A model to detect student's learning styles in the blended learning course

A model to detect student's learning styles

This is the subtitle of the paper, this document both explains and embodies the submission format for authors using Word

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Recently, personalized learning is becoming more and more popular, especially in blended learning courses. The student learning style is one of several factors to personalize content and appropriate learning activities for each learner. This article proposes a model to detect learning styles in blended learning courses to classify learners for personalization. The proposed model focuses on two phases: the online and face-to-face learning phases of the learning process. Besides, we also present several parameters to map resources and activities in a blended-learning course to a learning style model. Based on the identified criteria, the experimental results with 205 students' data when classifying learning styles by the Support Vector Machine method give an accuracy of 76.7% - 83.2% in the 04 dimensions of the Felder and Silverman model. Experimental results when applying two approaches: literature-based and driven-based, show that learners' styles are similar up to 83%. Findings show that the student's learning style does not change much in the learning process. As for course design implications, we also propose suggestions for developing content and designing learning activities.

CCS CONCEPTS • Applied computing • Education • E-learning

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1 INTRODUCTION

Learning style has impacted one student's learning outcomes [1]. When participating in the course, each learner has a different approach to learning resources as well as learning activities such as discussions, assignments, tests, and assessments. Identifying students' learning styles will help instructors and course designers provide appropriate learning resources and learning activities for students. For each learner, identifying their learning style will help he/she to self-regulate in the acquisition of knowledge to the best achievement[2].

In the current period, under the impact of the epidemic, online courses and blended learning are widely used solutions to maintain unbroken learning activities. Blended learning courses use a combination of online and face-to-face learning. Therefore, it is necessary to combine different solutions to determine a learner's learning style. An emerged question that many researchers focus on solving is how to identify learning styles in both online and offline learning phases. In other words, it is to find out the set of factors that form the basis for identifying the learners' learning style.

In the online learning phase, learners learn content and participate in learning activities mainly through a Learning Management System (LMS). The learners' interactions with the course are stored in the log system. These activity logs are the basis for classifying each learner's learning style. It is often harder to collect information about the learner model in the offline learning phase. Moreover, the student's learning style has changed with online or offline forms of learning.

Several models have been proposed to detect the learning style of learners. These studies focus on many aspects of the learner model, thereby recommending different dimensions to measure and determine the student learning styles. Two current popular approaches in detecting learning styles are the literature-based approach [3], [4] and the driven-based approach [5], [6]. For the former approach, questionnaires have been used to collect student responses. The collected data are input data for pre-designed rule sets that detect learning styles. For the latter approach, machine learning, big data, and learning analytics techniques have been used to automate analysis data obtained during the learner's participation, which is the basis for detecting learning styles. These two approaches are suitable for detecting learning styles for offline or online courses. However, there have not been many results in selecting the criteria that are the basis for detecting learning styles and how to detect the student learning styles in blended learning courses.

In this article, we proposed factors to measure the student learning styles in the online as well offline learning phases of the blended learning course. Based on these factors, we proposed a model to detect the student learning styles.

The remaining content of the paper is organized as follows: In the next section, we will review some contributions of related studies, focusing on detecting learning styles according to the two approaches mentioned above. The research method and proposed model will be presented in section 3. Some initial results when testing the model will be presented in section 4. Then, we will discuss and implication some issues related to the design of appropriate content and learning activities. In the last section, we will summarize some of the results achieved and directions for research development in the coming time.

2 LITERATURE REVIEW

In this section, we summarize some research results achieved in the detect learning style based on literature-based and driven-based approaches. In addition, methods and techniques applied in detecting students' learning styles will introduce.

2.1 Learning Style Model

Determining the students' learning style aims to provide the most appropriate learning resources and activities for each learner for personalized learning according to learners' needs. Recently, popular learning style models have focused on the learner's model aspect. Fleming's VARK model [7] identifies the learning style of learners based on learners' interactions when participating in learning activities classified into four groups: Visual (V), Auditory (A), Reading/Writing (R), and Kinesthetic (K). This classification is based on the observation that learners will get better results as they learn with appropriate content for their inclination. The model proposed by Felder and Silverman determines the student's learning style in absorbing and processing information in the learning process. The model classifies learners according to the following criteria: Sensory versus Intuitive, Visual versus Verbal, Active versus Reactive, Sequential versus Global [8]. In addition, the experiential learning model proposed by Klob is based on a transition loop from concrete experience to sensation, from thinking observation through observation to abstract conceptualization through thinking and active experimentation through action [9]. Moreover, these three popular models, several studies have been conducted to determine learning styles through learners' habits, behaviors, or thinking styles.

2.2 How to detect student learning styles

2.2.1 Literature - based approach

This approach for determining the learner's learning style is based on comparing the information collected from the learner with the designed rules. The information about learners is usually based on parameters according to some detect learning style models such as VARK, Felder and Silverman (FSLSM) collected through questionnaires. The approach doesn't identify the student's learning style automatically and continuously throughout the learning process. In addition, the limited survey questions do not cover all the information to detect learning styles [10]. However, the method is suitable for initial and the courses that didn't record student interactions.

2.2.2 Driven – based approach

Currently, many courses are deployed on LMS systems, supported by information technology, the data storage of learners is done automatically and throughout the learning process. With the support of data processing, machine learning, and learning analytics technologies, it is becoming more and more popular to identify students' learning styles by data driven-based approach. Clustering and classification techniques are used to analyze the data of a particular learner based on the available training dataset (usually from log files) to determine the his/her learning style [11]. The advantage of this approach is identifying the student learning styles in the course continuously, with high accuracy due to often using a combination of information in the learner model [10]. However, the research question when approaching this method is to choose which model and technique to improve the accuracy and speed in detecting students' learning styles.

2.3 Related works about detect learning style

C. Lwande et.al [12] conducted a study to answer whether detecting the student's learning style can be determined from the LMS system data or not. The authors have taken a literature-based approach. They designed a survey by combining the FSLSM model and the Cognitive Traits Model (CTM). It includes 44 questions for 11 dimensions. The findings showed that the time to focus on learning content is a factor that can determine the learner's learning style. Likewise, a driven-based approach, F. Rasheed and A. Wahid [13] proposed a model to determine the learning style based on machine learning and data mining techniques to analyze learners' learning activities and interaction from logs of LMS systems to classify student learning style. The authors implemented the experiment on 498 samples, using 07 algorithms tested for 4-dimension of FSLSM model. Experimental results show that the Support Vector Machine (SVM) algorithm is the most effective as it has an accuracy is greater than 83%. The FSLSM model is also used to detect students' learning styles based on learning behavior. The results showed in [10] when using the decision tree algorithm to classify 100 students who took the course implemented on the Moodle system, with an average accuracy of 87%. Research results are remarkable, although the data collected often depends on the number of resources and activities implemented in each course. The emerged question is which algorithm is effective in this driven-based approach? To answer that question, C. Troussas et.al. [14] also tested four different classification algorithms (Naïve Bayes, Multilayer Perception, Instance-based learning, Decision Tree J48) with the data of 105 students participating in the course implemented on Moodle includes 252 learning objects in one year. The findings showed that the Bayesian algorithm has the best performance.

In his research, C. Troussas et.al [15] stated that the accuracy for determining students' learning styles using a classification algorithm is 66% - 77%. To increase the efficiency of those algorithms, the authors proposed to use computational intelligence algorithms. The experiment results showed that the accuracy of the artificial neural network algorithm is up to 80.7%.

In addition to studies focusing on improving performance in detecting learning style, several studies also proposed models to determine learning styles when participating in Massive Open Online Course systems. B. Hmedna and colleagues [16] has suggested a model including five stages data collection, pre-processing, feature extraction, classification, adaptation to provide learning content suitable for learners' learning styles.

It can be said that many recent studies focus on using a driven-based approach in detecting learning styles because of its advantages. Student learning style is determined automatically and throughout the learning process. Efficient classification algorithms with data collected by LMS systems have high accuracy. However, not many studies have focused on detecting student learning styles in blended learning courses that combine online learning activities with the traditional teaching-learning approaches.

3 METHODS

3.1 Research context

This study implemented three Advanced programming courses from 2019 through 2021 in the blended learning form. The course's length is 15 weeks with offline and online activities. Online learning activities are implemented through the LMS Moodle system and online teaching using various channels such as Zoom, Google Meet, Microsoft Teams.

We designed content and activities as follows: fifteen PowerPoint files, fifteen pdf files, five hyperlinks for references, ten video YouTube links for recorded lessons, ten assignments using Code Runner [1] module for automatic test for programming, two quizzes for programming and one multichoice quiz, two forums -one for announcements and one for discussions.

[1] https://coderunner.org.nz/

Identifying learners' learning styles provides an additional information channel for learners to have a better approach to learning and helps teachers develop appropriate learning content and activities.

3.2 Participants and data collection

Data has been collected from 205 students participating in three experiment courses. We have developed a plugin to integrate with the Moodle system to make statistics and log analyses of the LMS system. It automatically collects the learners' interaction data as they participate in online learning. The statistical and analyzed information includes the interactive activities of learners with the system, such as the number of views, the number of posts, the number of exercises, the number of interactions on the forums, and the time spent in online activities. We also collected data from questionnaires to determine students' learning styles.
At the course beginning, we required learners to take a survey to gather feedback on their learning style. Our survey questionnaire was developed based on the Index of Learning Style Questionnaire[17].

3.3 A proposed model to detect learning style

The model for determining learners' learning styles in blended learning courses consists of two phases. The first phase is for determining learners' learning styles in offline learning. In this phase, learners respond to survey questions to detect their learning styles. After the learners took the survey, we used clustering techniques, conducted preliminary clustering learners into groups with similar learning styles. In the second phase - online learning, collected data from the LMS system is processed and classified to identify student learning styles. The learning style defined in this step has been verified with the results of the learning style determination in the previously clustering step. The architecture of the model showed in Figure 1.

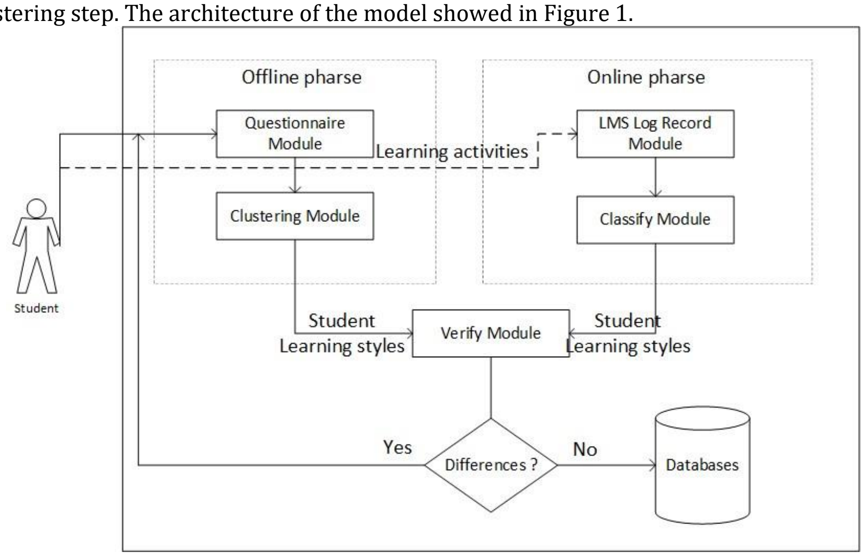

Figure 1: The model architecture for detecting learning style in a blended learning course.

Questionnaire module: We use the questionnaire tool in Moodle to collect surveys of learners. Currently, we use a set of 22 questions with 03 question types (Yes/ No, Multiple choices, Likert).

Clustering module: Perform data clustering to groups with different learning styles based on survey data. There are several components in this module as follows: data collection, data cleaning, data normalization, and clustering algorithms. The output of this module is to separate groups of learners with similar learning styles.

LMS Log Record module: This module performs analysis from the log database of the Moodle system. Due to the periodic log deletion mechanism of Moodle, we built a database to store the data of learners' interaction with the system using cron service to update data periodically. All learners' interactions when they participated in the system are recorded. This data is the basis for implementing the classifier to determine the learning style.

Classify Module: This component classifies learners according to different learning styles. By mapping learning activities to the parameters of a learning style model, this module classifies learners according to different learning styles. In this research, we only chose an effective algorithm which was demonstrated by other studies for classification.

Verify module: This module compares the classification through interactive online learning data with data collected through surveys. If there is no difference, the learner's learning style is determined. For cases where there is a difference, learners are considered to respond to the survey one again. In this experiment, we only resurvey one time in case of the result is different. It is a limitation of our approach because the learner's learning style does not change during the two learning phases in some cases. The issue needs further research.

3.4 Mapping learning activities to learning style model

3.4.1 Mapping online learning activities

As for online learning activities, learners interact through the LMS system. In the experiment courses, we specifically implemented the activities as follows:

Table 1: Learning activities in online phrase

Activities	Learners' action
Learning resources (PowerPoint, Pdf, Word, Hyperlinks, Glossary, Video, Audio)	Resource view
Assignments	Assign submit; Assign view
Forums	View discussion; Add topic; Reply post
Quiz	Quiz attempt; Quiz review

These learning activities will be mapped to the following dimensions in the specific FSLSM learning style model:

Visual / Verbal: leaners interact with system operations through Visual / Verbal related behaviors such as viewing content files (PowerPoint, text, hyperlink). Through the statistics of the learners' interactive activities, the factors related to the learners' visual and verbal are identified.

Sensitive/Intuitive: To measure this aspect, we mapped learners' learning activities as they perform view resources such as video, audio. We also used the engaged time factor for these learning resources to detect whether the learner is sensitive or intuitive. In addition, the activities such as taking assignments and quizzes of learners also reflect this factor when the sensitive learners often demonstrate in submitting assignments on time, not submitting assignments multiple times. They are consistent while doing assignments or quizzes. They don't review those many times. In contrast, intuitive learners often fail to turn in their tasks on time.

Active/Reflective: This aspect is reflected in the behavior of learners participating in the exchange and group work activities such as discussion forums, chat, communities, and assignments. As for active learners, they often participated in discussion forums by asking questions and participating in discussions. In addition, they also always actively perform the assignments on time and try to complete the maximum number of required tasks. In contrast, reflective learners often do not actively participate in forums (in case of these forums are not required to enroll) and usually only complete a minimum of the required exercises.

Sequential/ Global: This aspect is reflected through learners' behavior interacting with learning resources such as resources, assignments, engaged time when performing learning activities.

3.4.2 Mapping offline activities

The results of the learners' responses to the survey questionnaire mapped with specific aspects of the FSLSM model in which each dimension of the model includes five questions acts as the observed variable for the survey questions: Visual/Verbal, Sensitive/Intuitive, Active/Reflective, and Sequential/Global elements.

3.5 The Detect learning style procedure

Step 1. Learners respond to survey questions about their learning styles at the beginning of the course. The surveys were deployed using the questionnaire tool of the Moodle system.

Step 2. The survey data is normalized, cleaned, and clustered to group learners with similar learning styles at this initial stage. In this study, we did not focus on comparing the efficiency of the clustering algorithms, so in our experiment, we used the basis clustering method K-means for clustering.

Step 3. In the learners participating in online courses through Moodle LMS, we have developed a plugin to analyze the logs of the LMS system to automatically statistics and analyze the learners' interaction data. This data is used for classification, determining the student learning styles in the next step.

Step 4. Classification and labeling to identify learners with specific learning styles. In this test, the initial number of learning style labels is the number of clusters obtained in step 2. Technically, we choose the SVM classification algorithm to test the classification.

Step 5. Verify the results of determining the learner's learning style by comparing the step 4 results with step 2 results. If the results are similar, the learner's learning style in this course is determined and stored in databases. Otherwise, go back to step 1.

4 RESULTS

4.1 Learning style clustering results based on student's questionnaire responses

In the experiment, we analyzed the collected data from the learning style survey at the course beginning. There are 129 valid responses from students who participated in the survey. After cleaning and normalizing data, we used the K-means method to cluster students into groups, in which the learning style is similar. Instead of determining the number of groups at the beginning, we used the elbow method approach to find the best value of k. Experimental results showed that k = 3 is the best value for number clusters. The result of clustering students into groups showed in Figure 2.

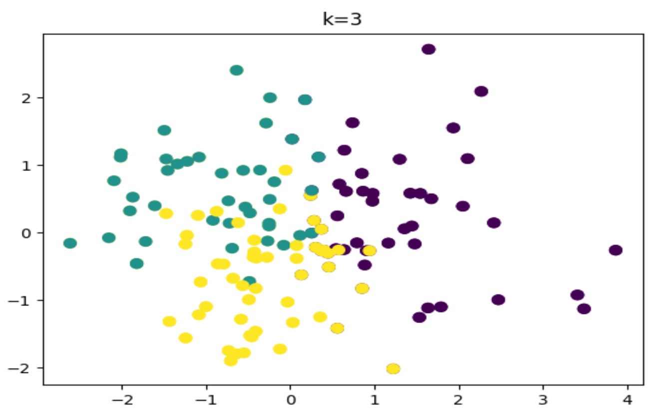

Figure 2. The 129 students are clustering into three learning style groups based on students' responses.

4.2 Learning style classification results based on learners' learning activities

4.2.1 Experimental results after 06 weeks

Experimental results when classifying learner style with 04 dimensions according to the FSLSM model shown in Table 3. The accuracy results of the classification of learner style with each criterion have accuracy from 71.7% to 79.2%. The experimental results for Sensitive/Intuitive criteria give the best accuracy because it based on collected data from activities of performing assignments and quizzes, which are usually required learning activities in the course. The Sequential/Global dimension has low accuracy because we based on the collected data from the learners' interaction with the system. We did not analyze the LMS log results in detail because we only obtained statistical numbers. We had not built specific parameters to measure the learners' activities for this dimension.

Table 3. Experiment results with collected data after six weeks

Performance	Visual/Verbal	Sensitive/Intuitive	Active/Reflective	Sequential/ Global
Accuracy	73.3%	79.2%	75.4%	71.7%
Error rate	26.7%	20.8%	24.6%	28.3%

4.2.2 Experimental results after 12 weeks

This experiment was performed with data obtained at the end of 12 weeks. The classification results described in Table 4. showed that the accuracy ranges from 76.7% to 83.2%, in which the best accuracy is the

Sensitive/Intuitive dimension. The results showed that the classification in all aspects has better accuracy than the experimental results with collected data from 06 weeks because the volume of learning resources and activities increases. Therefore, the student's interaction with the system is more clearly different to explain variation in results.

Table 4. Experiment results with collected data after twelve weeks

Performance	Visual/Verbal	Sensitive/Intuitive	Active/Reflective	Sequential/ Global
Accuracy	78.3%	83.2%	79.4%	76.7%
Error rate	21.7%	16.8%	20.6%	23.3%

5 DISCUSSION

The results of implementing automatic detecting learning styles identification through interactive activities of learners have classification accuracy for the components of the FSLSM model in the range of 76.7% - 83.2%. These results are similar to related studies. The accuracy showed in Fareeha and colleagues' research [13] is from 83.33% to 91.33%. Compared with the research result of Abdullah[18], as its accuracy is 90.0%, our experimental results had lower accuracy. It can explain this depending on the classification technique and the size of the dataset. Compared with the experimental results of Salazar[19], as its accuracy is in the range of 65.9% - 79.5% for different dimensions, our results are a bit better. However, identifying factors have affected the results of detecting learning styles. One emerging issue is how to identify the learning activities that affect the learning style in the online learning phase.

The similarity in the results of identifying learners' styles when determining the student's learning style based on both literature-based and driven-based approaches is up to 83%. The findings showed that the student's learning styles are only slightly changed in the learning process.

The results showed some limits to our research. Firstly, it is difficult to identify the factors to determine the student's learning style in the offline learning phase. In addition, the data collected through the survey depends on the subjective of learners' responses. Regarding the online learning phase, the selection of actions to map the collected data from the learner's interaction with a specific learning style model needs to be further studied because the number of activities is limited and often depends on the course design and the LMS's functionalities.

The experiment results showed that the number of learning resources and activities deployed in the course impact the results of detecting learning style results because the classification depends on the student interaction data that the system recognizes in the learning process. The interaction data collected is proportional to the number of resources and learning activities deployed in the course. Therefore, to effectively identify learners' learning styles, online courses need a large and varied amount of learning resources and activities.

To effectively map learners' interactions with the four dimensions of the FSLSM model in determining student learning styles, the course needs to fully and diversely deploy learning resources. It can be including resources such as doc, pdf, PowerPoint, audio, video, hyperlinks, and the following learning activities: assignments, quizzes, forums, chat, questionnaires. The flexible and diverse resources and activities will enrich the system interaction data in the course. It supports the mapping activities to the learning style model is more detailed to help the detection of students' learning styles more accurately.

6 CONCLUSION

In this study, we have proposed a detect learning style model in the blended learning course based on two literature-based and driven-based approaches for offline and online learning phases. Findings showed that identifying learning styles based on two methods has similar results. Research results also once again confirm that the classification method based on the SVM technique is effective. Our study also proposes mapping the interactive activities of learners corresponding to four dimensions of the FSLSM model. However, the results obtained are still limited. In further research, we will focus on mapping aspects of the FSLSM model with learners' activities to identify details and specifics on how learners' interactions affect the student learning styles detection. In addition, we improved the detect learning style model, especially verifying that identifying the learning style for online activities and offline activities.

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