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A Personalized Virtual Learning Environment Using Multiple Modeling Techniques

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***Abstract*—Student learning optimization is one of the main goals of education. A conventional e-learning system fails to accomplish its true purpose due to the lack or absence of personalization features. This paper presents an end-to-end approach for supporting students' diverse needs by classifying their learning styles in a virtual learning environment (VLE) and embedding the discovered knowledge in an adaptive e-learning system prototype. Furthermore, we validated different models' accuracies and comparative consistencies to manual methods using 704,592 interactions log data of 898 learners. Quantitative results show that the Support Vector Machine (SVM) achieves cross-validated accuracies of 88%, 86%, and 87% (processing, perception & input) of the Felder-Silverman Learning Style Model (FSLSM) and the Decision Tree (DT) for the understanding dimension with 86% accuracy.**

Keywords*—*adaptive learning environment, e-learning, learner modeling, machine learning, learning styles, personalization

I. Introduction

Virtual learning environments (VLE) are fundamental academic components of any modern higher education institution (HEI). It is the cornerstone of most e-learning implementations worldwide, positively affecting both learners and educators alike. Based on the global statistical reports, 77% of HEIs have included e-learning platforms in their curricula [1]. As the COVID-19 pandemic spreads, which resulted in school closures, an astounding 99% of educational institutions moved their classes online [2]. Conventional VLEs are successfully used on pure online courses or as a supplement to in-person instruction. However, these electronic mediums adhere to a rigid "one size fits all" approach by statically presenting the learning object's content and not adapting to an individual's needs. In this scenario, the user serves as a spectator, while learning continues to be a passive process controlled by others. Despite technological advancements, a traditional and centrally administered digital environment is reproduced [3].

In recent years, educational technology researchers have increased interest in adaptive or personalized e-learning systems. The principal goal of the dynamic solution is to customize the learning experience through differentiated instruction for each student. These systems, which emphasize "adaptive learning personalization", are expected to identify the optimal course content based on individual characteristics, cognitive capacities, and other criteria [4 – 6]. Hence, providing a meaningful and richer experience for the learners. Most adaptive mechanisms remained dependent on the person's existing knowledge via diagnostic evaluations as the primary procedure for adaptation [7]. While this is a critical feature of user modeling in general for adaptation strategy, it highlights profound limitations in the context of e-learning hypermedia. It does not address the underlying principal issue that students acquire knowledge in different ways. Each has distinct preferences on how they learn and interact with a given learning environment [8].

Researcher [9] conducted a comprehensive systematic assessment of the literature to ascertain the various methods for recognizing students' traits in a virtual learning environment. According to their research, 44.87% used learning styles. Most frequently, the Felder-Silverman model because it is the most appropriate with VLEs [10]. Their research found that the most often applied methodologies for trait identifications are questionnaires, computer-based recognition, and a combination of the two. Adaptation through a single questionnaire has a significant disadvantage over computer-assisted detection, as personal characteristics vary over time in response to the learning scenarios. Moreover, lengthy questionnaires take a significant amount of time to complete, reducing students' motivation leading to inaccurate results [11] [12]. A machine learning data-driven approach based on students' interaction log data in a VLE is deemed accurate because it responds instantly to variations in the learner's preferences and tendencies through sophisticated algorithms such as classification, clustering, and reinforcement learning [13] [14].

Numerous academic and research institutions are investigating individualized learning environments. Prior research has highlighted the complete implementation as a considerable challenge to the solutions proposed. Although [15 - 17] discusses promising principles for personalization from an educational perspective, a unified and comprehensive resolution (data acquisition, learner modeling, and adaptation mechanism) is still needed, as most publications reported incomplete or missing prototype implementations. Additionally, the instructional model can be further developed to incorporate both diverse learning sequences and learning styles.

Existing VLEs such as Moodle and Blackboard hold large amounts of data that analytics professionals can use as evidence for personalized learning, providing indispensable input for the adaptation mechanism. Numerous research articles [18 - 20] focus exclusively on algorithmic advancements to produce accurate models but not on their

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application at the system level. Different firms made multiple attempts to build adaptive VLEs. Among these is Knewton's *Alta* [21], a platform that purports to deliver dynamic and programmed personalization of students' learning paths based on their exam scores. It is customized to fit the student's learning goals by measuring their knowledge gaps and recommending supplemental resources. However, they are unwilling to share their user data modeling methods due to their commercial and proprietary nature. Rule-based systems such as *Desire2Learn* and *SmartSparrow* possessed critical weaknesses in terms of reliable intelligence. Fundamentally, rules do not scale efficiently. They logically grow in complexity as "rules explosion" occurs - leading to complicated, conflicting, and overlapping rules [22]. Furthermore, it is poor in dealing with partial or inaccurate data. It means that they are deficient in interpreting unforeseeable conditions. The initiatives cited in adaptability have a commonality. All are generally associated with evaluating students' performance to redirect their learning paths in the course appropriately. A more inclusive strategy must address the importance of learning styles while developing proficient adaptive VLEs [23].

Learning styles (LS) refer to students' malleable preferences for absorbing knowledge and responding to a learning environment. Each learner has varied LS and acquires knowledge differently from one another. Well-known educators and psychologists meticulously studied their direct influence on the learning process. Although experts continue to question their existence, various studies have demonstrated their beneficial effects on students' performance, satisfaction, and engagement [24]. There is sufficient proof that students learn best when the methods or material are tailored to their learning styles [25]. The works of [26 – 28] captured the features of a learner in a virtual learning environment through traditional questionnaires and dynamic detection using machine learning algorithms. Still, most research has focused mainly on improving the accuracy of prediction rather than its prototypical implementations.

According to our literature review, no research exists on combining learning styles and their system implementation. The decisive contribution of this work is the development of an e-learning system that integrates multiple machine learning algorithms for learner characterization and a framework of an adaptive VLE. This research will benefit educators at any level with an innovative instructional approach that caters to different learners' characteristics and needs.

II. METHODOLOGY

A. Learner Modeling

Figure 1 summarizes the steps taken to classify the learner's learning style. At the start of the course, students were requested and given adequate time to complete the learning styles questionnaires. Next, they started a Moodle course, specifically tweaked and modified to recognize multiple learner characteristics. Their log activity is collected, processed, and cleaned to train and test different classification algorithms.

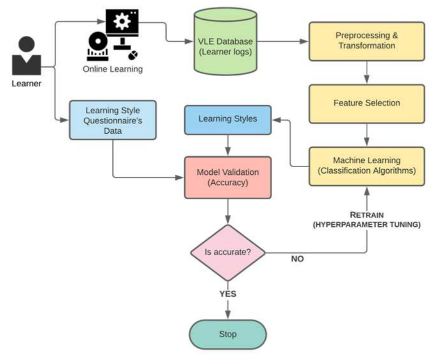

Fig. 1. Learner modeling methodology

B. Course Description and Log Data

A Moodle course in Programming (C++) at a state-funded university in the Philippines laid the groundwork for the research. The curriculum contains eighty-six (86) crafted learning objects organized into six (6) chapters. It included a range of activities such as self-assessment exams, exercises, simulations, and other elements to acquire coding skills. In addition, it incorporates a class forum, allowing users to discuss and collaborate on solving problems. The course was handpicked because it had the highest enrollment of 1028 students and the most active based on 989,872 recorded interaction logs spanning eight years (2012 – 2019). To avoid bias, we placed equal amounts of learning materials (e.g., visual & textual, concrete & abstract). We also removed data from 34 students who dropped out of the course to avoid possible outliers.

C. Learning Style Model

Distinct learning style theories have been explored thoroughly for most of history. For technology-enhanced education such as VLEs, the Felder-Silverman learning style model (FSLSM) is widely used [29]. It offers a comprehensive description of a person's learning style, distinguishing amongst preferences on four categories, contrasting existing models that categorize learners in only a few groups. These aspects can be independently interpreted and reflect how learners like to process, perceive, receive (input), and understand information (see Figure 2). The Index of Learning Style (ILS) questionnaire identifies learner traits predicated on the FSLSM.

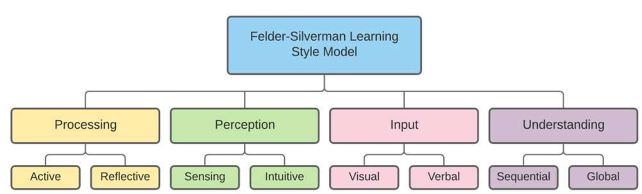

Fig. 2. Felder-Silverman learning style model's dimensions

Active learners prefer to digest information through applications. The most striking characteristic of an active learner is a propensity for discussion and interaction with other learners. Moreover, they complete self-assessment examinations, a form of test that is not rated. Reflective learners, on the other side, like to mull over the learning content and work individually. Active learners post more frequently to a forum on a VLE, whereas reflective learners are passive, primarily viewing but rarely participating. The reflective learner's disposition to reflect on the information leads to higher visits to learning materials that are textual.

Sensing learners frequently explore concrete learning resources containing facts and data, primarily when a learning item is associated with a real-world context. The opposite goes for intuitive learners who prefer abstract educational materials, including theories, glossaries, syntax, and concepts. In addition, they are meticulous students who like to re-examine their answers thoroughly when completing a graded test. The pattern is correlated from the number of attempted answer changes they conducted before submitting their final responses to graded assessments.

Visual learners get the most information from what they see. They view more learning objects that contain graphics such as videos, pictures, diagrams, and charts. Accordingly, the verbal learner's preference for an educational source is composed mainly of texts. They are also inclined to use the forum, and hence a high quantity of postings implies a verbal learning style.

Sequential learners are more at ease with details, while global learners are adept at holistic thinking. Because of this tendency, global learners are interested in obtaining the "whole picture". They place a premium on course summaries, whereas sequential learners frequently disregard these types of learning elements. A high rate of views to course page overviews and summaries indicates a global learning style. While sequential learners progress logically in linear steps to absorb information in small pieces, global learners frequently skip learning items in significant gaps in favor of mastering details. Therefore, the way students navigate a course is a conspicuous sign of their differences.

D. Feature Mapping

Table 1 depicts the mapping of students' extracted data from the VLE's database and log files following the chosen learning style model description detailed in the previous sections.

TABLE 1
STUDENTS' ATTRIBUTES BASED ON FSLSM

Learning Styles	Relevant Behavior	Value
Active	Posting in assigned class forums (f_post)	Total posts
	Completed self-assessment tests (c_asse)	Total completed assessments
Reflective	Viewing forum posts (v_post)	Total forum posts views
	Viewing textual learning objects (v_text)	Total visits
Sensing	Viewing concrete learning objects (v_conc)	Total visits
	Viewing examples (v_sample)	Total visits
Intuitive	Viewing abstract learning objects (v_abst)	Total visits
	Reviewing answers in graded tests (r_answ)	Total number of answer changes
Visual	Viewing learning objects with video & pictures (v_visu)	Total visits
Verbal	Viewing textual learning objects (v_text)	Total visits
Sequential	Navigating through the course step by step (n_sequ)	Sequence of navigational pattern
Global	Viewing overviews, outlines & summaries (v_over)	Total visits
	Navigating through the course by skipping learning materials (n_sequ)	Sequence of navigational pattern

E. Data Extraction, Preprocessing and Transformation

The data extraction was a representation of the students' learning styles corresponding to Table 1. We preprocessed the data by combining values for learner characteristics using a structured query language (SQL), more precisely, the number of interactions with a learning resource in a VLE. Each visit count (see Table 1) applies only if the learner spent at least 30 seconds on the material. By placing this rule, we avoid a learner opening links randomly without theoretically reading the material. This rule also applies to viewing forum posts (opening a thread & replies) and navigational sequences. The ILS tests at the beginning of the course represent their target classes for their diverse learning styles. We purposely removed 96 learner data to create a realistic and non-synthetic fairly balanced dataset to ensure that models are trained consistently across all classes. Table 2 shows the distribution of their learning styles based on the questionnaires.

TABLE 2
LEARNING STYLES DISTRIBUTION (N = 898)

Dimension	Category	No. of Students	Percentage
Processing	Active	437	48.66%
	Reflective	461	51.33%
Perception	Sensing	465	51.78%
	Intuitive	433	48.21%
Input	Visual	462	51.44%
	Verbal	436	48.55%
Understanding	Sequential	447	49.77%
	Global	451	50.22%

Figure 3 and Figure 4 depict the excerpts of the datasets. We applied a normalization transformation (*min-max scaling*) to scale the data by handling varying magnitudes to avoid over or under-fitting models.

student no.	f_post	v_post	c_asse	v_text	PROCESSING
22	7	9	3	9	REFLECTIVE
23	23	4	0	33	ACTIVE
24	4	11	2	32	REFLECTIVE
25	21	6	3	6	ACTIVE
26	1	16	2	2	REFLECTIVE

Fig. 3. Excerpt of dataset for processing dimension

student no.	v_conc	v_abst	v_sample	r_answ	PERCEPTION
184	5	7	9	13	INTUITIVE
185	17	8	10	10	SENSING
186	13	12	3	4	SENSING
187	14	5	7	9	SENSING
188	2	11	3	11	INTUITIVE

Fig. 4. Excerpt of dataset for perception dimension

F. Navigational Sequences Categorization

An additional modeling technique was required to extract values for the understanding dimension, which pertains to learners' navigational patterns (see Table 1). We utilized a coefficient of determination (R^2 or r-squared), a statistical measure that determines the proportion of variances between variables. In simple words, it indicates the degree to which the data fits a regression line. The reality is that no student will access learning materials in perfect sequence orders.

Thus, a threshold is necessary. Based on scales, a strong positive linear association R^2 value of greater than or equal to 0.85 indicates strong linearity, while a value less than 0.85 suggests weak linearity [30]. Figure 5 demonstrates a sample of students' navigational behavior in the course and our categorization.

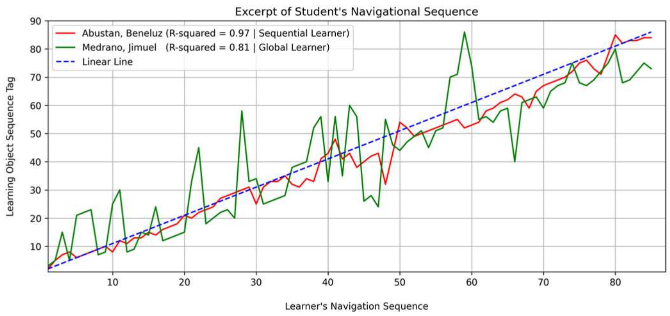

Fig. 5. Example of learners' navigational sequence pattern

G. *Feature Selection*

Dimensionality reduction effectively removes noisy and irrelevant data while boosting accuracy and decreasing calculation time. Since the data is non-complex for each learning domain category, we implemented a filter method of information gain [31] to determine the most valuable features for classification. Table 3 shows the rank and significance of each attribute.

TABLE 3
ATTRIBUTE SUBSET SELECTION RESULTS

Information Gain		
Dimensions	**Entropy Value**	**Selected?**
Processing		
c_asse	0.425	yes
f_post	0.331	yes
v_post	0.273	yes
v_text	0	no
Perception		
v_conc	0.363	yes
v_abst	0.316	yes
v_sample	0.224	yes
r_answ	0.217	yes
Input		
v_visu	0.392	yes
v_text	0.254	yes
Understanding		
n_sequ	0.417	yes
v_over	0.329	yes

The feature selection findings indicated that only 11 of the 12 identified attributes contribute to the predictions. While only one feature was discarded, this often overlooked procedure can considerably enhance the computational cost-effectiveness of any model.

H. *Classification Models and Hyperparameter Tuning*

With the reduced final dataset constructed, we subjected the data to various classification algorithms. For benchmarked comparisons such as Support Vector Machines (SVM), Naïve Bayes, K-Nearest Neighbor (KNN), Logistic Regression (LogReg), and Decision Trees (DT) using 70/30 training and testing split. We run each classifier on *Python* language with the *sklearn* library package. Hyperparameters' manual configuration for each model is an extensive and time-consuming task. We resolved the dilemma using a GridSearch technique to observe accuracy changes with automatic tuning.

I. *Model Evaluation Metrics*

Metrics quantify the accuracy and quality of predictions made by the machine learning algorithms. Accuracy, precision, recall, F1-Score (harmonic mean of precision & recall), cross-validated accuracy scores, receiver operating characteristics (ROC), and area under the curve (AUC) are the most often used metrics. AUC values between 0.70 and 1 indicate that a classification model can generalize unseen data. Table 4 presents a popular scale for assessing the quality of classification using AUC. Furthermore, the study measures the consistency of prediction by machine learning approaches against the ILS questionnaire results for each student. In this way, this will verify the machine learning's validity in concluding learning styles.

TABLE 4
TRADITIONAL ACADEMIC POINT SYSTEM

Range	Description
0.91 – 1.00	Excellent
0.81 – 0.90	Good
0.71 – 0.80	Fair
0.61 – 0.70	Poor
0.50 – 0.60	Fail

III. RESULTS

This section analyzes and evaluates the classification algorithms' metric evaluations. The following subsections also detail the results of each model's generalization capabilities and its consistency tests.

A. *Comparative Accuracy Scores*

Table 5 shows that the SVM outperforms other algorithms with an accuracy of 89.78% (processing). In terms of perception, the Decision Tree excels with a score of 90.17%. The highest accuracy for the input dimension was ascertained using Naïve Bayes at 91.85%. Finally, the results for the understanding dimension using Logistic Regression yield an accuracy of 90.65%.

B. *Cross-Validated Scores*

The accuracy variations across dimensions compel the researchers to conduct cross-validation. It is the recommended method for measuring the robustness of classification algorithms since it allows the model to train on multiple train-test splits. We performed 10-fold cross-validation of accuracy scores to gauge better the model's capability to handle unseen data. Table 6 demonstrates the SVM's superiority to other classification approaches with accuracies of 88% (processing), 86% (perception), and 87% (input) except for the understanding dimension wherein the LogReg obtained 87%. Since LogReg is prone to over fitting, we opted to use Decision Trees (86%) instead for the understanding dimension as there is only a 1% accuracy score difference.

C. *ROC and AUC Plots*

We further evaluate the classification quality of each model by generating curve plots. This is substantiated by Figure 6, where the ROC curves of the SVM were significantly above the random prediction line, indicating a non-random prediction with AUC scores of 0.912, 9.24, and 0.918, rated as "excellent". SVMs are recognized for their real-time and dynamic classification due to their high threshold to under or over fitting [32].

TABLE 5

SUMMARY OF CLASSIFICATION METRICS FOR DIFFERENT DIMENSIONS OF FSLSM (TEST DATA = 269)

Processing Dimension

Classifier	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	**89.78%**	89%	88%	88%
Naïve Bayes	86.72%	86%	85%	85%
K-Nearest Neighbor	79.63%	79%	80%	79%
Logistic Regression	81.82%	81%	81%	81%
Decision Trees	83.45%	82%	83%	82%

Perception Dimension

Classifier	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	88.33%	84%	85%	84%
Naïve Bayes	85.89%	86%	86%	86%
K-Nearest Neighbor	75.38%	75%	73%	74%
Logistic Regression	78.85%	77%	78%	77%
Decision Trees	**90.17%**	90%	89%	89%

Input Dimension

Classifier	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	88.48%	87%	86%	87%
Naïve Bayes	**91.85%**	92%	91%	91%
K-Nearest Neighbor	79.83%	79%	79%	79%
Logistic Regression	82.72%	83%	82%	82%
Decision Trees	85.83%	85%	85%	85%

Understanding Dimension

Classifier	Accuracy	Precision	Recall	F1-Score
Support Vector Machine	84.67%	85%	84%	84%
Naïve Bayes	87.38%	86%	85%	85%
K-Nearest Neighbor	77.31%	78%	77%	77%
Logistic Regression	**90.65%**	91%	90%	90%
Decision Trees	89.33%	88%	88%	88%

TABLE 6

10-FOLD CROSS-VALIDATED SCORES FOR EACH DIMENSION

Classifier	Dimensions			
	Processing	Perception	Input	Understanding
Support Vector Machine	**88%**	**86%**	**87%**	84%
Naïve Bayes	85%	84%	84%	83%
K-Nearest Neighbor	76%	74%	74%	73%
Logistic Regression	77%	75%	75%	**87%**
Decision Trees	80%	84%	84%	86%

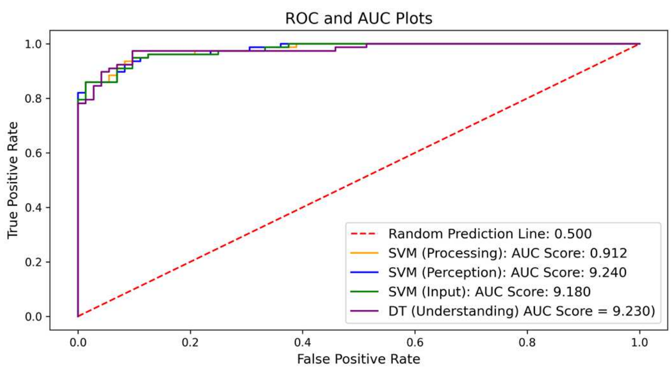

Fig. 6. ROC and AUC plots of selected classifiers

D. *Comparative Consistency Tests*

Table 7 summarizes the percentage consistency of the FSLSM's ILS questionnaire against the machine learning classification for 250 randomly selected students. This test adds to a models' validation verification. It shows that the percentage consistency varies from 82% to 88%. We observed the lowest mean consistency in the perception dimension with 84.49%. On the other side, the processing dimension got the highest mean rate of 85.97%. Nonetheless, most calculated consistency values are acceptable.

TABLE 7

MACHINE PREDICTION AND QUESTIONNAIRE RESULT CONSISTENCY

Dimension	Dimensions			
	Learning Style	ILS	Machine	% Consistency
Processing	Active	129	112	86.82%
	Reflective	121	103	85.12%
Perception	Sensing	142	118	83.80%
	Intuitive	108	92	85.18%
Input	Visual	163	145	88.95%
	Verbal	87	72	82.75%
Understanding	Sequential	108	93	86.11%
	Global	142	121	85.21%

IV. SYSTEM ARCHITECTURE OF AN ADAPTIVE VLE

This study separates itself from previous research articles by presenting learner modeling approaches and a system-level implementation of an adaptive VLE. Figure 7 illustrates the architecture of our system and its descriptions.

A. *Learner Model Data*

This component calculates a learner's preferences in the virtual environment based on machine learning algorithms. It is dynamic and changes as each user proceeds through the course. The content object module represents the information to be learned which contains the available learning resources and their structures. The content objects repository pertains to the different learning objects (e.g., test, examples, forum, etc.) while the metadata stores the learning objects' tag for categorization (e.g., visual, abstract, concrete, etc.).

B. *Learner Log Data*

This segment gathers data for the learner modeler module. The primary function of the learner log storage is to keep track of all interactions between the learner and the VLE. These records are crucial for categorizing students according to their learning preferences.

C. *Learner Modeler Module*

The component's significant role is to process and extract relevant user behavior, calculate (aggregate) necessary values, and determine the learner's preferred learning resources from the learner log data. Regarding this specific component, the generated outcome of learning styles is used following the result of the classification model connected to a Python API for seamless integration of machine learning algorithms in the system.

D. *Content Adaptation Module*

For each learner, this component produces personalized content that is adapted to their learning styles. Additional resources can be provided through hiding and showing learning contents. Metadata is used to search for learning objects in the content repository, and then the elected objects are matched to the learner model's learning style preferences. As the last step, the learning object assembler organizes and pulls together these resources utilized in the design adaptation module.

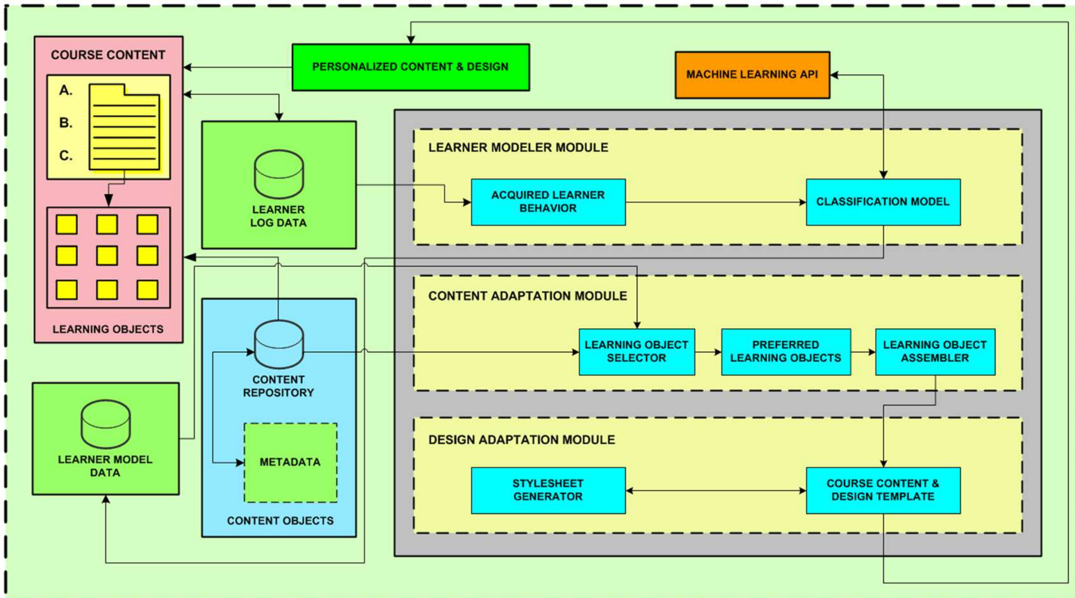

Fig. 7. System architecture of an adaptive virtual learning environment

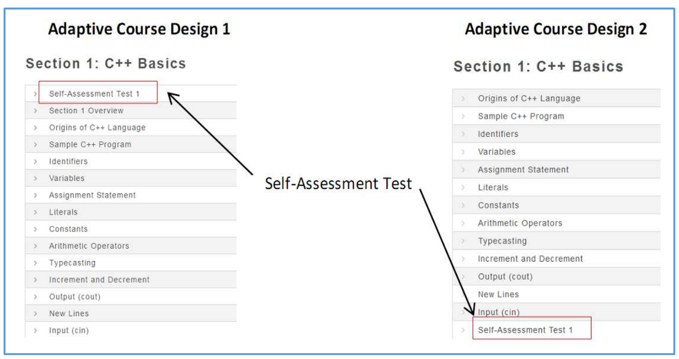

Fig. 8. Course navigation personalization (active vs. reflective)

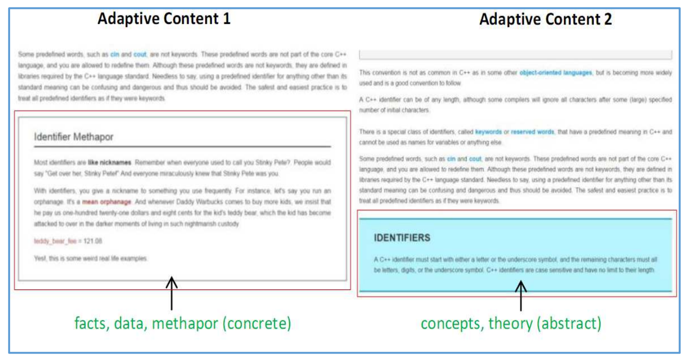

Fig. 9. Course content personalization (sensing vs. intuitive)

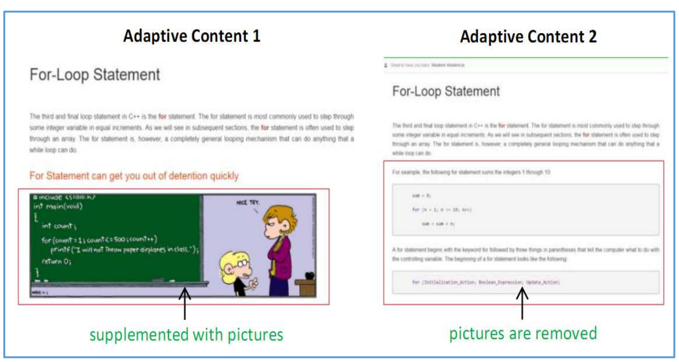

Fig. 10. Course content personalization (visual vs. verbal)

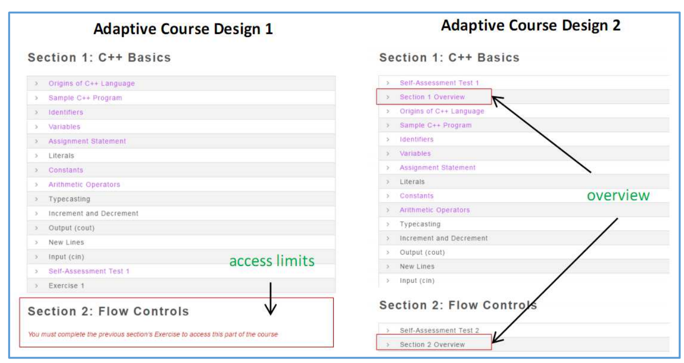

Fig. 11. Course navigation personalization (sequential vs. global)

E. Design Adaptation Module

A customized course design and contents are constructed based on the relevant information acquired from the two preceding modules (learner modeler & content adaptation). Each learning style has its specific design templates and configurations, subsequently used to display the personalized content back to the learner.

F. Adaptation Implementation

Reference [33] recommends that personalization in a VLE is categorized into two, presentation and navigational adaptation. The term adaptive "content presentation" refers to the systematic and responsive insertion or removal of a learning object's contents, either temporary or permanent. The concept of "adaptive navigation" refers to the process of structuring and rearrangements of hyperlinks, including their placements. In congruence to the FSLSM, active learners prefer to experiment, which is why we programed self-assessment tests at the start of each chapter. However, the opposite applies to reflective learners. Figure 8 demonstrates the adaptive differences. Sensing students benefit from adding facts (concrete) to the contents, whereas intuitive learners appreciate theories and concepts (abstract). A visual learner favors images, animation, and videos, while a reflective learner is an opposite. The addition and removal of these contents are highly recommended. Figure 9 and Figure 10 show the content adaptation for these kinds of learners. Sequential learners follow a linear path of learning as they grasp new information in defined progressions. In contrast, global learners learn in giant leaps as they are weak in partial knowledge. Therefore, we decided to place chapter overview links and restrict navigational access limits to differentiate the two. Figure 11 shows the adaptation. Although we made significant progress in programmed adaptation, the users can switch from the static or adaptive version of the course if they want to, as we promote the ethical concept of “graceful degradation” or non-authoritarian learning environments.

V. Discussions

This research reports that students possess different traits based on collected data from various sources. We extracted, processed, and analyzed 704,592 student interaction logs from a VLE spanning eight years to cater to this diversity. We then benchmarked multiple modeling techniques using machine learning algorithms to classify individual learning styles. The empirical results show that the Support Vector Machine exceeds other classification algorithms for FSLSM’s three dimensions, with cross-validated accuracies of 88% (processing), 86% (perception), and 87% (input), except for the understanding dimension where the Decision Tree yields 86% correctness. To further test the generalization capability of our classification, we compared our machine predictions against the manual questionnaire method. The consistency results show an acceptable mean of 85.49% across all learning style dimensions, proving the ILS questionnaires’ validity in unveiling learning styles. To fully realize e-learning personalization, learner modeling must first be understood. As embarkation from previously published researches on personalized learning [34 – 37], we further extend our undertaking by developing an adaptive VLE prototype focusing on learning styles based on sound system architecture. Our study is far from perfect as we cannot capture other learners’ tangible and intangible features because the reality is that learning can happen anytime, even outside the confines of a VLE.

VI. Conclusions and Future work

VLEs are prevalent and successfully implemented in most educational spheres, but it is built on the assumption that students are all the same. The role of the learner in these environments confines them to its default functions. Often, the content experience is identical for all users, irrespective of their distinct educational needs. Adaptive VLEs compared with existing conventional “static” e-learning systems provide new engagement levels necessary for the evolving and unique breed of learners. With breakthroughs in artificial intelligence, digital learning environments can be revolutionized into flexible learning spaces by handing over power to students with increased control over content and design. Within the context of this study, we discovered accurate machine learning models for classifying learning styles in a VLE and embedding the knowledge into a practical prototype. We firmly attest that this study has significant educational implications on the effects of adaptive e-learning on education as a whole. For future work, we plan to improve the learner modeling strategies by including other significant non-cognitive data such as grit and evaluate the impacts of the adaptive VLE in terms of students’ academic performance.

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A Personalized Virtual Learning Environment Using Multiple Modeling Techniques

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II. Methodology

III. Results

IV. System Architecture of an Adaptive VLE

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Student learning optimization is one of the main goals of education. A conventional e-learning system fails to accomplish its true purpose due to the lack or absence of personalization features. This paper presents an end-to-end approach for supporting students' diverse needs by classifying their learning styles in a virtual learning environment (VLE) and embedding the discovered knowledge in an adaptive e-learning system prototype. Furthermore, we validated different models' accuracies and comparative consistencies to manual methods using 704,592 interactions log data of 898 learners. Quantitative results show that the Support Vector Machine (SVM) achieves cross-validated accuracies of 88%, 86%, and 87% (processing, perception & input) of the Felder-Silverman Learning Style Model (FSLSM) and the Decision Tree (DT) for the understanding dimension with 86% accuracy.

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I. Introduction

Virtual learning environments (VLE) are fundamental academic components of any modern higher education institution (HEI). It is the cornerstone of most e-learning implementations worldwide, positively affecting both learners and educators alike. Based on the global statistical reports, 77% of HEIs have included e-learning platforms in their curricula [1]. As the COVID-19 pandemic spreads, which resulted in school closures, an astounding 99% of educational institutions moved their classes o

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A Personalized Virtual Learning Environment Using Multiple Modeling Techniques
Renato R. Maaliw III
2021 IEEE 12th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)

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