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Adaptive Virtual Learning Environment based on Learning Styles for Personalizing E-learning System: Design and Implementation

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Abstract: ***Most virtual learning environment fails to recognize that students have different needs when it comes to learning. With the evolving characteristics and tendencies of students, these learning environments must provide adaptation and personalization features for adaptive learning materials, course content and navigational designs to support student's learning styles. Based from the data mining results of learner behavioral features of five hundred seven (507) tertiary students, an accurate model for classification of student's learning styles were derived using J48 decision tree algorithm. The model was implemented in a prototype using a framework and a proposed system architectural design of an adaptive virtual learning environment. The study resulted in the development of an adaptive virtual learning environment prototype where learner's preferences are dynamically diagnosed to intelligently personalize the course content design and user interfaces for them.***

Keywords : adaptive e-learning, personalization, data mining, prototype

I. INTRODUCTION

The interest for adaptive or personalized e-learning systems had recently gained traction in the area of educational technology researches for the past years. Adaptive e-learning's primary objective is to personalize the learning experience for each learner [1]. This system creates a profound and richer experience for a learner through emphasis on "adaptive learning personalization". Traditional and conventional approaches to adaptive e-learning were mainly based on the learner's prior knowledge through diagnostic assessments as the main adaptation strategies.

While this aspect is crucial for user modeling in general when it comes to adaptation strategy, its limitation is highlighted for e-learning hypermedia for the reason that it does not address the far more fundamental problem that learners learn in variety of ways and each of them have a specific preference when it comes to how they learn and interacts in a specific learning environment. They have specific learning styles. Learning styles (LS) and their direct influence on the learning process have been carefully studied by notable educational experts and theorist. Multitude studies have attested their positive impact on learner's performance [2][3][4][5], learner's satisfaction [6][7][8] and it shortens learning time [9][10]. Identification and learning how a learner learns can greatly enhance both learning and teaching aspects. It can also provide teachers an insight and a deeper understanding of how their students prefer to learn in order to improve their learning progress. Students are learning based on their abilities and on their level of preparations but significantly they are learning with much efficiency and with enjoyment when pedagogical approaches are in congruence with their learning styles. Difficulties arises when learning styles are not supported by the learning environment, it impedes their learning progress, efficiency and restricts their capabilities [11].

Personalized environment at present times have become prevalent and increasing its importance in many areas such as e-commerce, e-tourism, digital libraries and e-learning to name a few [12]. In education, it has become synonymous with technology-enhanced learning as compared to traditional and conventional learning which aims to provide a flexible learning environment to allow students to interact with the learning materials that is suited with their needs [13]. The advantages of personalized learning are to streamline and optimize student's learning process in order for them to acquire knowledge more efficiently and effectively [14]. Higher Educational Institutions (HEIs) have successfully implemented Virtual Learning Environment Systems (VLE) or e-learning systems such as Moodle, Blackboard, and WebCT which are vital infrastructures for delivering pure online courses to supplementing face-to-face courses. However these platforms are strictly following a "one size fits all" approach by presenting courses in a static manner.

Unlike the traditional face-to-face form of teaching where teachers can observe the behaviors and preferences of the students on how they learn best, VLEs do not have the luxury to be able to tailor fit the teaching methodologies to support each student.

Most, if not all VLEs do not have the capability to identify each student's behaviors and how they learn in the course for it is virtual in nature. These lacking features in most VLEs affects student's motivation to learn which in turn result to difficulties when it comes to their learning.

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Based from the study [15], students in a personalized learning environment becomes fully motivated and tends to strive harder than most peers to obtained more information. A true personalized learning environment can be realized through identification of different tendencies and behaviors of students such as their affective styles, cognitive styles and their learning styles.

Several researches recommended a personalized learning environment using feedback from questionnaires, prior cognitive levels and material difficulty.

Much research had given emphasis on adaptation based on a learner's previous knowledge through diagnostics tests but limited adaptation strategies when it comes to their learning styles. According to reference [16][17], a learning style is the way a student assimilates and process information in their own unique ways in which they are most likely to learn. Each of them has their own preferences of acquiring new knowledge. There are sufficient evidences for the diversity in individual's thinking and ways of processing various types of information and shown that students will learn best if taught in a method deemed appropriate for their learning style [18]. It is considered that if learning styles of the learners can be determined by the learning environments and learning environments are designed most accordingly to the learning style, academic achievement of the learners will increase [19]. The work of [20][21] points out that a teacher can "bridge the gap to the learner through attitude, action and understanding the learner's preferred ways to learn". The research results revealed that quality of student's performance in an instructional activity are highly coupled from the methodologies in teaching and activities that supported and matched their learning styles.

Several learning style models have been carefully studied throughout history but for identification of learning styles in in an e-learning environment the Felder-Silverman Learning Style Model is recommended (FSLSM) [22]. According to reference [22][23], "the model defines four dimensions such as processing (active/reflective), perception (sensing/intuitive), input (visual/verbal), and understanding (sequential/global)".

The Index of Learning Styles (ILS) is a 44-item questionnaire developed for identifying learning styles that is based from FSLSM. Multiple research studies have attested the validity and reliability of the ILS such as the research done by [23] in Appalachian State University in North Carolina where fifteen thousand (15,000) students participated. In terms of the psychometric analysis of the reliability of the ILS, the study conducted by [24] reveals that it produces consistent results for learning preferences of engineering students regardless of their cross-cultural differences and suggested that it is a valid instrument for diagnosing learning styles in order to improve academic achievements.

There is a need for an adaptive virtual learning environment in present times as students are also evolving with different tendencies and characteristics. E-learning systems should personalized and adapt learning contents to meet each individual needs [25]. Most e-learning systems do not cater to the individuality of the learners and neglects their needs and preferences [26]. Problems such as this incites researchers to develop adaptive learning systems to render its design, components and interface to adapt to a specific set of user characteristics [27][28]. Different students have different interest when it comes to the pieces of information presented to them and in a virtual environment there is a need for an automatic content and design adaptation based from their browsing behaviors so that each learner can be classified and can have a personalized experience when it comes to their learning [29][30].

At present, with the inception of machine learning, the innovative and intuitive technique in personalizing the learning environment is employing data mining and this technique served as the primary basis for learner modeling and for the creation of an adaptive virtual environment prototype based on a novel architectural design that serves also as the motivations of this study.

II. CONCEPTUAL FRAMEWORK OF THE STUDY

To review the detailed overall conceptual framework of the study as can be seen on Figure 1, participating students answered the ILS questionnaires to define the class labels in terms of their learning styles. When students progresses in the course every activities while they are logged-in to the system are recorded in the VLE's database as interaction logs. Student's behavioral patterns and navigational patterns were retrieved from the VLE's database based on the characteristics as described accordingly to the Felder-Silverman Learning Style Model (FSLSM) and these patterns are extracted as numerical attributes for the preliminary formation of data sets. Examples of attributes such as the accumulated instances a student interacts with learning objects, number of posts a student made to a forum, the number of exercise submitted attempts just to name a few. These derived variables together with the results of the ILS questionnaire was transformed into fields, assigned with proper data attributes, and stored into a file. Feature selection technique was implemented to find the most meaningful attributes for processing and analysis. The data mining phase detailed in the previous papers [31][32] of the author included analysis for predictive or classification purposes. Different classification algorithm techniques were applied to find the most accurate classification model. Acquiring the best model is crucial in learner modeling for personalization of course contents and design of the adaptive VLE by serving to the students their preferred learning objects based from their classified learning styles. Finally, the implementation phase of the study aims to investigate content and navigational adaptation features of the developed prototype.

III. RESEARCH METHODOLOGY

To be able to fully comprehend and to have a clear understanding of this section including the succeeding results and discussion, the study is a product of five (5) years of data gathering, two (2) years of

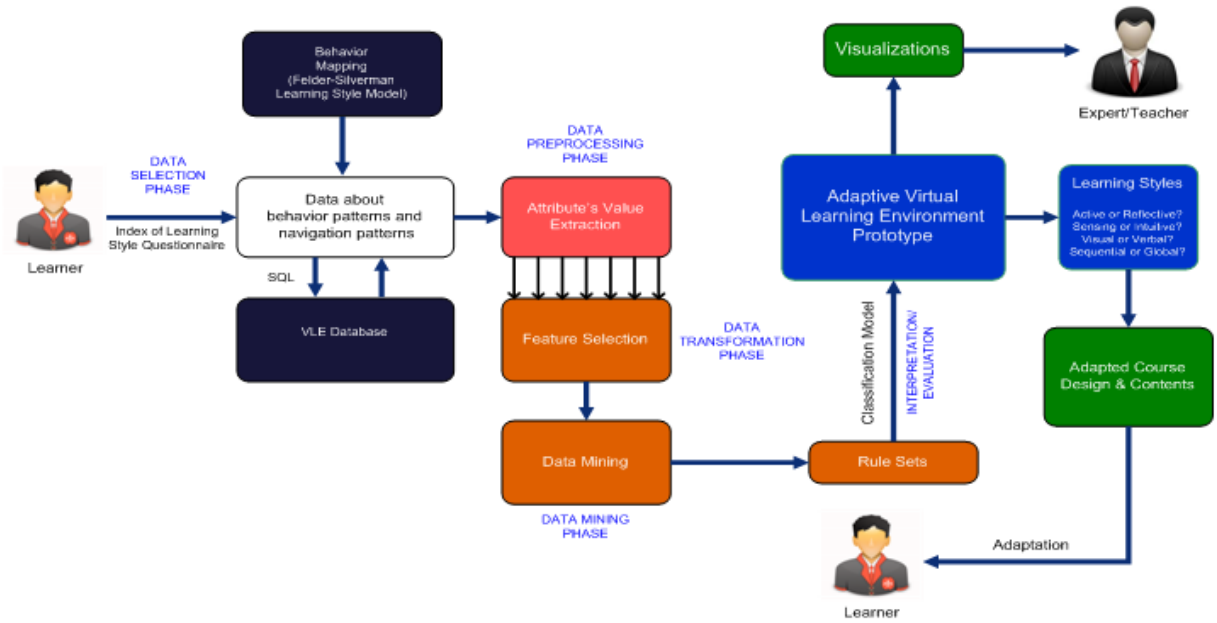

Fig. 1 Conceptual Framework

prototype development and a year of actual implementation and decomposed to several paper publications. To understand how a personalized learning environment is generated based from the learner's learning styles, it employs the result of classification model generated from fifty two thousand eight hundred fifteen (52,815) rows of data extracted from five hundred seven (507) student's interaction logs as thoroughly detailed in previous published researches by the author [31][32][33] and unpublished dissertation manuscript [34].

A. Course Description

The study is grounded on an e-learning course (Computer Programming 1) at Southern Luzon State University in Lucban, Quezon, Philippines. The course content is a product of seven (7) years of teaching experience and has also been significantly enhanced with the end result of creating an adaptive prototype of e-learning. The course selected comprises of seventy nine (79) carefully designed learning objects composed of five (5) chapters. Different activities that include self-assessment tests, exercises, simulations and various activities were provided in the course that allows student to practice their programming skills. Included also in the course is a forum to encourage students to interact and solve problem among other students. It was chosen because it has the most enrolled students and the most active course as to the number of interaction logs generated. In addition, the course structure is the most appropriate for the selected learning style model.

B. Data Source

Five hundred forty one (541) students are enrolled in the course collectively for the period of five (5) years (2012-2016) but only five hundred seven (507) students had finished the course. The remaining students who did not complete the course are excluded from the gathered data so as to prevent outliers. Student who completed the course were asked to answer the Index of Learning Style (ILS) questionnaires. To prevent contamination of data, students are given a considerable amount of time to complete the questionnaire and each item is carefully explained to them.

The result of the ILS shows the distribution of their learning styles as can be seen in Table 1.

Table 1: Distribution of Learning Styles from ILS

Dimension	Processing	No. of Students	Percentage
Processing	Active	244	48.13%
	Reflective	263	51.87%
Perception	Sensing	348	68.64%
	Intuitive	159	31.365
Input	Visual	388	76.53%
	Verbal	119	23.47%
Understanding	Sequential	250	49.31%
	Global	257	50.69%

The ILS questionnaire reveals that there is a fairly balanced distribution of learning styles of students when it comes to processing information for active and reflective learners with 48.13% and 51.87% respectively. In terms of the perception dimension, most students fall on the sensing category (68.64%) rather than intuitive (31.36%) which means that students prefer learning objects that are based from facts and data as described in the FSLSM. The data also reveals that most students in the course are visual learners (76.53%) when it comes to their preferred presentation (input) of learning objects. Finally, there is also balanced distribution when it comes to the understanding dimension with sequential learners (49.31%) and global learners (50.69%) which means that students varies in characteristics when it comes to their preferred ways in learning progressions.

C. Mapping of Attributes to Learning Styles

For the creation of data sets for data mining, essential and relative attributes of student behaviors in the course are mapped-out and extracted from the VLE's database as can be seen in Table 2.

Table 2: Mapping of Attributes to Learning Styles

Learning Style	Relevant Behavior	Attribute Name	Attribute Value
Active	Post more often in discussion forum	forum_posts	no. of posting in forum
	Perform more self-assessment tests	self_assesment	no. of completed attempts
Reflective	Reading post but rarely posting by themselves	forum_view	no. of viewed post in forum
	Prefers learning material in textual form	text_materials	no. of visits
Sensing	Prefers concrete learning materials (facts, data)	concrete_materials	no. of visits
	Prefers examples	examples	no. of visits
Intuitive	Prefers abstract learning material (definition, theories, syntax, flowcharts)	abstract_materials	no. of visits
	Prefers to review answers in graded exercise tests	exercises_rev	no. of attempted answer reviews
Visual	Prefers learning materials supplemented with pictures, diagrams, graphs	visual_materials	no. of visits
	Prefers learning materials presented in a video format	video_materials	no. of visits
Verbal	Prefers learning material presented in text or audio	text_materials	no. of visits
	Post more often in discussion forum	forum_post	no. of posting in discussion
Sequential	Prefers to go through the course step by step (linear way)	nav_pattern_dist	sequence of navigational pattern
Global	Prefers overviews, outlines	course_overviews	no. of visits
	Prefers to learn in large leaps by skipping learning material & jumping to more complex materials (non-linear way)	nav_pattern_dist	sequence of navigational pattern

D. Navigational Sequence Data Collection

A different treatment was needed to be able to extract specific values for the understanding dimension (sequential/global) as this refers to the navigational pattern (nav_pattern_dist) behavior of students when they accessed the course. Euclidean distance formula was used to address the differences and similarities of the navigation characteristics of a student in order to describe their navigation sequences in the VLE. These are described in the previous published paper of the author [31].

E. Attribute Extraction

This phase is the next step in the construction of the data sets for feature selection and data mining. Data extracted are based from the mapping of learning behaviors conducted in Table 2. Data transformation was performed in order to aggregate learner behavior values using SQL (structured query language) specifically as to the number of interaction a particular student interacts with the learning objects in a VLE. The results of the ILS answered by the students served as the class labels for their learning styles. An excerpt of data extracted can be seen in Figure 2 and full excerpts for each learning dimensions can be seen on reference [34].

No.	Student	forum_post	forum_view	self_assesment	text_materials	PROCESSING
1	ABUSTAN, BENELUZ	1	2	8	27	ACTIVE
2	ABUAN, SIDNEY JANE	11	6	3	0	REFLECTIVE
3	ABULAR, MA. FREDA MAE	21	10	7	29	ACTIVE
4	ABULENCIA, APPLE GEM	9	2	8	1	ACTIVE
5	ABUSTAN, AUDREY CASSIE	4	3	8	17	ACTIVE
6	ACERO, CHANTREA FELICHE	15	11	0	14	ACTIVE

Fig.2 Processing dimension dataset (excerpt)

F. Variable Subset Selection

Before patterns can be discovered using appropriate data mining techniques, feature selection is necessary to identify the fittest and best attributes for the classification of learning styles. Information Gain attribute (Filtering method) was selected to quantitatively confirm the performances of each predictor as can be seen in Table 3

Table 3: Variable Subset Selection Results

Information Gain Attribute Evaluation		
Processing Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
forum_view	0.449	yes
self_assessment	0.338	yes
forum_posts	0.267	yes
textual_materials	0	no
Perception Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
concrete_materials	0.353	yes
exercises_rev	0.241	yes
examples	0.107	yes
abstract_materials	0.093	yes
Input Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
video_materials	0.382	yes
visual_materials	0.269	yes
forum_posts	0	no
textual_materials	0	no
Understanding Dimension Attributes	**Rank Value**	**Significant? (yes/no)**
course_overview	0.285	yes
nav_pattern_dist	0.039	yes

The results of feature selection confirmed that out of the fourteen (14) extracted attributes only eleven (11) attributes are contributing to the classification of learning styles. This procedure can significantly improve the performance of data mining and its computational cost-effectiveness.

G. Knowledge Discovery and Evaluation

Various classification (supervised learning) algorithms were tested on the final data set to empirically select the best model for the classification of learning styles such as Simple Logistic, Naïve Bayes, Conjunctive Rule and J48 decision tree.

The results of their accuracy were compared with each other and evaluation efficiency was also carried out using the Receiver Operating Characteristics (ROC) and Area under the curve (AUC) plots to support the final selection of the model for the development of a prototype system. As can be seen in Table 4, the traditional academic point system served as a reference for defining the model's classification consistency.

Table 4: Traditional Academic Point System

Range	Description
.90 – 1.00	Excellent
.80 - .90	Good
0.70 – 0.80	Fair
.60 - .70	Poor
.50 - .60	Fail

IV. RESULTS AND DISCUSSION

Comparative performance results of various classification algorithms were carried out and the J48 decision tree classifier gained the highest accuracies of 92% for the processing dimension, 88% for the perception dimension, 86% for the input dimension and 82% for the understanding dimension. The J48 decision tree having high accuracies in classification across all learning style dimensions totally outperforms the other classification algorithms. All training and testing evaluation was done using a stratified 10-fold cross validation. Details of the classification results are shown in Table 4.

Table 4: Comparative Classification Results

Processing Dimension (Active/Reflective)				
	Simple Logistic	Naïve Bayes	Conjunctive Rule	J48
Correctly Classified Instances	85.99%	89.34%	75.14%	**92.50%**
Incorrectly Classified Instances	14.01%	10.65%	24.85%	7.49%
Kappa Statistics	0.719	0.786	0.497	0.849
Perception Dimension (Sensing/Intuitive)				
	Simple Logistic	Naïve Bayes	Conjunctive Rule	J48
Correctly Classified Instances	81.65%	82.24%	68.63%	**88.16%**
Incorrectly Classified Instances	18.34%	17.75%	31.36%	11.83%
Kappa Statistics	0.550	0.586	0	0.699
Input Dimension (Visual/Verbal)				
	Simple Logistic	Naïve Bayes	Conjunctive Rule	J48
Correctly Classified Instances	85.79%	85.99%	76.52%	**86.58%**
Incorrectly Classified Instances	14.20%	14.00%	23.47%	13.41%
Kappa Statistics	0.582	0.634	0	0.677
Understanding Dimension (Sequential/Global)				
	Simple Logistic	Naïve Bayes	Conjunctive Rule	J48
Correctly Classified Instances	80.27%	74.95%	81.26%	**82.44%**
Incorrectly Classified Instances	19.72%	25.04%	18.73%	17.55%
Kappa Statistics	0.605	0.500	0.624	0.647

Four (4) ROC curves were simulated to further check the consistency of the J48 decision tree classification accuracy, as can be seen in Figures 3, 4, 5 and 6. The curve plots indicated that there is significant precision in classification as the curves showed that it did not slip below the 0.5 guessing line, hence it suggested the classification is not random and did not happen in any way by chance only. Values obtained from AUC plots are 0.91 (excellent), 0.83 (good), 0.90 (excellent) and 0.81 (good) for the processing, perception, input and understanding dimensions respectively.

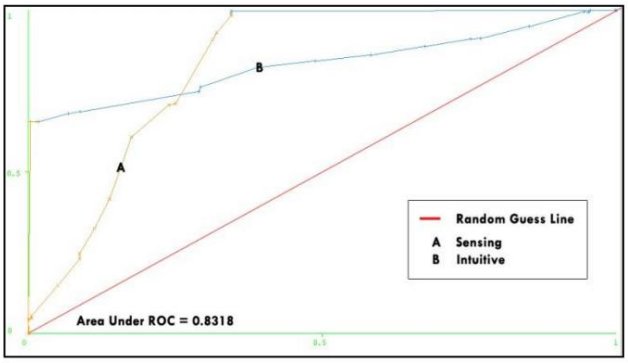

Fig. 3 ROC and AUC plot (processing dimension)

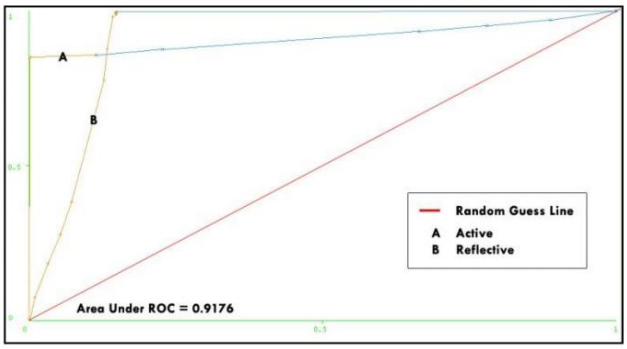

Fig. 4 ROC and AUC plot (perception dimension)

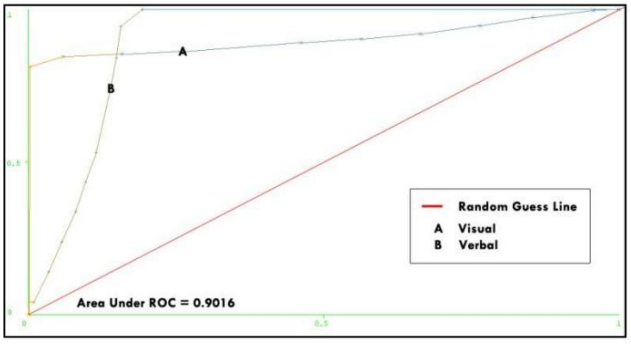

Fig. 5 ROC and AUC plot (input dimension)

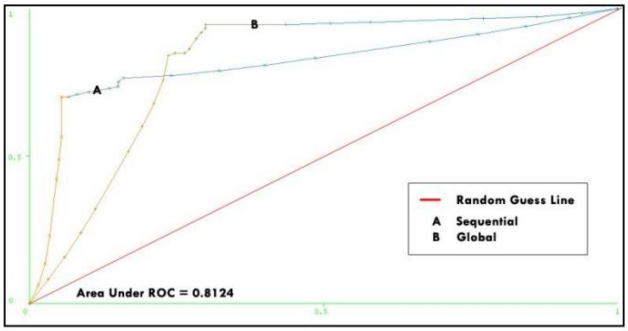

Fig. 6 ROC and AUC plot (understanding dimension)

With the result of accuracy and classification quality established, the rules derived from the J48 decision tree (see Appendix A) can serve as the basis for an automated or data driven adaptation strategy for content aware adaptation of a virtual learning environment. The system architecture is discussed in detail in the next section.

System Architecture

The system architecture of the adaptive virtual learning environment is shown in this section and each component of the system is described. The system's infrastructure design consists of five (5) major central components, as shown in Figure 7. The figure demonstrates the key components and subcomponents, as well as each description of their characteristics and interaction among them.

A. Learner Model

One of the most challenging and important questions in an adaptive virtual learning environment is how a particular system can provide a rich representation of the learner. This component provides reliable information and makes a representation of a particular learner. Information considered in this component includes their user identification, personal name and the preferred type of educational or learning objects. This component changes dynamically as each learner progresses in their course. The content object module is the representation of concepts to learn, these are the available resources to the learners and how elements are structured. It is composed of two parts: content repository and metadata. The content repository contains resources that deal with domain concepts. These resources can be presented as a course overview, definition, tests, examples, simulation, forum, and varieties of learning objects. Each of these resources can be presented in various formats such as text, image, video and animation. The metadata part stores information that tags a resource that has been created as to what it truly represents such as an abstract learning material, concrete learning material, self-assessment test, example and exercises.

B. Learner Log Data

The main role of the learning log data is to record all the interaction between the learner and the VLE. These recorded interaction logs are crucial in classifying each learner on their preferred learning styles and all information recorded in this component will be directly fed to the learner model engine for processing.

C. Learner Model Engine

The primary role of this component is to process and derive relevant user behavior of the learner, to aggregate needed values to identify their preferred learning objects based from the learner log data. On this particular component, the result of their derived learning behavior works in conjunction with the decision model that are composed of rule sets (J48 rules, see Appendix A) to classify each learner to the four learning style dimension of the Felder-Silverman Learning style model. Finally, it permits to update the dynamic part of the learner model.

D. Content Adaptation Engine

This specific component produces individualized content based on the learner model of each learner. It allows providing similar content, additional content, and alternating or hiding contents. It allows searching learning objects from the content object's content repository based on their metadata then it filters out the preferred learning objects and matches it based from the learning styles derived from the learner model. Finally, the learning object assembly organizes and brings these learning objects that will be transferred later to the design adaptation engine.

E. Design Adaptation Engine

By combining the filtered learning object information with the style sheets (cascading style sheets) for the presentation of the course design and content, the course design and content can be adapted to the specific needs of each learner. Each learning styles has its own course design template and the new adapted course design is then shown to the learner.

F. Visualization Reports

The all-important interaction of users with the VLE through its interface results in large amounts of data that can be visualized for the expert's usage. The visualization reports generated from the system is a part of the system that can be used by the teachers or experts in order to have more in depth understanding of the learners by understanding their learning process.

Adaption Features

The study not only provided a model for adaptation strategy in a VLE but extends to offer a novel system architectural design as well. A prototype of an adaptive virtual learning environment was also developed. An adaptive system that is able to provide content information in a way that adapts to different classified or identified learning styles. Adaptation features were created so that course design and contents can change for each learner with different learning styles. Such revolutionary features are focused on the types of learning objects displayed and their availability to be flexibly presented in different context. With reference to [10], "adaptation features are distinguished into two groups, namely adaptive content presentation and adaptive navigation support". Adaptive navigation support provides the re-organization of links including its placement and sequence of arrangements. On the other hand, adaptive presentations are features based on the dynamic and flexible supplementation of additional or the removal of contents to learning objects.

With respect to the Felder-Silverman learning style model, it states that active learner's preferences when it comes to their particular learning style is that they are more effective when they try things out and they learn best interacting with others. It is far better to design the navigation so as to present self-assessment test at the beginning of each chapters for active learners which is the complete opposite for reflective learners who learn much better by reflecting and thinking things through. Therefore, a decreased in self-assessment tests is recommended for this kinds of learners. Moreover, active learners can learn effectively if navigation wise, a link to a forum where he can interact with other learners is highly advisable. Navigational adaptation of the prototype system is shown in Figure 8. Sensing learners in terms of perception learn best and tends to visit learning materials with content of facts, data and whenever the context of the learning material is linked to real life occurrences or situations while intuitive learners prefers and learn best with learning object with contents of theories, definitions, concepts and abstracts. Therefore, content wise, these kinds of learning materials should be provided to them. Content adaptation is shown in Figure 9.

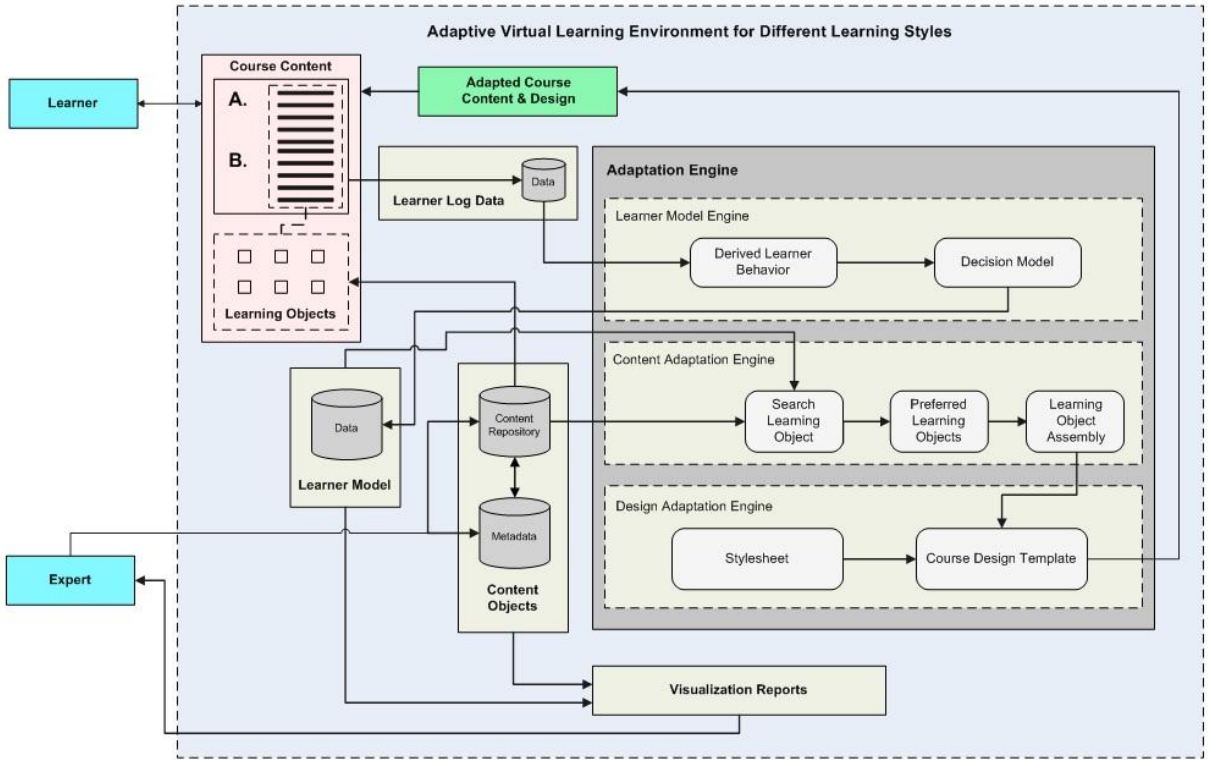

Fig. 7 System Architecture of an Adaptive VLE

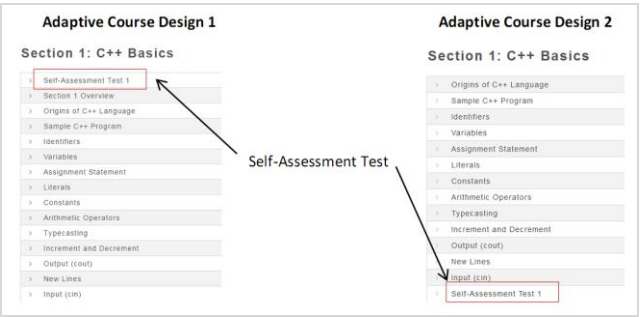

Fig. 8 Self-Assessment Test placements for Active and Reflective Learners

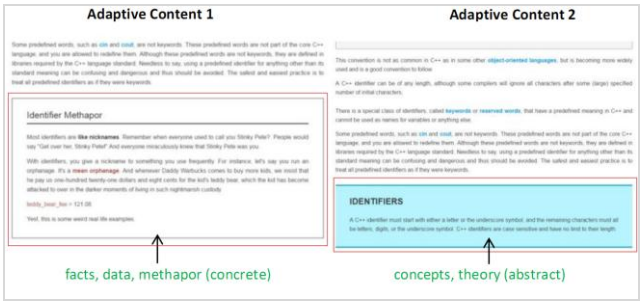

Fig. 9 Learning Content Adaptations for Sensing and Intuitive Learners

Visual Learners prefer representational graphics such as pictures, charts and videos to name a few. Therefore, supplementing learning object contents adaptively with graphical content is highly recommended while for verbal learners supplementing or reduction in graphical content is advisable. Since verbal learner's strength lies in reflecting on the contents and focusing on explanations, supplementing their learning objects with audio recordings are suggested. Supplementation and removal strategy are shown in Figure 10.

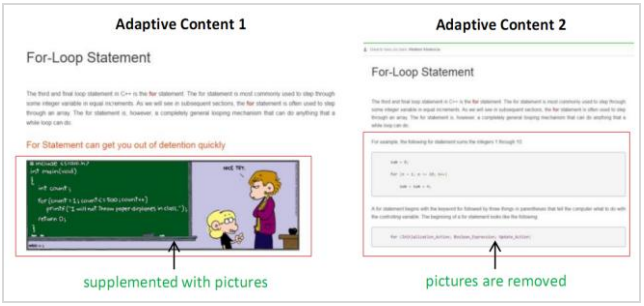

Fig. 10 Learning Content Adaptations for Visual and Verbal Learners

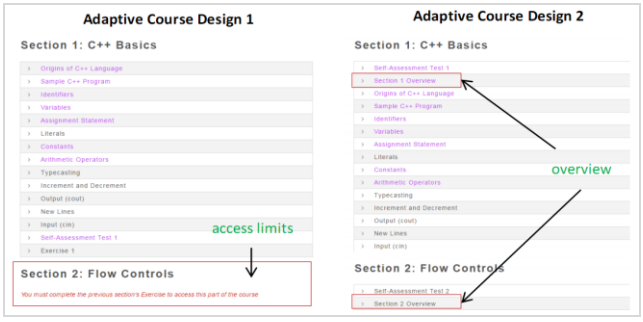

Fig. 11 Learning Object Access Limits of Sequential and Global Learners

Finally, sequential learners learn in a pre-defined sequential learning path with gradual increase in complexity on the learning materials. They learn in a defined progressions; adaptation strategy navigation wise is to limit access to learning objects in order for them to acquire pre-requisite knowledge in order to learn effectively. In contrast, global

learners tends to learn in large gaps and they are weak against having partial knowledge. It is important for them to have a grasps of the overall picture first. Therefore, navigation wise the limits to accessing advanced complex learning materials is removed and the presence of chapter overviews at the beginning of each chapters is highly recommended for them. This is exhibited in Figure 11.

V. CONCLUSIONS AND RECOMMENDATIONS

Most VLE primarily focuses on aiding, supplementing and supporting teachers in creating, administration and managing e-learning courses. Most systems provide very little, or in most cases, no adaptation for learners. On the other hand, adaptive system support learners by providing course designs that specifically matches their needs and characteristics but these are rarely used in real practice due to their lack of support for teachers. This lacking adaptation features in most VLEs signifies a complete failure of this systems to ultimately serve their ultimate purpose.

An adaptive VLE platform has been built with the ability and flexibility to adapt to different learning styles based on the Felder-Silverman learning style model using data driven approach (data mining) to answer these problems regarding e-learning systems.

To fully undertake the adaptation regarding learning styles in a virtual learning environment, learner's learning styles must be understood in the first place. Hence, an automated learner modeling method for classifying learner types was discovered in the context of the study.

Within the realms of this study, a framework and architecture of an adaptive VLE was presented. By creating an adaptive VLE, teachers can continue holding courses with adaptation by leveraging the advantages of e-learning systems. On the other hand, learners are supported in learning by being provided with course design and contents that fit their respective learning styles.

Further studies are required to improve the adaptation strategy and features of the developed prototype as it does not consider the degrees (levels and intensities) of preferences of a student towards a particular learning object and the developed prototype should be experimentally tested in order to empirically assess the impacts of the developed adaptive virtual learning environment prototype on student's academic performance.

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APPENDIX

A. Classification Rules extracted from J48 Classification Model

PROCESSING DIMENSION		
Rules	**Active/Reflective**	**Instances**
IF (self_assessment) > 3	Active	129
IF (self_assessment) <= 3 , AND (forum_post) > 14	Active	52
IF (self_assessment) <= 3 , AND (forum_post) <= 14, AND (forum_view) <= 4	Reflective	26
IF (self_assessment) <= 3 , AND (forum_post) <= 14, AND (forum_view) > 4	Reflective	300/37
Summary: Number of Leaves: 4, Size of the Tree: 7		
PERCEPTION DIMENSION		
Rules	**Sensing/Intuitive**	**Instances**
IF (exercises_rev) > 12	Intuitive	59
IF (exercises_rev) <= 12, AND (concrete_materials) <= 4	Intuitive	24
IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) > 14	Intuitive	19
IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) > 4	Sensing	345/42
IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) <= 2	Intuitive	6
IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) > 2, AND (concrete_materials) > 6	Sensing	49/5
IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) > 2, AND (concrete_materials) <= 6	Intuitive	5/1
Summary: Number of Leaves: 7, Size of the Tree: 13		
INPUT DIMENSION		
Rules	**Visual/Verbal**	**Instances**
IF (video_materials) > 12	Visual	235
IF (video_materials) <= 12, AND (visual_materials) > 13	Visual	87
IF (video_materials) <= 12, AND (visual_materials) <= 13	Verbal	185/66
Summary: Number of Leaves: 3, Size of the Tree: 5		
UNDERSTANDING DIMENSION		
Rules	**Sequential/Global**	**Instances**
IF (course_overviews) > 2	Global	275/59
IF (course_overviews) <= 2, AND (nav_pattern_distance) > 8	Global	42/15
IF (course_overviews) <= 2, AND (nav_pattern_distance) <= 8	Sequential	190/14
Summary: Number of Leaves: 3, Size of the Tree: 5		

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