object selection and their delivery elevates learning which in turn improves learner understanding in that subject.

Keywords Learning style · Intelligent tutoring system · Personalized e-learning Teaching-learning process · Taxonomy of e-learning

1 Introduction

Technology enabled Teaching-Learning (TL) process has transformed the conventional way of imparting education. The transformation helped to overcome the limitation of the conventional approach such as distance, language, rigidity, lack of personalization etc. This multi fold transformation in TL process using several electronic tools and appropriate methodologies is broadly referred as e-learning.

Effective instructional delivery in on-line learning enhances learners' experience [12]. Learning Style is one of the factors used and tested to improve learning efficiency of the learner [4]. Learning Style refers to the way learner understands the subject. Initially, psychiatrist and psychoanalyst C.G. Jung proposed this theory. In 1940, Myer-Briggs Type Indicator (MBTI) test which is based on Jung's theory,

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became very popular and widely used. If teacher knows learners' learning style, then he/she can change teaching style(instructional delivery) to improve learners' learning experience. In open and distance education system separate instructional delivery is possible to every learner using technology. "Can we incorporate learning style in the instructional delivery to improve learning of the students?", was the million dollar question that we have pursued and satisfactorily answered.

Today there is a complete paradigm shift from technology enabled single terminal group learning to e-learning based personalized self learning system. Mulwa et al. [7] discussed about Technology Enhanced Learning (TEL) with specific reference to Adaptive Educational Hypermedia System (AEHS). Adaptivity can be achieved by personalization in AEHS by measuring Learning Style (LS) of every learner. Mulwa et al. discussed various models of Learning Styles and emphasized the importance of incorporating LS in various AEHS. They claimed that such blending of educational psychology and technology helped to increase efficiency in learning experience and achieved better learning outcomes.

In this research, we highlight the transformation in e-learning with respect to learning approach. We categorize research work in e-learning using Teaching Learning mode and learning approach aspects. Our focus is on personalized/adaptive e-learning approach and Furthermore we analysed nine different research experiments. The analysis shows following observations.

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

This analysis shows that there is paradigm shift to personalised e-learning which enhances learning experience. This also shows that very few researchers have partially implemented LO level personalization, so there is wide scope for personalization at LO level. Further sections describes our model and explains experimental work conducted based on the model. At the end we describes analysis of of experimental works and conclusion.

In this paper we discusses the outcomes of our two research experiments based on our personalized e-learning architecture. This paper is subdivided in three sections. In Proposed model and experiments section, our personalized e-learning architecture is discussed and explained experimental methodology in detail. Experimental results are analysed and presented in Result Analysis section. The paper ends with conclusion section.

2 Proposed Model

Based on the observations, we decided to propose new Personalized e-learning architecture as shown in Fig. 1. This architecture suggest personalization at Learning

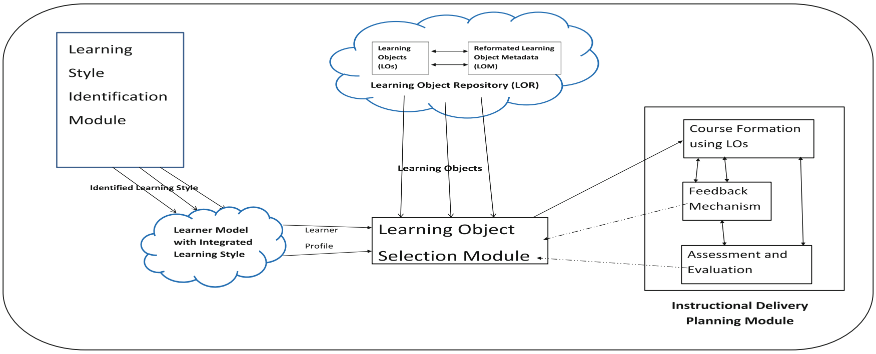

Fig. 1 Personalized e-learning architecture

Object (LO) level. This proposed model is subdivided in three module namely Learning Style Identification module, Learning Object Selection module and Instructional Delivery Planning module.

1. **Learning Style Identification Module (LSIM)**: In this module, we used Felder-Silverman Learning Style Model (FSLSM). 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.
2. **Learning Object Selection Module (LOSM)**: The selection of LOs from Learning Object Repository (LOR) has been done in accordance with LM. LOR contains LOs and its metadata called LOM. LOM contains various characteristics and attributes of LOs in the form of elements. Every elements has name and the value.
3. **Instructional Delivery Planning Module (IDPM)**: This module delivers the LOs selected in LOSM. This delivery has been done through Learning environment.

In this section we suggested LO level personalization based new personalized e-learning architecture. Next section discusses implementation strategy and experimental work in detail.

3 Experimental Work

Our experimental work is categorised in two parts. Each part of the experiment was conducted to test different but inter-related hypothesis.

3.1 Automatic Classification

The first part of the experiment was done to check empirical role of LS in Teaching Learning process. There are two streams of thought on the usefulness of Learning Style. Both sides have presented and supported their claims. We need to test the usefulness of LS by providing different Learning Objects to students with varying LS. The hypothesis that is tested in this experiments is "Learners prefer Learning Object(s) that suit to their Learning Style". We used automatic classification model—decision tree classifier to test our hypothesis. A decision tree is a predictive machine-learning model that decides the target value (dependent variable) of a new sample based on various attribute values of the available data. The next subsection describes decision tree classifier and decision tree induction algorithm and why we use it in testing our hypothesis?

3.1.1 Decision Tree Classifier

According to Han and Kamber [3] any prior knowledge or parameter setting is not required to construct decision tree classifier. Relatively learning speed is faster and accuracy is higher in decision tree classifier. Classification rules generated by decision tree classifier are simple and easy to understand. Hence we decided to use decision tree classifier for our experimentation and used J48 algorithm. J48 algorithm is an implementation of C4.5 algorithm suggested by Quinlan [9, 10]. J48 algorithm follows greedy approach and tree is constructed in top-down recursive divide and conquer manner. The J48 Decision tree classifier uses information gain. The algorithm for inducing decision tree from the training sample.

For experimentation we have used data mining tool called weka version 3.6.13. This tool has facility for various data mining techniques like classification, clustering, association etc. We use J48 decision tree classifier algorithm. We are experimenting with three dimensions of LS proposed by Felder-Silverman Learning Style Model (FSLSM) namely Active/Reflective, Visual/Verbal,and Sequential/Global. Apparently, we have developed eight distinct LOs that corresponds to combination of these three dimensions as **Active(0)/Reflective(1)**, ı**Visual(0)/Verbal(1)** and **Sequential(0)/Global(1)**.

In order to carry out the experiments to test the hypothesis, it is subdivided in three phases namely Sample selection, Preparation and selection of Learning Objects and actual experimentations. The complete process is explained in next sub-section.

3.1.2 Sample Selection

We have used random sampling technique and ensured that the selected learners must have following criteria.

- Selected Learners (sample) must have computer background.
- Selected Learners must have same level of knowledge about LOs' domain.

3.1.3 Preparation and Selection of Learning Objects

All learners are computer literate. We selected Learning objects from various domains viz. science, arts, commerce etc. LOs on common topic were selected, which require primary level knowledge to understand the subject, so every learner should understand it easily. Every learner has basic knowledge about the subjects, also they (learners) have same level of knowledge, hence we selected LOs on common topics of that subjects.

As all participants are from Computer background, LOs were selected mostly from non-computer domain. We ensured that these LOs are from varied domains of knowledge and most of our users did not have prior knowledge of these topics. These LOs are tagged with the corresponding LS as proposed by us [5].

3.1.4 Experimentation

The main objective of the experimentation was to collect data from the participants and obtain automated classification rules to investigate whether our proposition is true or false? Data was collected from learners at various locations by conducting the experiment. Experiment was conducted in the group of 20 students.

The procedural steps followed for each group of students are enlisted below

1. Each Learner has to complete 2-choice Index of Learning Style (ILS) questionnaire which was used to identify learners' Learning Style.
2. There are total 8 LOs, each tagged with unique LS, but we did not disclosed these styles to the learner.
3. We presented each LO one after another to the learners and instructed them to comprehend it. Depending on the type of content of LO, learners watch/listen, carried out activities in order to understand the subject presented in LO.
4. At the end of each LO, learners were asked to fill-up feedback of questionnaire which ask learner to write her/his preferred LO
5. This questionnaire has two part
   (a) Based on the understanding of the LOs, learner was asked to rank these LOs on the scale of 1(least preferred) to 5(most preferred).
   (b) The learner was also asked to mention the most preferred LO with the reason at the end of the experiment.

3.1.5 Observations

A J48 classification algorithm on Weka platform revealed that participants LS and the tag of the most preferred LO is matching for most of the participants. The data shown in the Table 1 depicts observations.

Some of the classification rules in the form of decision Tree are as shown in Fig. 2.

Table 1 Data output from J48 classification algorithm

LS of learner	Total number of learners	LS of preferred LO	Number of learners	Percentage of matching (%)
LS000	40	LS000	25	80
LS001	30	LS110	15	50
LS010	12	LS010	06	50
LS011	05	LS011	04	80
LS100	30	LS100	25	83
LS101	26	LS110	15	58
LS110	04	LS101	03	75
LS111	06	LS111	03	50

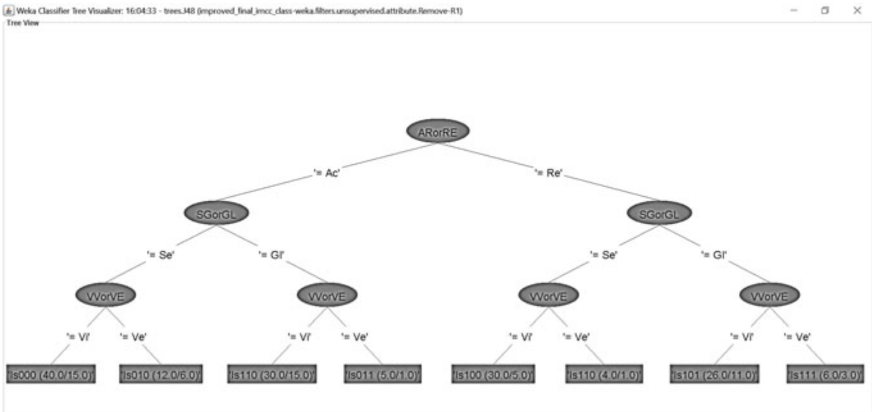

Fig. 2 Classification tree of learners

From decision tree, we observe that out of 30 Re-Vi-Se learners, 25 prefers LO with same tagging. This corresponds to the rule

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if (ACorRE = "Re" and SEorGL = "Se" and VIorVE = "Vi"
then LO with tagging LS100 get selected
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In general more than 50% learners prefer matching LOs except Ac-Vi-Gl(LS001) learners and in particular, more than 75% of learners with learning style Ac-Vi-Se, Ac-Ve-Gl, Re-Vi-Se and Re-Vi-Gl prefers matching LOs. 50% of Ac-Vi-Gl(LS001) learner prefers LOs with Re-Ve-Se tagging.

Our observation justifies correctness of the hypothesis that Learners prefer Learning Object(s) that suit to their Learning Style.

Our next experiment explores the possibility when if delivery of matching LO shall have more impact on elevation of understanding as compared to delivery of non-matching LO. The hypothesis and method to justify its correctness presented in next session.

3.2 Learning Style Driven Instructional Delivery

The automatic classification methods used in previous experiment revealed that Learning Style of most of the learners and the LS of the most preferred LO selected by these learners is matching. Hence, we decided to implement our Personalized e-learning architectures as shown in Fig. 1 explained in previous section. In continuation with first experiment, this experiment was conducted to test multiple hypothesis:

1. Active/Reflective learners improves learning experience which in turns improves learners' understanding, after absorbing Active/Reflective learning objects.
2. Visual/Verbal learners improves learning experience which in turns improves learners' understanding, after absorbing Visual/Verbal learning objects.
3. Sequential/Global learners improves learning experience which in turns improves learners' understanding, after absorbing Sequential/Global learning objects.

As researcher is from computer field, we decided to select subject from computer domain. Hence we chose Data Structure as subject for this experiment. As Learning Objects to be developed and/or to be selected, we decided to use stack as subtopic for this experiments.

3.2.1 Selection of Participants

We have to test impact of Learning Style based LOs selection and delivery on learners understanding. For this experiment also we have used random sampling techniques with some criteria listed below

- Selected learners are from computer background.
- Selected learners without any prior knowledge of Data Structure.
- Selected learners are from under graduate category.

We selected participants who do not have prior knowledge of subject i.e. Data Structure. We selected 176 students studying in First Year of B.Sc.(CS), B.Sc.(IT) and BCA. Data Structure is the part of their second year syllabus.

3.2.2 Experimentation Methodology

This experiment was conducted in three different phases. This section is subdivided in 3 subsections which are three phases of this experiment.

3.2.3 Learning Style Identification Phase

In this phase we asked student to fill Felder-Soloman Index of Learning Style (ILS) questionnaire [1]. For experimentation we developed a web-based interface where students

1. created login by filling up necessary information.
2. after successful login, students attempted ILS questionnaire, which comprises of 33 two choice questions.
3. upon completion and submission of ILS questionnaire, the system identifies Learning Style of student and consequently appropriate Learner Model is created.

Out of 176 learners, 146 learners successfully completed first phase of experiment. These 146 learners has been distributed in Learning Style Dimension wise.

3.2.4 Learning Object Selection Phase

The selection of LOs was done in accordance with Learner Model (LM) generated in previous phase. LOs for each subtopic of DS, with different attributes are stored in Learning Object Repository (LOR). We also developed some activity based learning objects for this experiment. Each LO in LOR has been tagged as per our reformatted Learning Object Metadata (LOM). Learner Model of each learner contains values for each dimension Active(0)/Reflective(1), Visual(0)/Verbal(1), Sequential(0)/Global(1).

As proposed in our Personalized e-learning architecture, we selected LOs at each subtopic level. This process of selection was done using manual match-making of LOM and LM.

E.g. For "Operation on Stack" topic under "stack", we had different LOs with different tagging like Ac-Vi-Se(000), Re-Vi-Gl(101) etc. This tagging was done based on content type, activity and delivery mechanism. We did manual match-making and selected appropriate LOs for respective LM.

3.2.5 Instruction Delivery Phase

In Intelligent Tutoring System (ITS), tutoring module decides tutoring strategies based on student module and domain module. Instruction delivery phase decides delivery of LOs selected in Learning Object Selection phase, based on Learners' model. Instruction delivery mechanism ensures accurate delivery of LOs in appropriate manner. We used Learning Content Management System—MOODLE as an agent of delivery.

Course formation is the first step in this delivery. For every group, selected LOs were delivered in appropriate way. Courses created delivered to learner who shows respective learning style. Participants were added as student user in each course

Table 2 Learner distribution—course-wise

Course name	Number of learners	Course name	Number of learners
LS000	16	LS100	15
LS001	18	LS101	21
LS010	23	LS110	20
LS011	15	LS111	18

according to their Learning Style identified in Learning Style Identification phase. All 146 learners distributed among these eight different courses. Tabular information of distribution is given in Table 2.

3.2.6 Evaluation

In each course, before delivery of LOs, Pre-learning test was conducted. The purpose of the test is to investigate learners' prior knowledge about the subject.Out of 146 learners, 111 learners participated this phase of experiment. Every learner completed the course and feedback in the form of Post-learning test was taken. Grading in Pre-learning test and Post-learning test are used as performance indicator in this experiment.

3.2.7 Observations

We analysed grades obtained by learners in Pre-learning Test and Post-learning test. In this analysis performance improvement has been investigated. All learners have been provided with LOs. Hence, it is apparent that the performance of each student will improve as compared to the performance of Pre-learning test grades. In order to cross-check this hypothesis, we propose to use Performance Indicator (PI) which is calculated as

$$PI = G_{pos} - G_{pre} \tag{1}$$

where G_{pos} is grade received in Post-learning test while G_{pre} is grade received in Pre-Learning test and PI is performance Indicator.

Learner with positive PI is termed as Improved Learner. Following table shows data of Improved learner when matching LOs has been delivered to each learner.

Combining of learning style dimension effect on the percentage of Improved learner. The data in Table 3 shows that combined LS dimensions increases percentage of Improved learner except LS010 and LS101. In other combined LS dimension, percentage of Improved learners increases significantly.

Table 3 Performance improvement chart—combined LS dimension wise

Combined LS dimension	Number of learners with matching LOs	No. of improved learner	Per. (%)
LS000	8	6	75
LS001	10	6	60
LS010	6	2	33.33
LS011	3	2	75
LS100	9	8	88.88
LS101	10	3	30
LS110	2	2	100
LS111	3	2	75

4 Conclusion

The aim of this research is to evaluate the effect of Learning Style in personalized e-learning system. Many researchers [2, 6, 11] are in favour of using learning style in personalization. On the other hand, doubts about the concept of Learning Style itself are raised and its usage in learning process is questioned [8]. Amidst these 'for and against' claims, our research revealed some important findings.

Students from five different institutions of four different cities (from rural and urban area) were selected for experimental study. Although the developed course was new for all the students few students might have been already aware of few topics of the course. Hence, all students were evaluated before delivering course contents (LOs) to them. This pre-learning test score is later used as a base to appraise the performance of students. Instead of using absolute post-learning test score, we used relative difference in performance to ensure that the experimental results are not biased.

It was observed that lower at 53% of Global learner to higher 71% Sequential learner who have been provided with LOs matching to their learning style improvised their performance. Even if we use combined LS dimension (LS000, LS001, LS011, LS100, LS110, LS111) then percentage of Improved learner increases i.e. lower 60% to Higher 100%. This shows that if we use combined LS dimension then result is improved. Although, this emphasizes the need of instructional delivery of LO as per the LS of user, we also came across some interesting observations.

In short, our research builds a bridge between two strong opposite opinions on use and effectiveness of Learning Style. We have demonstrated how a learning environment for learning style based instructional delivery can be set. We are certain that it will be used in future for on-line e-learning personalized systems.

Acknowledgements The data references/selected Learning objects from various domains viz. science, arts, commerce etc. LOs on common topic were selected, which require primary level knowledge to understand the subject. The information has also been collected from different authentic sources such as textbooks, journals and sorted data sources.

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