IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 28, 2022, accepted March 10, 2022, date of publication March 16, 2022, date of current version April 7, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3160177

AI-Based Learning Style Prediction in Online Learning for Primary Education

BENS PARDAMEAN[1,2], TEDDY SUPARYANTO[1], TJENG WAWAN CENGGORO[1,3], DIGDO SUDIGYO[1], AND ANDRI ANUGRAHANA[4]

[1]Bioinformatics and Data Science Research Center, Bina Nusantara University, Jakarta 11480, Indonesia
[2]Computer Science Department, BINUS Graduate Program—Master of Computer Science Program, Bina Nusantara University, Jakarta 11480, Indonesia
[3]Computer Science Department, School of Computer Science, Bina Nusantara University, Jakarta 11480, Indonesia
[4]Faculty of Teacher Training and Education, Elementary School Teacher Education Study Program (PGSD), Sanata Dharma University, Yogyakarta 55281, Indonesia

Corresponding author: Bens Pardamean (bdsrc@binus.edu)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of Bina Nusantara University under Approval No. LSET062021-569 04.

ABSTRACT Online learning has been widely applied due to developments in information technology. However, there are fewer relevant evaluations and applications for primary school students. All innovation efforts in learning are directed at improving the quality of education by creating an active learning atmosphere for students. Students' participation in the teaching-learning process can be improved by selecting appropriate learning materials suitable to the student's learning style. The research aims to develop and measure the impact of an Artificial-Intelligence (AI)-based learning style prediction model in an online learning portal for primary school students. The subjects were recruited from Indonesian primary school students in grades 4 to 6. To fulfill the principle of personalized learning, the AI model in the online learning portal was designed to recommend learning materials that suit students' learning styles. We formulated a new AI approach that enables collaborative filtering-based AI models to be driven by learning style prediction. With this AI algorithm, the online learning portal can provide material recommendations tailored specifically to the learning style of each student. The AI model performance test achieved satisfactory results, with an average RMSE (Root Mean Squared Error) of 0.9035 from a rating scale of 1 to 5. Moreover, students' learning performance was improved based on the results of t-test analysis on 269 subjects between the pre-test and post-test scores.

INDEX TERMS Online learning, learning style prediction, artificial intelligence, personalized learning, primary school.

I. INTRODUCTION

Effective learning in primary schools requires more effort to improve the quality of education. Various research methods are applied to increase motivation and independent learning in primary schools through an interactive learning environment [1]. The results of previous research stated that effective learning would be achieved if students were active in the learning process, such as the use of the Team-Based Learning (TBL) method [2], [3], advances in information technology [4]–[8], and online learning [9], [10]. The teacher as a learning manager must be able to creatively choose the appropriate learning method so that students can be active during the learning process. This can be achieved by taking the advantage of technological advances to improve the outcomes of the learning process. Teachers can also build and maintain student motivation and independent learning through technology such as online learning, which encourages an active learning environment [11].

Currently, online learning continues to be developed following advances in information technology. Through the application of online learning, students can access various learning resources that have been prepared by the teacher. The types of learning resources referred to include learning through video lectures, animated videos, slides, e-books, and Internet articles. These learning resources can

The associate editor coordinating the review of this manuscript and approving it for publication was Yu-Da Lin.

be organized by teachers in the online Learning Management System (LMS) portal to make them more accessible to students, such as Moodle [12].

One of the advantages of implementing online learning is the consideration of individual differences in students [13]. In the field of education, a learning model that is based on the consideration of differences in students is often referred to as personalized learning. Personalized learning can be viewed as a comprehensive integration across schools and an intensification of these ideas across all values and areas of study. This system has become more feasible recently through the availability of technology support [14]. Personalized learning allows students to get instruction and direction when they need it [15]. Personalized learning can also allow for a better breakdown in topic coverage and a more flexible pathway for student success. Therefore, a student would traditionally take a course in calculus, statistics, or accounting, mastery-based systems could allow students to study selected parts of each subject, adapted to the student's interests or to meet the demands of the desired career path [14].

Personalized learning, especially digital personalized learning with pre-packaged curricula, assessment, and continuous data collection, is now a clear area of student growth in learning [16]. Personalized learning on a digital platform can be realized using Artificial Intelligence (AI) [17]–[21]. One of them is used in determining the learning style of the student concerned [22]. Learning styles can be defined as the tendency or the way students absorb and communicate information effectively which can be represented in speech patterns, learning methods, how to do assignments, how to respond to others, and other preferred activities [23].

From the review above, one way to improve the quality of education is to create an active learning atmosphere for students. The activeness of these students can be increased by choosing appropriate learning materials by paying attention to student learning styles. In an effort to increase student activity and take advantage of developments in information technology, this research aims to develop and measure the impact of developing an AI-based online learning portal. The AI model installed in the online learning portal was designed to recommend suitable learning material based on the student learning style. For this purpose, we formulated a novel approach that enables a collaborative-filtering-based AI model to be driven by learning style prediction. At the same time, the approach also enables the AI model to be an unsupervised classification model for learning style prediction. Different from AI-based approaches in previous studies, our proposed algorithm is not supervised on the learning style that is determined by humans. The proposed algorithm is modified to be unsupervised by attaching a softmax prediction layer on top of the latent learning material vectors in the collaborative filtering framework. With its unsupervised nature, the proposed algorithm eliminates human bias in recommending materials based on the student learning style. With this AI algorithm, the online learning portal can give recommended materials tailored to each student's learning style, which serves the principles of personalized learning.

II. MATERIAL AND METHOD

A. ONLINE LEARNING

According to Khan [24], online learning is an online instruction with an innovative approach that instructs remote audiences via the Web medium (Internet). Currently, the utilization of technology in electronic-based learning (e-learning) is dominated by online learning. In e-learning, information technology becomes a bridge of interaction between teachers, students, and learning content (in Figure 1). The Internet can be used as a communication medium to connect teachers, students, and learning content to learning activities. However, the implementation requires an application with a Learning Management System (LMS) that manages an online information system in the progress of students who have been supervised and accompanied by teachers.

Moodle is an LMS-based open-source course application that effectively forms online learning communities [12]. Moodle has various module activities (forums, chat, etc.) and types of course materials, both static (text pages, images, web pages) and interactive (lessons, surveys, quizzes, assignments, etc.). Logs storage from Moodle uses databases (MySQL, PostgreSQL, Oracle, etc.) that are flexible and more powerful than text log files. The utilization of databases in Moodle can gather and access information from high-level usage data collected in the LMS. The Moodle application can show statistical information through an assessment scale in grade or rate used by the teacher or instructor to evaluate student learning performance [25]. From the online learning evaluation, LMS can support personalized learning by finding the fit learning style.

Several other systems and applications such as WELSA (Web-based Educational system with Learning Style Adaptation) and TSAL (Two-Source Adaptive Learning system) are used to observe students' academic performance through materials and assignments according to their learning styles [26]. Klašnja-Milićević *et al.* [27] also used the online course on Protus (Programming Tutoring System) module to support student learning activities in online learning. The Apriori algorithm was applied to the Protus module for analyzing learning/cognitive personality styles based on the Felder-Silverman Learning/Teaching Style model.

The effectiveness of online learning approaches has been reported by the Association of Higher Education (ASHE) to be better compared to traditional learning (requiring face-to-face and classrooms) [28]. In the ASHE report, it was mentioned that the K-12 education system in America shows an increase in reflective learning, integrative thinking, and order thinking skills in online learning compared to conventional learning (classroom-based).

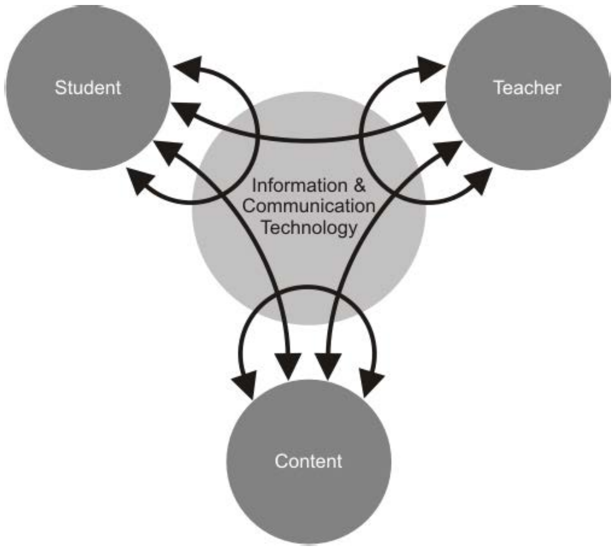

FIGURE 1. Interaction of students, teachers, and learning content in e-learning [29].

B. ONLINE LEARNING FOR PRIMARY EDUCATION

The application of online learning is currently an alternative learning activity for the increasing number of primary schools. Various benefits can be obtained by implementing online learning in primary schools. The benefits can improve the ability of the students to communicate and collaborate in a learning environment. However, to obtain the benefits, the teachers have to support their students to maintain the independence and motivation of the students in learning [11].

Application of online platforms such as SNSs (Social Networking Sites) platform and VLE or Moodle open-source platform generally used online learning activities in primary schools [12], [30], [31]. For instance, grade 1 primary school students in Canada and Singapore use Twitter to solve math problems together. Meanwhile, grade 2 students in the primary classroom use Twitter to review and evaluate their learning outcomes [31], [32]. However, under the COPPA (Children's Online Privacy Protection Act) regulation, the use of SNSs is restricted for children under 13 years. Therefore, it is better to use other platforms that are devoted to online learning instead. One of the platforms is Edmodo, which is a safe and private educational SNSs platform for online learning activities in primary schools. Edmodo has several features that make it easier for teachers to do online learning including submitting homework, participating in discussions, and sharing learning materials [33]. The application of platforms generally used for online learning other than SNSs includes Google Classroom and Moodle/VLE. Moodle/VLE on online learning is widely applied for research to improve the quality of student learning in an authentic environment [34]–[36].

C. PERSONALIZED LEARNING AND LEARNING STYLE

Personalized learning is a learning approach based on students' abilities and interests to support their mastery of the material and their self-learning [37]. The learning system also provides instructions and directions to improve students' abilities according to their needs and wants [15]. Personalized learning, especially digital personalized learning with prepackaged curricula, assessment, and continuous data collection, is now a clear area of student growth in learning [16]. The digital platform currently makes personalized learning convenient by using various types of media in the form of illustrated images, videos, and audio that support the learning styles of preschool and primary school students [38]. Furthermore, personalized learning on a digital platform can be realized using AI to support learners, such as determining the learning style of the student concerned. The application of AI in personalized learning allows teachers to design the material and learning styles necessary and more efficiently. The necessity for appropriate learning styles from AI analysis can improve students' performance [22].

Learning styles can be defined as the tendency or the way students absorb and communicate information effectively which can be represented in speech patterns, learning methods, how to do assignments, how to respond to others, and other preferred activities [23]. Learning styles based on personality are thought to help students with varying capabilities and habits in monitoring learning situations improve their cognitive skills. In the study by Cassidy [39], the application of modules and assessments that refer to the learning/cognitive personality style performance to predict learning styles correspond to the interests and habits of students in primary schools. The LSI (Learning Styles Inventory) learning style model is the most commonly applied to primary and secondary schools using perceptual strengths as one of the keys of assessment in determining learning strategies [40]. The perceptual strengths of students were assessed from the results of the three types of learning activities, namely kinesthetic, visual, and auditory [39]. Hawk and Shah examined the five learning style instruments, which are the Kolb Learning Style Indicator, the Gregorc Style Delineator, the Felder-Silverman Index of Learning Styles, the VARK Questionnaire, and the Dunn and Dunn Productivity Environmental Preference Survey. Those five learning styles can help students with different learning styles improve their learning performance based on their classroom activities [41]. A model instrument such as VARK (Visual, Aural, Read/Write, and Kinesthetic) learning style [42] and the Felder-Silverman learning/teaching style [43] defined individual student characteristics based on their perceptual power in capturing and processing information. Both instrument models were assessed based on visual, auditory, and kinesthetic perceptual modes to observe trends in the student's learning style.

D. ARTIFICIAL INTELLIGENCE MODEL FOR LEARNING STYLE PREDICTION AND LEARNING MATERIAL RECOMMENDATION

For the goal of giving learning material recommendations based on learning style, we normally need two separate AI models. The first model is used to predict the student learning

	Learning Material 1	Learning Material 2	Learning Material 3	Learning Material 4	Learning Material 5	Learning Material 6
User 1	2	2	4	3	4	1
User 2	1	5	4	4	3	4
...	...	...	...	...	...	...
User n	1	4	3	2	5	2

FIGURE 2. An example of rating data for collaborative filtering for six learning materials and n users. Each element is typically filled with a value from 1 to 5, where 1 indicates a user did not like the learning material and 5 indicates the user extremely like the learning material.

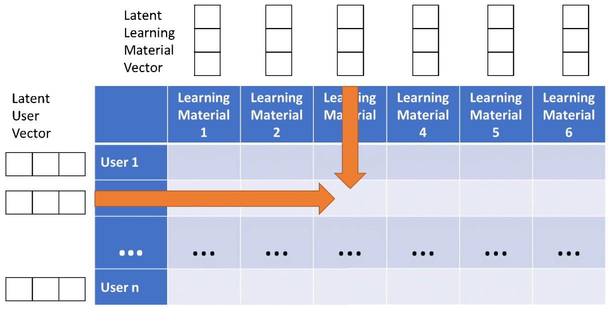

FIGURE 3. The illustration of matrix multiplication process for rating prediction in MF-based collaborative filtering.

style. The second model gives learning material recommendations based on the learning style prediction provided by the first model. The first model is typically a supervised learning model. Meanwhile, the second model is usually based on collaborative filtering algorithms. Because each model has its error, using two models for a single task can accumulate the errors to the final output. Thus, we designed a single model that performs both prediction and recommendation using mutual latent information extracted from data. To achieve this goal, we modified a collaborative filtering model, which is originally used for recommendation tasks, to also predict the student's learning style.

In standard collaborative filtering, the users' interest is captured by letting them rate the learning material they have accessed. Figure 2 illustrates the rating data that is captured for collaborative filtering with six learning materials. Each element is usually filled with a value within the range of 1 to 5, given by the users. To give a recommendation, an AI model can be trained to predict the rating data. The recommendation to a user is formulated as the predicted rating for previously unrated learning material by the user.

The currently most common AI models to predict the rating data are based on the Matrix Factorization (MF) technique proposed by Koren *et al.* [44], which we refer to as the standard MF-based model for the rest of this paper. This model is typically used as a model of our recommendation system. That models the users' rating by assigning a latent vector with the same size to each user and learning material. The rating of learning material from a user is predicted by multiplying the corresponding learning material and user vector, as illustrated in Figure 3. In inference mode, the input to this model is the index of a user in the rating matrix that is illustrated in Figure 3. The output is the rating in the corresponding row, which can be interpreted as the prediction of the model to the rating that most likely will be given by the user. To train the model to generate an accurate prediction, the learning material and user vectors are fitted to the known rating via a gradient descent algorithm. This should be contrasted with the other popular variant of the MF technique that used Singular Value Decomposition (SVD) to analytically find the material and user latent vectors, such as the model that was developed by Paterek [45], Ba *et al.* [46], and Vozalis and Margaritis [47].

In Figure 4, we illustrate our modification to the standard MF-Based collaborative filtering model. To add learning style prediction capability in our proposed model, we first define each content to whether suitable for visual, auditory, and kinesthetic learning styles. Afterward, we fix the latent vector size of each learning material to three elements, which each element separately represents visual, auditory, and kinesthetic learning styles. During training with gradient descent, we supervise the latent content vectors to their corresponding learning style suitability by applying the softmax function to the vectors and exposing them to categorical cross-entropy loss. Additionally, we also regularize the model with L2 regularization. Thus, the loss function $\mathcal{L}$ of the model is defined as follows:

$$\mathcal{L} = \eta \sum_{i} \sum_{j} (1-\alpha)\mathcal{L}_{MF}(r_{iu}, q_i, p_u) + \alpha \mathcal{H}(\hat{q}_i, q_i) \quad (1)$$

where r_{iu} is the value of the ground truth ranking matrix for the i^{th} item and u^{th} user, q_i is the item vector of the i^{th} item, p_u is the user vector of the u^{th} user, $\hat{q}_i$ is a one-hot vector with the value equals 1 corresponds to the learning style suitability of the learning material, and $\mathcal{H}$ is a cross-entropy loss. $\mathcal{L}_{mf}$ in Equation 1 is calculated as follows:

$$\mathcal{L}_{MF}(r_{iu}, q_i, p_u) = (r_{iu} - q_i p_u)^2 + \lambda(||q_i||_2 + ||p_u||_2) \quad (2)$$

where $||q_i||_2$ and $||p_u||_2$ are the L2 norm of q_i and p_u, respectively. The objective of the model is to minimize the loss value from Equation 1, which in effect minimizes $\mathcal{L}_{mf}$ in Equation 2 and the cross-entropy loss $\mathcal{H}$ between the true learning style representation of the learning materials q_i and the prediction of the model for the representation $\hat{q}_i$. The $\mathcal{L}_{mf}$ loss in Equation 2 has two separate terms. The first term $(r_{iu} - q_i p_u)^2$ is the squared error between the corresponding value of the ground truth ranking matrix and the dot product of the item vector q_i and the user vector p_u. The second term is an L2 regularization loss term that minimizes the L2 norm of q_i and p_u.

Overall, the loss function $\mathcal{L}$ has three hyperparameters: η, λ, and α. The hyperparameter η acts as the learning rate of the model. Meanwhile, λ controls the magnitude of the

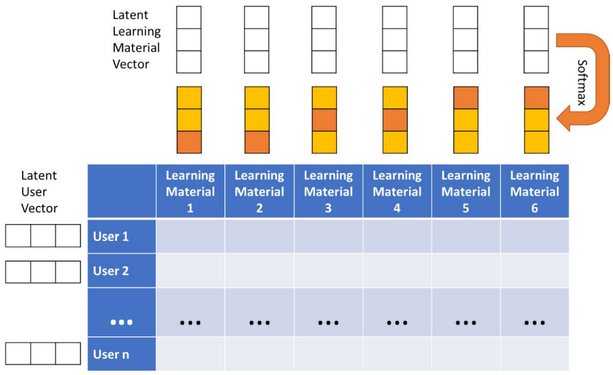

FIGURE 4. Our proposed modification to the standard MF-based collaborative filtering model.

L2 regularization and α controls the balance between the standard MF loss $\mathcal{L}_{MF}$ and the cross-entropy loss $\mathcal{H}$.

In effect, because of the vector multiplication for rating prediction, this approach channels the learning style information to the latent user vectors. It ultimately guides each element in the latent user vectors to represent the learning style of the student. By taking the argmax of the latent user vector, the model can provide a classification of the user learning style. In other words, our proposed method allows the standard MF model to be an unsupervised learning style classification model. In contrast to the typical learning style prediction models that are based on supervised learning, our proposed model does not require student learning style data determined by a questionnaire. Assuming that the questionnaire may contain subjective bias, our proposed AI model can be considered to be more objective than the other learning style prediction models.

E. SUBJECT

Subjects were enrolled from eleven primary school classes grade 4 to 6 in three provinces in Indonesia, specifically Central Java, DI Yogyakarta, and DKI Jakarta. These three provinces are located on the island of Java, which is the most populous island in Indonesia. The age range of the subjects was between 10-12 years old. The total number of subjects was 322 with the distribution as shown in Figure 5. Among the 322 subjects, only 269 students were able to successfully access our online learning portal.

The subjects were the students of eleven teachers with the profiles as presented in Table 1. The teachers had a mean age of 30.46 years old with a standard deviation of 7.70. Most of the teachers were specializing in primary education, with only one teacher specializing in physics education. On the gender profile, eight of the teachers were female and the other three were male. The teachers were uniformly distributed in the three areas in this study (three from Central Java, four from DI Yogyakarta, and four from DKI Jakarta). The distribution of the teachers based on their specialization, gender, and area are graphically presented in Figure 6, Figure 7, and Figure 8, respectively.

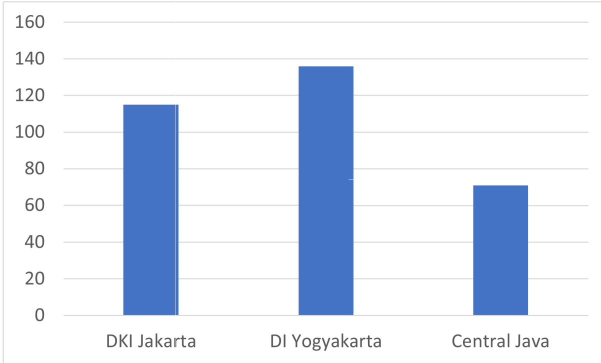

FIGURE 5. Research subjects distribution.

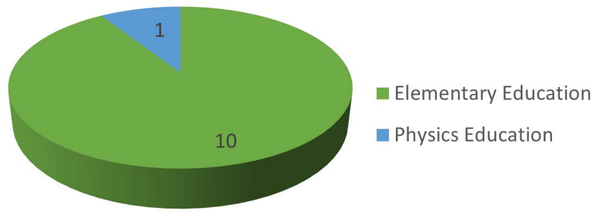

FIGURE 6. Distribution of the teachers based on their specialization.

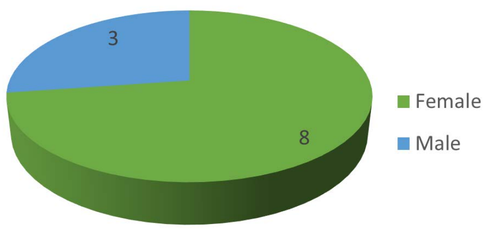

FIGURE 7. Distribution of the teachers based on their gender.

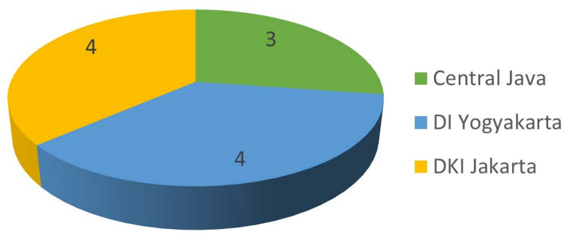

FIGURE 8. Distribution of the teachers based on their area.

F. METHOD

The online learning portal used in this study was built using the Moodle framework version 3.9.3. This portal was subsequently installed on a server with specifications using Intel Xeon E5-2620 processor, NVIDIA Tesla K40 graphical processing unit, 32 GB of RAM, and 4 TB of storage media with RAID 5 configuration. Installation was performed using a cloud computing-based system based on Docker virtualization technology. The process began with the creation of a container containing the latest version of the Moodle framework. The additional software modules were then installed into the

TABLE 1. The teachers' profiles.

Teacher ID	Area	Specialization	Gender	Age
T01	Central Java	Elementary Education	Female	27
T02	Central Java	Elementary Education	Female	24
T03	Central Java	Elementary Education	Female	24
T04	DI Yogyakarta	Elementary Education	Female	38
T05	DI Yogyakarta	Elementary Education	Male	28
T06	DI Yogyakarta	Elementary Education	Female	45
T07	DI Yogyakarta	Physics Education	Male	41
T08	DKI Jakarta	Elementary Education	Female	23
T09	DKI Jakarta	Elementary Education	Female	23
T10	DKI Jakarta	Elementary Education	Female	31
T11	DKI Jakarta	Elementary Education	Male	31

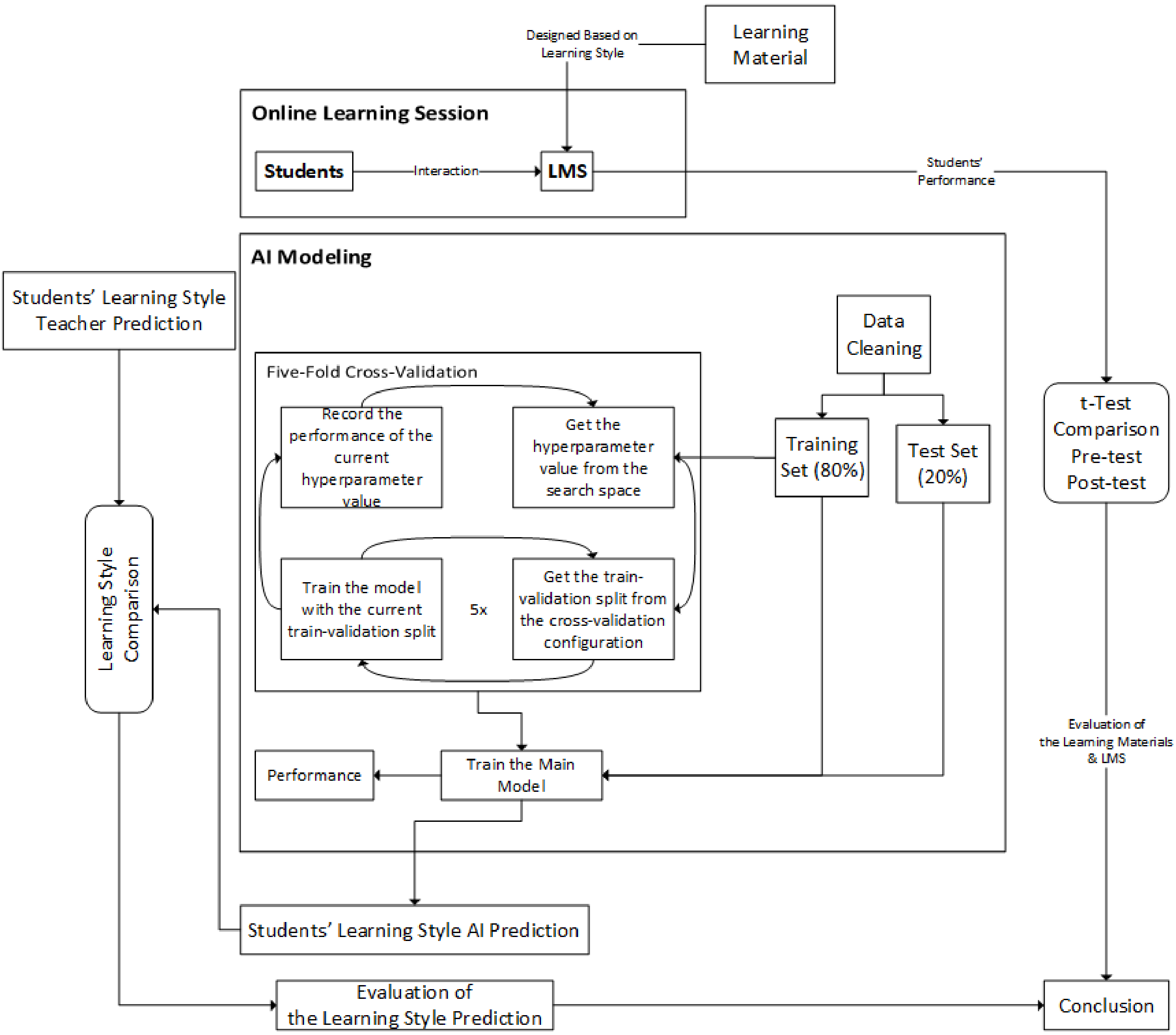

FIGURE 9. Research model.

container to devise an online learning portal as proposed in this study.

The research process in this study shown in Figure 9 consisted of 2 major stages: (1) the online learning session and (2) the AI modeling. In the online learning session, the students were given six learning materials to learn about the concept of numbers. The learning materials were tailored and validated by experts to be suitable for the visual, auditory, and kinesthetic learning styles, based on the dePorter *et al.*'s variant of the VARK model [48]. After the learning session, the students were asked to rate the six learning materials from 1 to 5 according to their preference. These ratings were compiled into a ranking matrix to train the AI.

In the next stage, the process of AI modeling was started by cleaning the data by removing incomplete records. Afterward, the cleaned data were split into two sets: training and test. The proportion was 80% and 20% of the total data, respectively. To search for the most optimal hyperparameters value, we conducted five-fold cross-validation using the training set. The hyperparameters to be searched were α, η, and λ. The search space for α was $\{0.1, 0.15, 0.2, 0.25, 0.3\}$. Meanwhile, both the η and λ search space was $\{0.01, 0.005, 0.001, 0.0005, 0.0001\}$. The optimal configuration was afterward used to train the main model with the whole training set. The training process in the cross-validation step and the main training step used the Adam optimizer [49]. Then, the final model was tested on the test set to determine its generalization capability. The metric of the test was Root Mean Squared Error (RMSE), which is a common metric to evaluate regression models. It is calculated by raising the difference between the prediction and the ground truth to the power of two and taking the root of the result. RMSE is calculated as follows:

$$RMSE = \frac{1}{N}\sqrt{\sum_{n=1}^{N}(\hat{y}_n - y_n)^2} \tag{3}$$

where N is the total number of students in the test set, $\hat{y}$ is the predicted student's rating, and y is the true student's rating. Finally, the prediction from the optimal AI model was compared to the teachers' prediction of the student's learning style to understand the behavior of the AI model.

Furthermore, to measure the effect of using the online learning portal, we conducted a test for all students before and after using the online learning platform (pre-test and post-test). The test consisted of 10 multiple-choice questions. The pre-test and post-test results were analyzed using paired t-test to see if the online learning portal can improve the students' performance.

III. RESULT

In Table 2, the result of the t-test from the pre-test and post-test is presented. The average score of the students was improved by 0.49 points with a scale of 0 to 10. The improvement was statistically significant with the p-value below 0.05.

Meanwhile, the performance of the proposed model is given in Table 3. In general, the test performance was satisfactory, with an average RMSE of 0.9035 based on a 1 to 5 rating scale. Compared to the standard MF-based model, the proposed model delivered better performance with 0.0313 lower in the RMSE value. Hence, the proposed model has not only an extended capability to predict the learning style of the students but also resulted in better performance as a recommendation system.

TABLE 2. Results of paired T-test on learning outcomes. N is the number of samples, SD is the standard deviation of the data, and DF is the degree of freedom of the test.

N	Mean (SD)		t (DF)	p-value
	Pre-Test	Post-Test		
269	7.32 (2.35)	7.81 (2.10)	4.03 (268)	0.00007892*

*Significant at p-value < 0.05

TABLE 3. Comparison of the standard MF model and the proposed model.

Model Name	RMSE
Standard MF-Based Model	0.9348
Proposed Model	**0.9035**

TABLE 4. Comparison of predicted learning style results from teachers and AI.

		Teacher Prediction		
		Visual	Auditory	Kinesthetic
AI Prediction	Visual	22.97%	5.41%	8.11%
	Auditory	21.62%	8.11%	9.46%
	Kinesthetic	17.57%	2.70%	4.05%

After the performance evaluation of the proposed model, we presented the comparison of the learning style prediction from the teachers and AI in Table 4. The mutual prediction between the teacher and AI was only 35.13%. In particular, we highlighted that a large portion of the students that were predicted to have a visual learning style by the teachers was predicted by AI as having auditory (21.62%) and kinesthetic (17.57%).

IV. DISCUSSION

Figure 5 indicates the number of involved subjects was 322 students. However, only 269 students can access the LMS that was created for this study. The common problems that caused this issue were the limited time and tools that students can use. From the teachers' reports, some students still depended on the mobile devices owned by their parents, which were not always available to the students. Only 172 out of 269 students can log in to the LMS system according to the instructions given by the teacher. Based on the discussions with teachers, not all students were able to follow the instructions conveyed via video instruction or written guidance. These results are in line with the result from a previous study, which highlights that the teachers have to support their students to maintain the independence and motivation of the students in learning [11]. Based on Table 2, there has been a significant test performance improvement (p-value < 0.05) between the pre-test and post-test results. It can be concluded that structured LMS can improve student learning outcomes for students in primary school. This finding is aligned with the result of the study by Hubalovsky *et al.* [50] which confirms the fact that educational objectives can be achieved more effectively only by several pupils. The average improvement was slight due to the limited time given to students to study the teaching materials that have been prepared on the LMS portal.

In assessing the result of this study, it is worthwhile to notice that the characteristics of our proposed algorithm are substantially different from the algorithms in the previous study. Most of the previous algorithms rely on the use of supervised learning models [22], [51]–[62] to predict students learning styles before generating a material recommendation. The employed models were mostly neural network [22], [52], [55]–[61] or any machine learning models available in WEKA [22], [51], [54], [62], [63]. The supervised learning models were mostly trained with learning style ground truths that were manually collected by questionnaires, which required laborious work. In other studies, the ground truths were generated by using clustering methods [64]–[68] instead of a manual collection. Although viable, the validity of ground truths generated by the clustering algorithm is questionable. Based on the learning style prediction from the supervised model, in most previous studies, the material recommendation was generated by handcrafted rules. This approach is prone to inherit the subjectivity of the rule designer. A better approach for recommendation using collaborative filtering was adopted by Klašnja-Milićević *et al.* [27]. However, in the study, the students learning style was identified manually via questionnaire instead of algorithmically. In contrast to the previous approaches, our proposed algorithm directly injected the learning style information into a collaborative filtering algorithm. This approach eliminated the need for students learning style ground truths, which were expensive to be collected. The recommendation of our algorithm is also expected to be more objective towards students' preference because it prevents biases from humans for the learning style of the students that can be injected from the manually-collected learning style ground truths.

Table 4 shows the results of the evaluation of the prediction of teacher learning styles compared to the predictions of AI. The mutual prediction between the teacher and AI was only 35.13%. Based on Table 3, the performance of predicting learning styles with AI was satisfactory, thus it can be assumed that the AI model is objective because it is driven by data. Therefore, we can conclude that there is a shift in learning styles between face-to-face learning and online learning. This learning style shift is also stated in the research by Clariana and Smith [69]. According to Zapalska and Brozik [70], the shift is caused by the flexible learning experience provided by online learning. The shift can also be caused by the changes in students' learning environment and individual maturity levels. The subjects selected were in the age range of 11 to 14 years who were mostly at the adolescence stage which was the stage of change from childhood to adulthood. Therefore, it can be concluded that a shift in learning styles in online learning can occur in subjects.

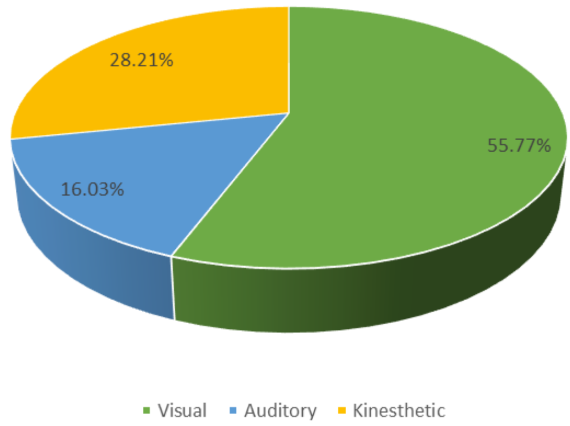

FIGURE 10. Teachers prediction on students' learning style.

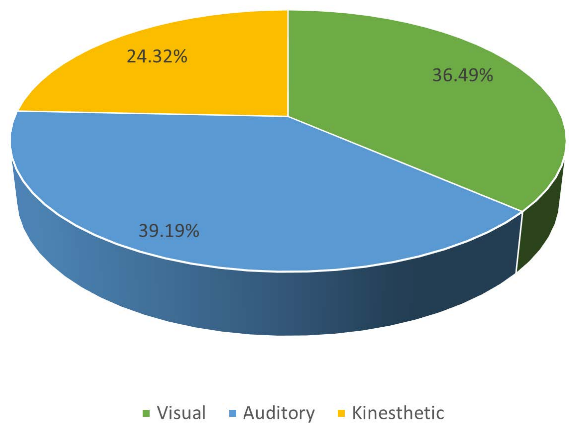

FIGURE 11. AI prediction on students' learning style.

Presented with the astonishingly low mutual prediction percentage (35.13%), we inspected the distribution of teachers' and AI predictions. From Figure 10, teachers predicted that 55.77% of the students have a visual learning style, followed by 16.02% and 28.21% respectively for auditory and kinesthetic learning styles. On the other hand in Figure 11, AI predicted that 24.32%, 39.19%, and 36.49% of the students have visual, auditory, and kinesthetic, respectively. The large percentage of visual learning style prediction from teachers may stem from the largely accepted fact that 65% of the human population has a visual learning style. This fact is widespread in popular media, although the original academic paper that scientifically to prove it cannot be found. However, the teachers can capture that the percentage of kinesthetic students was larger than the auditory students. This fact agrees with the distribution of prediction from AI, while differs from the widespread fact that 30% and 5% of the human population have an auditory and kinesthetic learning style, respectively. Because it is not hazed by the unproven widespread fact, the teachers' prediction that tends to favor kinesthetic learning style might be true based on their observation. Interestingly, the AI also put a large percentage of students as kinesthetic. This could be a hint that the AI prediction is a better estimate of the true distribution of the learning style from the primary school students population. However, we should notice that this comparison result was not derived from a typical analysis in psychological studies. Thus, we should not interpret the result as a proven fact from a psychological perspective.

V. CONCLUSION

The new approach that we used in this study enables collaborative-filtering-based AI models to be driven by predictive learning styles. The testing performance of this AI model was satisfactory, with an average RMSE of 0.9035 based on a rating scale of 1 to 5. It was better than the standard MF-based model with 0.0313 lower in the RMSE value. Not only does it has a better performance, but the proposed method also eliminates the need for learning style ground truth from human because it does not employ any supervised learning.

From the result of this study, we observed a shift in learning styles on application online learning that could occur in primary school students. This shift should be of concern to teachers because of changes in student learning environments. Thus, teachers must be more active to explore learning materials adapted to students' learning styles, which can be helped by having the teachers use the online learning platform that we developed in this study. Not only for the teachers, but the online learning platform in this study is also beneficial to be used by students, which is proved by the improvement of the student's performance in this study.

APPENDIX

The study protocol was approved by the Ethics Committee of Bina Nusantara University (approval number LSET062021-04). Concern participants were elementary school students who have been permitted by teachers and students' guardians.

ACKNOWLEDGMENT

The authors express their gratitude to NVIDIA—BINUS AIRDC for providing the GPU Tesla P100 that they utilized to train the AI model for this study.

REFERENCES

[1] E. Bodur, F. Özkan, E. Altun, and Ö. Şimşek, "The role of teacher in web enhanced learning activities in primary school information technologies lesson: A case study," *Proc. Social Behav. Sci.*, vol. 1, no. 1, pp. 1043–1051, 2009.

[2] B. Pardamean, H. Prabowo, H. H. Muljo, T. Suparyanto, E. K. Masli, and J. Donovan, "The development of blended-learning teaching portfolio course using TBL approach," *Int. J. Virtual Pers. Learn. Environ.*, vol. 7, no. 1, pp. 30–43, Jan. 2017.

[3] B. Pardamean, J. Donovan, E. Masli, T. Suparyanto, H. Muljo, and H. Prabowo, "Team based learning as an instructional strategy: A comparative study," *New Educ. Rev.*, vol. 50, no. 4, pp. 134–145, Dec. 2017.

[4] K. Gunawan and B. Pardamean, "School information systems design for mobile phones," *J. Comput. Sci.*, vol. 9, no. 9, pp. 1140–1145, Sep. 2013.

[5] B. Pardamean, "Enhancement of creativity through logo programming," *Amer. J. Appl. Sci.*, vol. 11, no. 4, pp. 528–533, Apr. 2014.

[6] B. Pardamean, T. Suparyanto, E. Masli, and J. Donovan, "Enhancing the use of digital model with team-based learning approach in science teaching," in *Proc. Inf. Commun. Technol.-EurAsia Conf.* Denpasar, Indonesia: Springer, 2014, pp. 267–276.

[7] B. Pardamean, T. Suparyanto, and E. Evelyn, "Improving problem-solving skills through logo programming language," *New Educ. Rev.*, vol. 41, no. 3, pp. 52–64, Sep. 2015.

[8] F. Xiao and B. Pardamean, "MOOC model: Dimensions and model design to develop learning," *New Educ. Rev.*, vol. 43, no. 1, pp. 28–40, 2016.

[9] B. Pardamean, T. Suparyanto, and R. Kurniawan, "Assessment of graph theory e-learning utilizing learning management system," *J. Theor. Appl. Inf. Technol.*, vol. 55, no 3, pp. 353–358, 2013.

[10] B. Pardamean and T. Suparyanto, "A systematic approach to improving E-learning implementations in high schools," *Turkish Online J. Educ. Technol.*, vol. 13, no. 3, pp. 19–26, 2014.

[11] V. Ham and R. Davey, "Our first time: Two higher education tutors reflect on becoming a 'virtual teacher,'" *Innov. Educ. Teaching Int.*, vol. 42, no. 3, pp. 257–264, Aug. 2005.

[12] *Moodle Doc*, Moodle, Perth, WA, Australia, 2010.

[13] S. Malik and A. Rana, "E-learning: Role, advantages, and disadvantages of its implementation in higher education," *Int. J. Inf. Commun. Comput. Technol.*, vol. 8, no. 1, p. 403, 2020.

[14] J. Pane, "Strategies for implementing personalized learning while evidence and resources are underdeveloped," RAND, Santa Monica, CA, USA, Tech. Rep. PE-314-RC, 2018.

[15] A. Kim, "Personalized learning playbook," in *Proc. IGARSS*, 2014, pp. 4–5.

[16] F. Boninger, A. Molnar, and C. M. Saldaña. (2019). *Personalized Learning and the Digital Privatization of Curriculum and Teaching*. National Educational Policy Center. Whitepaper. [Online]. Available: https://nepc.colorado.edu/publication/personalized-learning

[17] J. Beck, M. Stern, and E. Haugsjaa, "Applications of AI in education," *XRDS, Crossroads, ACM Mag. Students*, vol. 3, no. 1, pp. 11–15, 1996.

[18] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: A review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020.

[19] J. Kay, "AI and education: Grand challenges," *IEEE Intell. Syst.*, vol. 27, no. 5, pp. 66–69, Sep. 2012.

[20] *Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development*, UNESCO, Working Papers on Education Policy, Paris, France, 2019.

[21] C. Yeo, M. Green, and R. Lemery, "Wide complex tachycardia in a patient with pre-excitation: What is the mechanism?" *HeartRhythm Case Rep.*, vol. 3, no. 6, pp. 315–318, 2017.

[22] R. Bajaj and V. Sharma, "Smart education with artificial intelligence based determination of learning styles," *Proc. Comput. Sci.*, vol. 132, pp. 834–842, Jan. 2018.

[23] E. Nugraheni and N. Pangaribuan, "Gaya belajar dan strategi belajara mahasiswa jarak jauh: Kasus di universitas terbuka," *Jurnal Pendidikan Terbuka dan Jarak Jauh*, vol. 7, no. 1, pp. 68–82, 2006.

[24] B. H. Khan, *Web-Based Instruction: What is it Why is it?*. Englewood Cliffs, NJ, USA: Educational Technology Publications, 1997.

[25] C. Romero, S. Ventura, and E. García, "Data mining in course management systems: Moodle case study and tutorial," *Comput. Educ.*, vol. 51, no. 1, pp. 368–384, Aug. 2008.

[26] T.-C. Yang, G. J. Hwang, and S. J. H. Yang, "Development of an adaptive learning system with multiple perspectives based on students' learning styles and cognitive styles," *Educ. Technol. Soc.*, vol. 16, no. 4, pp. 185–200, Dec. 2013.

[27] A. Klašnja-Milićević, B. Vesin, M. Ivanović, and Z. Budimac, "E-learning personalization based on hybrid recommendation strategy and learning style identification," *Comput. Educ.*, vol. 56, no. 3, pp. 885–899, Apr. 2011.

[28] *Research on the Effectiveness of Online Learning*, Online Learn., Cost Efficiencies Online Learn., ASHE Higher Educ. Rep., Beaverton, OR, USA, 2011.

[29] T. Suparyanto and B. Pardamean, "The effects of computer skill in student's achievement through the use of learning management system," in *Proc. Conf., Int. Seminar Integrating Technol. Educ.*, 2010, pp. 1–5.

[30] D. M. Boyd and N. B. Ellison, "Social network sites: Definition, history, and scholarship," *J. Comput.-Mediated Commun.*, vol. 13, no. 1, pp. 210–230, Oct. 2007.

[31] D. Maher, "Online learning in primary schools," in *Online Learning: Common Misconceptions, Benefits, and Challenges*, P. Lowenthal, C. York, and J. Richardson, Eds. Hauppauge, NY, USA: Nova, 2014, pp. 125–136.

[32] M. Waller, "It's very very fun and ecsiting'-using Twitter in the primary classroom," *English*, vol. 39, pp. 14–16, Jul. 2010.

[33] Y. Ariani, Y. Helsa, S. Ahmad, and R. Prahmana, "Edmodo social learning network for elementary school mathematics learning," *J. Phys., Conf.*, vol. 943, Dec. 2017, Art. no. 012056.

[34] K. A. Azhar and N. Iqbal, "Effectiveness of Google classroom: Teachers' perceptions," *Prizren Social Sci. J.*, vol. 2, no. 2, pp. 52–66, 2018.
[35] P.-C. Chen, T.-S. Lan, S.-C. Chiu, and Y.-H. Lan, "A study of investigating the learning effectiveness of applying the MOODLE E-learning in Taiwan's elementary school," *J. Internet Technol.*, vol. 15, no. 7, pp. 1191–1194, 2014.
[36] N. Omar and R. Geer, "Virtual learning environment (VLE): Its impact on primary school children's learning," in *Proceedings of EdMedia + Innovate Learning*, 2018, T. Bastiaens *et al.*, Eds. Amsterdam, The Netherlands: Association for the Advancement of Computing in Education, Jun. 2018, pp. 1916–1922.
[37] J. D. Basham, T. E. Hall, R. A. Carter, and W. M. Stahl, "An operationalized understanding of personalized learning," *J. Special Educ. Technol.*, vol. 31, no. 3, pp. 126–136, Sep. 2016.
[38] N. Kucirkova, "Personalized learning with digital technologies at home and school: Where is children's agency?" in *Mobile Technologies in Children's Language and Literacy: Innovative Pedagogy in Preschool and Primary Education*, G. Oakley, Ed. Bingley, U.K.: Emerald, 2018, pp. 133–155.
[39] S. Cassidy, "Learning styles: An overview of theories, models, and measures," *Educ. Psychol.*, vol. 24, no. 4, pp. 419–444, 2004, doi: 10.1080/0144341042000228834.
[40] J. W. Keefe, "Assessment of learning style variables: The NASSP task force model," *Theory Into Pract.*, vol. 24, no. 2, pp. 138–144, Mar. 1985.
[41] T. F. Hawk and A. J. Shah, "Using learning style instruments to enhance Student learning," *Decis. Sci. J. Innov. Educ.*, vol. 5, no. 1, pp. 1–19, Jan. 2007.
[42] N. D. Fleming, "I'm different; not dumb. Modes of presentation (VARK) in the tertiary classroom," in *Proc. Res. Develop. Higher Educ., Annu. Conf. Higher Educ. Res. Develop. Soc. Australasia (HERDSA)*, vol. 18, 1995, pp. 308–313.
[43] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Eng. Educ.*, vol. 78, no. 7, pp. 674–681, 1988.
[44] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30–37, Aug. 2009.
[45] A. Paterek, "Improving regularized singular value decomposition for collaborative filtering," in *Proc. KDD Cup Workshop*, 2007, pp. 5–8.
[46] Q. Ba, X. Li, and Z. Bai, "Clustering collaborative filtering recommendation system based on SVD algorithm," in *Proc. IEEE 4th Int. Conf. Softw. Eng. Service Sci.*, May 2013, pp. 963–967.
[47] M. Vozalis and K. Margaritis, "Using SVD and demographic data for the enhancement of generalized collaborative filtering," *Inf. Sci.*, vol. 177, no. 15, pp. 3017–3037, Aug. 2007.
[48] B. DePorter and M. Hernacki, *Quantum Learning: Unleashing the Genius in You*. New York, NY, USA: Dell, 1992, pp. 109–122.
[49] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, *arXiv:1412.6980*.
[50] S. Hubalovsky, M. Hubalovska, and M. Musilek, "Assessment of the influence of adaptive E-learning on learning effectiveness of primary school pupils," *Comput. Hum. Behav.*, vol. 92, pp. 691–705, Mar. 2019.
[51] M. Abdullah *et al.*, "A novel adaptive E-learning model matching educator-student learning styles based on machine learning," in *Communication, Management and Information Technology*, S. de Alencar, Ed. London, U.K.: Taylor & Francis, 2016, pp. 787–796.
[52] J. Bernard, T.-W. Chang, E. Popescu, and S. Graf, "Learning style identifier: Improving the precision of learning style identification through computational intelligence algorithms," *Expert Syst. Appl.*, vol. 75, pp. 94–108, Jun. 2017.
[53] Y.-C. Chang, W.-Y. Kao, C.-P. Chu, and C.-H. Chiu, "A learning style classification mechanism for e-learning," *Comput. Educ.*, vol. 53, no. 2, pp. 273–285, 2009.
[54] L. D. Ferreira, G. Spadon, A. C. Carvalho, and J. F. Rodrigues, "A comparative analysis of the automatic modeling of learning styles through machine learning techniques," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2018, pp. 1–8.
[55] E. Gomede, R. Miranda de Barros, and L. de Souza Mendes, "Use of deep multi-target prediction to identify learning styles," *Appl. Sci.*, vol. 10, no. 5, p. 1756, Mar. 2020.
[56] M. S. Hasibuan, L. E. Nugroho, and P. I. Santosa, "Model detecting learning styles with artificial neural network," *J. Technol. Sci. Educ.*, vol. 9, no. 1, pp. 85–95, 2019.
[57] B. Hmedna, A. El Mezouary, O. Baz, and D. Mammass, "A machine learning approach to identify and track learning styles in MOOCs," in *Proc. 5th Int. Conf. Multimedia Comput. Syst. (ICMCS)*, Sep. 2016, pp. 212–216.
[58] A. Latham, K. Crockett, and D. Mclean, "Profiling Student learning styles with multilayer perceptron neural networks," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Oct. 2013, pp. 2510–2515.
[59] J. Lo and P. Shu, "Identification of learning styles online by observing learners' browsing behaviour through a neural network," *Brit. J. Educ. Technol.*, vol. 36, no. 1, pp. 43–55, Jan. 2005.
[60] J. Melesko and E. Kurilovas, "Semantic technologies in e-learning: Learning analytics and artificial neural networks in personalised learning systems," in *Proc. 8th Int. Conf. Web Intell., Mining Semantics*, Jun. 2018, pp. 1–7.
[61] R. Torres-Molina, J. Banda-Almeida, and L. Guachi-Guachi, "Artificial neural networks in mathematical mini-games for automatic students' learning styles identification: A first approach," in *Proc. Int. Conf. Intell. Data Eng. Automated Learn.* Manchester, U.K.: Springer, 2019, pp. 53–60.
[62] Y. Wei, Q. Yang, J. Chen, and J. Hu, "The exploration of a machine learning approach for the assessment of learning styles changes," *Mech. Syst. Control Formerly Control Intell. Syst.*, vol. 46, no. 3, p. 21, 2018.
[63] D.-M. Shien, T.-Y. Lee, W.-C. Chang, J. B.-K. Hsu, J.-T. Horng, P.-C. Hsu, T.-Y. Wang, and H.-D. Huang, "Incorporating structural characteristics for identification of protein methylation sites," *J. Comput. Chem.*, vol. 30, no. 9, pp. 1532–1543, Jul. 2009.
[64] M. Bursać, D. Milošević, and K. Mitrović, "Proposed model for automatic learning style detecting based on artificial intelligence," in *Proc. 11th Int. Sci. Conf. Sci. Higher Educ. Function Sustain. Develop.*, Užice, Serbia, May 2019, pp. 47–54.
[65] O. Aissaoui, Y. E. M. Alami, L. Oughdir, and Y. Allioui, "A hybrid machine learning approach to predict learning styles in adaptive E-learning system," in *Int. Conf. Adv. Intell. Syst. Sustain. Develop.* Tangier, Morocco: Springer, 2018, pp. 772–786.
[66] O. E. Aissaoui, Y. E. A. El Madani, L. Oughdir, and Y. E. Allioui, "Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles," *Proc. Comput. Sci.*, vol. 148, pp. 87–96, Jan. 2019.
[67] B. Hmedna, A. Mezouary, and O. Baz, "A predictive model for the identification of learning styles in MOOC environments," *Cluster Comput.*, vol. 23, no. 2, pp. 1–26, 2019.
[68] A. S. Kuttattu, G. S. Gokul, H. Prasad, J. Murali, and L. S. Nair, "Analysing the learning style of an individual and suggesting field of study using machine learning techniques," in *Proc. Int. Conf. Commun. Electron. Syst. (ICCES)*, Jul. 2019, pp. 1671–1675.
[69] R. B. Clariana and L. Smith, "Learning style shifts in computer-assisted instructional settings," in *Proc. Annu. Meeting Int. Assoc. Comput. Educ. Held Conjunct. Amer. Educ. Res. Assoc.*, New Orleans, LA, USA, Apr. 1988.
[70] A. Zapalska and D. Brozik, "Learning styles and online education," *Campus-Wide Inf. Syst.*, vol. 23, no. 5, pp. 325–335, Oct. 2006.

BENS PARDAMEAN received the bachelor's degree in computer science and the master's degree in computer education from California State University at Los Angeles (USA) and the Ph.D. degree in informatics research from the University of Southern California (USC). He currently holds a dual appointment as the Director of the Bioinformatics and Data Science Research Center (BDSRC) | AI Research and Development Center (AIRDC) and an Associate Professor of computer science at Bina Nusantara (BINUS) University, Jakarta, Indonesia. He has over 30 years of global experience in information technology, bioinformatics, and education. His professional experiences include being a practitioner, a researcher, a consultant, an entrepreneur, and a lecturer.

TEDDY SUPARYANTO graduated from the Mathematics Teacher Education Faculty. He received the master's degree program in information technology from Bina Nusantara University. He has a deep understanding of developing and managing IT systems in the educational and agro-industry sector. He currently holds an appointment as a Research Associate at the Bioinformatics and Data Science Research Center (BDSRC) | AI Research and Development Center (AIRDC) and a Lecturer of agricultural informatics engineering at STIPER Agricultural University, Yogyakarta, Indonesia. He has an educational background in mathematics, teaching skills, educational psychology, pedagogy philosophy, teaching strategy, and learning media. His expertise in statistics is very helpful in the data analysis process.

TJENG WAWAN CENGGORO received the bachelor's degree in information technology from the STMIK Widya Cipta Dharma and the master's degree in information technology from Bina Nusantara University. He is currently an AI Researcher whose focus is in the development of deep learning algorithms for application in computer vision, natural language processing, and bioinformatics. He has led several research projects that utilize deep learning for computer vision, which is applied to indoor video analytics and plant phenotyping. He has published over 20 peer-reviewed publications and reviewed for prestigious journals, such as *Scientific Reports* and IEEE Access. He also holds two copyrights for AI-based video analytics software. He is also a Certified Instructor at the NVIDIA Deep Learning Institute.

DIGDO SUDIGYO received the bachelor's degree in biology from Gadjah Mada University, in 2016, and the master's degree in biotechnology from the Graduated School of Gadjah Mada University, in 2020. He is currently a Research Assistant at the Bioinformatics and Data Science Research Center (BDSRC). He is involved in bioinformatics research, especially in the molecular and cancer fields and data analysis projects.

ANDRI ANUGRAHANA received the master's degree in basic education from Yogyakarta State University, Indonesia. She currently holds a position as an Elementary School Teacher Education Lecturer at Sanata Dharma University, Yogyakarta, Indonesia. She has more than ten years of experience in the field of education, especially relating to elementary school education, mathematics, Montessori, ethnomathematics, and education technology. Her professional experiences include being a practitioner, a researcher, a consultant, a trainer, and a lecturer.