Education and Information Technologies (2024) 29:571–593
https://doi.org/10.1007/s10639-023-12287-2

A model to create a personalized online course based on the student's learning styles

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Received: 3 April 2023 / Accepted: 13 October 2023 / Published online: 11 November 2023

Abstract
This article presents the results of an experiment in personalizing course content and learning activity model tailored for online courses based on students' learning styles. The main research objectives are to design and pilot a model to determine students' learning styles to create personalized online courses. The study also addressed an effective method to identify learning styles and evaluate how student's learning styles impact students' learning outcomes. With an aim to personalize suitable content and learning process for each student, machine learning techniques have been used to detect students' learning styles and classified them into learning styles based on the VARK model by analyzing learning activity data. Based on students' learning styles, rules were proposed to select appropriate content and learning processes. The research results show that the SVM method performs the best among classification methods used to determine students' learning styles. In addition, a plugin was developed on the Moodle system to support the automatic identification of students' learning styles, based on which a learning process and appropriate content were generated to test the model's results. The experiment results also indicate that students with a visual learning style had better learning outcomes in theory-oriented courses. In contrast, students with a kinesthetic learning style had better learning outcomes in practice-oriented courses. Although the experiment was only conducted on a small scale, the positive results show that the model can fully meet the needs of large-scale LMS systems.

Keywords Student learning styles · Personalized learning · Machine learning · Learning analytics

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1 Introduction

Given the rapid development of information technology, E-Learning has grown enormously and become more popular than ever, with MOOCs and LMS systems being deployed in many education systems. These systems cover various topics, including fundamental subjects such as mathematics (Tang et al., 2022) and specialized courses incorporating technology, such as virtual reality (Cheung et al., 2023). However, the "One size fits all" model is no longer effective because it does not consider the individual characteristics of each learner in the learning process. Therefore, researchers are currently looking for ways to integrate Personalized Learning into E-Learning systems to overcome the shortcomings of the traditional "One size fits all" model (Matar, 2011), (Şahin et al., 2016).

Personalized Learning involves tailoring learning content and activities to suit the needs of each learner (Barbara & Kathleen, 2013). One challenge in creating personalized courses is determining which learning materials are appropriate for each learner based on their learning style. This is particularly difficult in traditional learning settings where teachers struggle to identify the learning styles of each student, making it hard to create a curriculum that suits everyone. However, E-Learning courses have an advantage of capturing data on learners' interactions with different learning materials, advancements in Machine Learning, and big data processing which enable automated identification of learners' learning styles.

Identifying the learning style of learners is crucial in creating customized courses. Various methods and techniques are available to identify students learning styles. Self-assessment tools or quizzes can be used where students are asked to choose their preferred learning strategies, such as visual or verbal learning or hands-on or abstract learning. (Moutafi et al., 2013). Instructors or course designers can also observe the behavior and interactions of students during online activities or discussions to recognize patterns in their learning styles. Students can also create their learning materials, such as videos or blog posts, which can provide insight into their learning styles (Müller & Christandl, 2019). Questionnaires, surveys (Dziedzic et al., 2013; Sangvigit, 2012), and learning analytics (Aguilar et al., 2022; Oliveira et al., 2020) can also be utilized to identify students learning styles by asking them about their preferred learning strategies, the time they spend on specific activities, or the types of resources they access.

Research on learning styles currently uses the classification of learners according to popular learning style models such as David Klob, Honey-Mumford, VARK, Felder and Silverman (FLSM). Learners' learning style is determined as the basis for answering the question "How to learn?" when students participate in a course. Statistical results of using parameters to build courses from 2009–2020 by A.H. Nabizadeh and colleagues indicate that learning style parameters account for a significant proportion compared to the other studied parameters such as time, level, and background (Nabizadeh et al., 2020). However, currently, only a few learning systems support the creation of courses according to learners' learning styles.

Over the last few years, numerous online courses of VNU-UET have been introduced in blended learning models across all courses with varying degrees of online learning involvement. One of the challenges encountered when designing materials, lectures, and activities for blended-learning courses is creating content that is customized to each student's learning style in order to improve their learning effectiveness.

Moodle LMS has been chosen to implement over 600 courses for each semester. To effectively implement these courses, it is essential to research models, methods, and techniques to detect the students' learning styles when participating in the courses and to implement personalized learning activities on the LMS system.

The primary objectives of the research are to understand how to detect the students' learning styles, explore the impact of personalized learning on students' performance, design a comprehensive model for personalized courses, and evaluate its effectiveness through user-learning outcomes. This research aims to develop a model for determining students' learning styles in online learning systems for personalized course creation that provides appropriate learning resources tailored to each student's learning style. We conducted testing of the model by developing a plugin integrated with the Moodle system and implementing it experimentally in courses. The study also answers two questions through experiment and evaluation: 1) What is an effective method to identify learning styles? 2) How learning styles impact a student's learning outcomes.

In the following section, we will review studies regarding the building of personalized courses in online learning systems, particularly those that consider students' learning styles as a basis for creating personalized courses. Additionally, we summarize significant results in determining students' learning styles in recent years. In Section 3, Models, we describe the architecture of the personalized course creation system based on the learning styles of students, as well as the architecture of the plugins used to implement the model on Moodle LMS. In Section 4, Methods, we provide an overview of the methods used to determine learning styles and select appropriate learning materials, as well as the participants, data, testing, and evaluation processes used in the model. The results obtained in building and implementing the model are presented in the Results section. The Discussion section will present some discussions based on the results obtained. We summarize some findings of the study in the Conclusion section.

2 Literature Review

The widespread use of educational software and the availability of online courses have contributed to the diversification and abundance of educational resources for learners. As a result, it has become increasingly important to personalize these resources to meet the needs and desires of individual learners. In this section, we summarize some research findings related to developing personalized courses, creating personalized courses according to learning styles, and methods and techniques to detect the students' learning styles. In addition, we examine several LMS systems that create personalized courses based on learning styles.

2.1 Personalized online courses based on student's demand

Each student is unique, and different students prefer different learning ways. Gaining insights into different learning styles offers means to design and provide interventions tailored to individual needs. Recent studies on personalized learning have attempted to provide learning materials tailored to each person's level and needs (Christudas et al., 2018) presented an evolutionary approach for personalizing learning content for individual learners from a massive database in an e-learning system. Klašnja-Milićević et al. (2011) introduced a recommendation model to suggest online learning activities to learners based on their learning styles, knowledge, and preferences.

Yang et al. (2018) suggested a personalized feedback generation model called PRGDDA based on interactive activities and learner feedback during the learning process. This model adapts the domain using a dual learning approach, optimizing the feedback and lesson generation models to utilize suitable and unsuitable target domains efficiently. The experimental results demonstrated that the PRGDDA model generated excellent personalized feedback for diverse users.

In assessment activities, (Ye & Manoharan, 2019) supported the creation of personalized anti-cheating multiple-choice tests by approaching the problem with a software framework that generates multiple versions of the test questions, each corresponding to a participating individual.

Assessing personalization in learner support activities, (Kühl & Zander, 2017) conducted an experimental study using questionnaires, pre-tests before applying the Hypochondria scale, psychological and cognitive scales, and a personalized assessment test in a multimedia environment. The study explored aspects of personalization that may not perform well in practice and could have a reverse reaction to negative emotional impacts.

2.2 Personalized online courses based on students' learning styles

In addition to personalized course creation models based on learners' knowledge (Adorni & Koceva, 2015; Niknam & Thulasiraman, 2020; Zhou et al., 2018) and goals (Li et al., 2016; Nabizadeh et al., 2017), personalized course creation models based on learning styles are currently of interest, especially in the context of courses being offered in online and blended learning environments. (Christudas et al., 2018) personalized the delivery of content in e-learning systems based on learners' behavior to create compatible learning materials. The study was tested on 240 learners with learning styles determined by Felder-Silverman combined with compatibility levels, difficulty levels, knowledge levels, and learner interactions. (McKenna et al., 2018) surveyed two learning styles, Kolb and VARK. The study aimed to investigate the learning styles of two groups of nursing students participating in a master's program. The research results showed that the students had greater preference for practical learning styles that involve bringing ideas together, and less preference for learning through concrete experiences. (Pasina et al., 2019) used the Average

Linkage Clustering technique to cluster learners based on their learning styles characterized by eight features corresponding to 8 learning styles of the FSLM model so that instructors can evaluate and adopt appropriate teaching strategies to present course materials in the classroom. Bursac et al. (2019) clustered learners by using the FSLM method, then performed clustering using the C-Means algorithm combined with the use of Neural Network to predict new data segments. El Aissaoui et al. (2019) conducted a study using data based on learner interactions with learning materials such as videos, charts, graphs, images, narrations, and lessons to perform clustering based on the FSLM model and used the Naive Bayes network to predict learning styles. With a big data approach, (Viloria et al., 2019) analyzed the learning styles of students by using a dataset that included data from 1854 male and female university students from different fields such as Psychology, Journalism, Art, Philosophy, History, and Education Science at the University of Mumbai. The experimental results showed that university students preferred the reflective learning style, which is followed by the theoretical, pragmatic, and active learning styles.

2.3 How to detect the students' learning styles

Accurately identifying the students' learning styles is crucial in developing courses catering to their individual learning needs. Currently, two main methods are being used in research to detect learning styles: 1) collaborative techniques, which are based on a questionnaire and, 2) automatic approaches, which use learners' behavior and actions during learning sessions to automatically detect their learning styles (Truong, 2016). Learning styles are commonly assessed through surveys and questionnaires that allow students to self-evaluate their learning preferences. This is useful in traditional classroom settings where it is difficult to observe and assess students' learning styles throughout the learning process. Some surveys including those conducted by Vermunt (Vermunt, 1998) and Felder-Silverman (Felder & Silverman, 1988), may contain over 40 questions, making it difficult for them to be updated. However, this method has several limitations similar to any qualitative survey. Firstly, as relying on students' perceptions, it can be biased. Secondly, it only captures a snapshot of the learning style, whereas many theories suggest that learning styles can change over time. The behavior of learners is used in several methods based on collaborative techniques that involve filling out a questionnaire designed by various learning styles models such as Honey and Mumford, Kolbs, VARK, and FSLM. Afterwards, data mining, machine learning, or simple rule-based techniques are applied to determine the learning style. This approach has been studied in various fields, such as history, nursing, and computer programming (Carol, 2015; Chookaew et al., 2014; Hung et al., 2016; McKenna et al., 2018).

Regarding the automatic techniques, clustering and classification techniques have been experimented by many studies to determine the learning style of learners, such as Fuzzy C means (Azzi et al., 2020; Bursac et al., 2019; El Aissaoui et al., 2019), Decision Tree (Liyanage et al., 2016; Sheeba & Krishnan, 2018), Neuron Network (Bursac et al., 2019; Hasibuan et al., 2019), SVM (Rasheed & Wahid, 2021).

2.4 LMS systems create personalized courses according to students' learning styles

The integration and implementation of some personalized learning models have also been widely tested in LMS systems. Hmedna et al. (2017) examined the perspective of the course's documents and solutions for integrating an adaptive system in MOOCs. Learners responded to ILS to determine labels, and then interaction data was used as input for the neural network. However, the results have not been specifically evaluated. (Zhou et al., 2018) trained a Long Short-Term Memory (LSTM) model to predict the learning path and performance. The learning path was selected from the predicted results, and a specific learning path was recommended to the learners. The study presented a convincing algorithm using the LSTM model. Although the accuracy is good compared to other algorithms, it is still in a quite low level. (Segal et al., 2019) developed the Edurank system using interaction filtering method to suggest appropriate level of question difficulty for learners. (Rasheed & Wahid, 2021) used machine learning technique to determine learning styles. Learners would answer a survey when they enroll in the course to identify their learning styles. Then, the system would use interaction data on the course to predict and validate the results. The good point of this study is the use of real data to apply machine learning methods.

Building personalized courses based on learners' learning styles has yielded significant results, primarily through machine learning methods and big data processing, to automatically determine learning styles and develop effective learning processes for each learner. However, only some studies still focus on creating learning content and activities suitable for learners' learning styles.

3 Methodology

3.1 Research design

We designed a quantitative study using an online educational program evaluation method to design a model for creating personalized learning courses based on student's learning styles. 1) To identify the students' learning styles, we use machine learning classification and clustering techniques to automatically identify them based on their interactions with the LMS system. 2) To design a comprehensive model of personalized courses: It provides tailored learning materials for each student by identifying their learning style. 3) To evaluate the effectiveness of the proposed model through the student's learning outcomes, we implemented the course to test the model and analyze the collected data using quantitative methods to evaluate its effectiveness through users' learning outcomes.

3.2 Participants

There were 110 first-year students randomly selected to attend the course "Introduction to Information Technology,"—a theoretical course that presents foundational concepts for information technology deployed in the LMS Moodle system. We used collected data for training, testing, and model selection in detecting the students' learning styles. These students were selected because they attended different high school institutions to ensure sample diversity. In addition, this course is the first, so the subject content is new knowledge of the field for participating students.

To evaluate the proposed model's impact on student's learning outcomes. We selected 240 first-year students, all Information Technology students of VNU-UET, who enrolled in the "Advanced Programming" courses. We selected all students in the major to participate in the course to test the model and evaluate its impact.

To avoid barriers to using technology in the learning process, one more criterion for selection is that the students participating in the course should be proficient in using computers and tools to engage in the online class.

3.3 Materials & Data analysis

Data was collected from three different sources including: (1) *the survey*: The Appendix described the questionnaires with twenty-one questions based on the VARK learning style (VARK learn limited, 2023) and the FSLM questionnaire (Felder & Soloman, 2004) combined with questions related to the learners' psychology and personality from educational psychology experts in order to survey learners in some aspects such as learning style in class, learning style at home, preferred type of learning materials, ability to concentrate; (2) *students' interactive activities data*:. To collect this data, we have developed a module to automatically collect data on learners' interaction, including the number of views, posts, exercises, forum interactions, and time spent on online activities; (3) *the student's learning outcomes*: after completing the course, including formative assessment evaluation and summative assessment results.

We use several statistical analysis methods to evaluate the proposed model's effectiveness, including descriptive and inferential statistics, to analyze student learning outcomes.

3.4 Procedure

The MOOC course is delivered over 15 weeks. Students use the LMS system weekly to learn learning content and perform learning activities: assignments, discussion forums, formative tests and final exams. Each learning content is designed with many different formats of learning materials suitable for each learning style determined by the VARK model.

First, the LMS system asks students to take a learning style survey. We use machine learning clustering and classification techniques to identify students' learning styles. Based on each student's learning styles, the system provides personalized learning materials suitable to the student.

During the course, interactive activities between students and the system are collected. This data is used to classify students' learning styles during the learning process. Along with student learning outcomes when performing formative and summative assessment activities, this data is used to analyze and evaluate the model's effectiveness at the end of the course.

3.5 Detecting students' learning styles process

Two phases were taken to detect students' learning styles. In this first phase, students responded to survey questions to detect their learning styles. From the survey results, clustering techniques were applied to conduct preliminary clustering of learners into groups with similar learning styles.

In the second phase, collected data from the LMS system was processed and clustered to identify student learning styles. The detail is described as follows:

Data preprocessing The collected data was cleaned and normalized to apply to different machine learning models. The basic processing steps are as follows: (1) Encoding categorical data fields: With the collected data from the survey that has 21 questions including 19 categorical and 02 numerical data fields, we used Label Encode and One Hot Code methods to encode categorical data fields into numerical for machine learning models and to evaluate the teamwork mood: poor, fair, or the time spend on daily learning. (2) Normalizing the data to bring them to a specific range creates a balance for the data because the difference between the minimum value when encoded is 0 and the maximum value is 20 after the encoding step. This difference may cause unevenly distributed points, and many points may be noisy.

Data clustering Some different methods were used to compare and cluster data, such as K-Means, and Spectral Clustering, and to collect the algorithm that gave the best results. Since the data volume needs to be genuinely diverse for the dataset on system interactions, the basic K-Means algorithm was chosed to perform data clustering. The elbow method was applied through graphical visualization to select the number of groups that best fit the experimental model.

Data classification The clustering algorithm selects k groups of students. Based on that, we label students with corresponding learning styles to the clusters found in the previous step. This set of data is labelled in order to label students with similar learning habits and goals, forming groups of students with the same learning style. After labelling the data, we checked the accuracy of each label by applying classification algorithms. In this study, we experimented with SVM, XGBoost, and Logistic Regression using cross-validation accuracy to select the best model. Because the test data is small, we only chose fivefold to evaluate, then compared the accuracy of the classification algorithms on the test data to choose the optimal algorithm that was most suitable for our data. From there, the best prediction results can be made for detecting the learning style of a new student and accurately evaluating the learning style of a new student based on the previously determined label.

3.6 Method of selecting appropriate learning materials personalized for each student

If–then rules are applied to select learning materials suitable for each learner. Students with identified learning styles would be assigned appropriate learning materials and activities during the learning process. Each learning material provided by the instructor or course designer to the learning system was identified as appropriate for a specific learning style.

During the course, each student's learning style was automatically determined on a periodical basis through data analysis. Therefore, the learning materials and activities for the following weeks could be adjusted accordingly to the updated learning style of the learner. In addition, teachers could also redefine the appropriate learning materials for each learning style during the learning process.

4 Results

4.1 A model to create a personalized online course

4.1.1 The model architecture

We propose a model for creating courses with learning materials that match the learning style of each learner, as described in Fig. 1. The main components of the model include two modules: The Detect Learning Style module that automatically identifies the learning styles of learners, and the Generate Personalized Learning Resource module that identifies the learning materials that match each student's learning style.

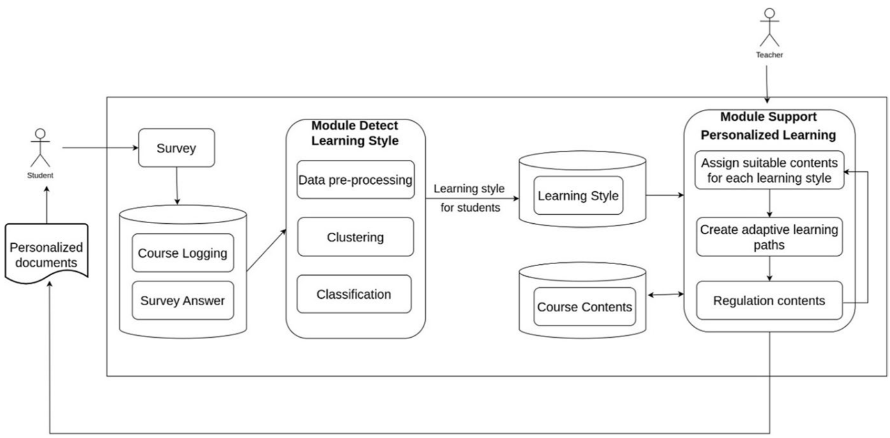


Fig. 1 The architecture of the model to create the personalized course

4.1.2 Operation

At the beginning of the course, learners respond to survey questions as a preliminary assessment of learners' learning styles. During the learning process, the learners' interaction data in the online learning phase, including access time to the course, the number of times spend on viewing the course material, the number of times spent on viewing forum posts, the number of times spent on posting questions on the forum, learners' quiz scores, and the status of submitted assignments are collected and stored in the Course Log database. The learners' interaction data is the basis for the Detect Learning Style module to determine the learning style through primary data preprocessing, clustering, labelling, training, and classification functions. When updating learning resources or related learning activities, the instructor or course designer must determine that resource is suitable for which learning style through the Assign Content for a Learning Style component. During the online phase of the course, learners with a determined learning style through the Detect Learning Style module will have access to appropriate learning resources and related learning activities.

During the learning process, the learning style of learners can be adjusted by instructors to suit learners through (1) adjusting the content, modifying the learning materials to fit specific learning styles, and (2) adjusting the learning style of learners. This adjustment process usually takes place after each assessment phase of the course. The basis for adjusting the learners' learning style is based on automatically identifying the learning style and assessing learners' progress. In this study, a learner's learning style is checked and adjusted if there is no progress is made in assessment results during the learning weeks.

4.2 Testing and Evaluating

4.2.1 Developing a plugin integrated with Moodle LMS system

We have developed two new modules, Learning Style Analysis Service and Personalized Learning Plugin, and combined them with existing modules such as Questionnaire Plugin: to create the questionnaire and Moodle database to archive new tables generated by two new modules as depicted in Fig. 2.

The Learning Style Analysis Service module is built by using Python and is designed to receive learning style analysis events from the Moodle system through REST API. It then queries the database, determines the learner's learning style, and updates it in the database. *The Personalized Learning Plugin* allows teachers to adjust and determine which learning materials serve which learning styles through an interface. Specifically, to personalize learning content, we have developed an additional "restriction" plugin that allows for adding learning style criteria, as shown in Fig. 3.

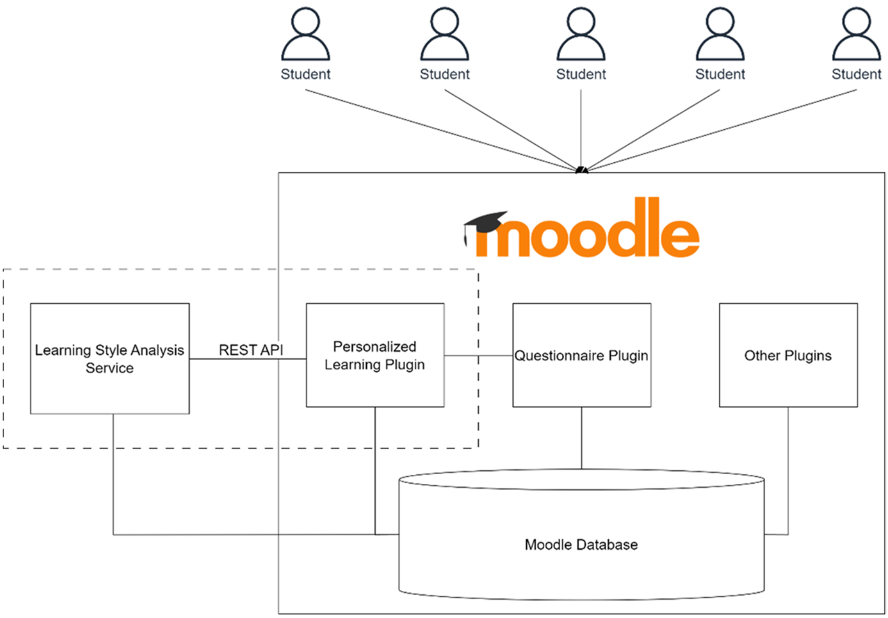
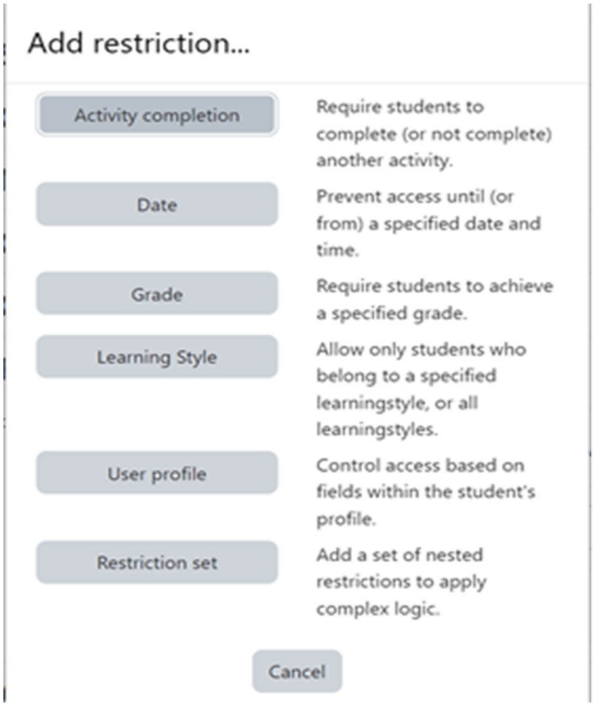


Fig. 2 Two new plugins for LMS Moodle

Fig. 3 Setting the Lesson Access Rights according to "Learning Style"



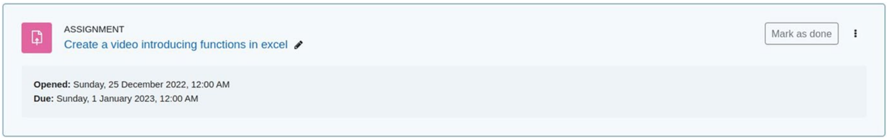


Fig. 4 Students having a "learning style" that matches the content of the lesson

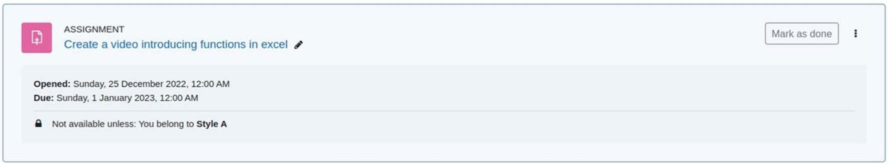


Fig. 5 Students having neither a "learning style" that matches the content of the lesson

Only learners whose learning style matched each learning material or lecture can access it. In that case, the system will allow learners to see the respective content, as shown in Fig. 4. Conversely, it will not provide content by not displaying it in the course, as shown in Fig. 5.

4.2.2 Model assessment

To detect the students' learning styles, clustering is used as a method performed based on the interaction data of learners with the system during the online learning phase. The interactive data of participants in the course "Introduction to Information Technology" is summarized in Table 1, including views counted when students accessed learning materials (read or download), number of posts when the student completed quizzes, submitted assignments, responses in forums, and total online time in the system.

According to Table 1, on average, a student spent about 277.36 visits to view the material with about 18.5 visits per week on average. The LMS Moodle system records an average of 38.85 times, where the minimum value of this field is relatively low, indicating that some students neither participated nor care about this post, which is similar to the number of interactions with the forum, with the minimum value being 0. Most students spent much time of the course to participate in learning, with a reasonably high average value of 32210.08 s. Based on the data presented in Table 1, students spent sufficient time engaging in online courses and interacting with the system to ascertain their learning styles through their learning activities.

Table 1 Descriptive statistics of learner interactions in the experimented course

	Minimum value	Maximum value	Average value	STD	Median
Number of views	46	904	277.36	195.67	208
Number of posts	8	168	38.85	25.36	36
Forum viewing figures	0	312	38.42	62.09	15
Time spent on course (seconds)	4932	98560	32210.08	19124.29	26221

However, to verify the results and evaluate the accuracy of the clustering model, we continued to label that dataset as the identified clusters and divided the data into training and testing sets on different classification algorithms.

Statistical analysis of the learning outcomes of learners was conducted to determine which learning style is most suitable for the course being deployed. It allowed us to guide teachers and course designers in designing most appropriate content and learning activities. To evaluate the accuracy of identifying a learner's learning style, we analyzed their learning outcomes through process evaluations. If there was improvement in evaluated results, the identified learning style was considered as appropriate. Otherwise, the teacher or course manager needed to make adjustments.

4.3 An effective method to identify learning styles

The number clusters value is chosen at three as optimal based on the elbow method. After finding the number clusters, we performed a classification test with XGBoost, SVM, and Logistic Regression by cross-validation method with five folds and made evaluation based on accuracy. Though the fivefold cross-validation increases computational complexity compared to a single train-test split, its benefits outweigh this drawback, particularly when data size is limited. With data size of 110 rows, each fold contains around 22 data points. The process begins by training the model on four out of the five folds (88 data points) while using the remaining folds (22 data points) for testing.

Table 2 shows that SVM would give the best results, followed by XGBoost and Logistic Regression when comparing overall test results. As clustering k-means is used to detect the number of groups of the sample and the data size of the training set is not large enough during classification process, overfit occurs in some algorithms. Therefore, the accuracy value for some Folds is 1. Based on the results of model, SVM was used for classifying and detecting students' learning style.

Given experimental data, we determined the number of students in three learning styles labeled as learning style A, B, C. Learning style A consisted of 7 students, learning style B consisted of 85 students, and learning style C consisted of 18 students.

Table 3 shows the statistics of interactions by groups. Students using learning style A had the most interactions, with an average of 793 times, followed by those with learning style C and learning style B with much less interaction being 562 and 187 turns respectively. Learning style A has an average of 4 times more views than learning style B, and learning style A's forum views are nearly 16 times higher than learning style B's. Students in the learning style B and C rarely engaged

Table 2 The result of cross-validation processing with metric as accuracy

Classification Method	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
SVM	0.95	1	1	0.95	1
Logistic Regression	0.86	0.9	0.9	0.81	0.86
XGBoost	0.9	0.95	0.95	1	1

Table 3 Statistics of learner interactions group by the learning styles

		Number of views	Number of posts	Viewing forum figures	Time spent on course
Learning style A	Average value	793.1	83.4	240	77603
	Maximum value	904	168	312	98560
	Minimum value	648	40	184	61296
	Std	96.93	46.61	51.43	11249
	Median	792	64	256	75552
Learning style B	Average value	187.2	31	15.2	23542
	Maximum value	358	80	112	41104
	Minimum value	46	8	0	4932
	Std	65	14.6	18.7	8290.3
	Median	184	26	8	22624
Learning style C	Average value	502.44	58.33	69.44	55488
	Maximum value	768	128	160	78056
	Minimum value	322	8	4	34696
	Std	132.3	27.8	40.3	12764
	Median	472	52	76	56468

in interactive activities such as joining a forum or posting content. The statistics show that all three learning styles focus on the Visual learning style. Nevertheless, students with learning style A tended to be interested in both posting and viewing forums, so students with learning style A had the same characteristics as VRK (Visual, Read/write, and Kinesthetic) learning style, learning styles B and C did not show this trend in mean and minimum values. Hence, these two learning styles only have Visual characteristics.

4.4 How learning styles impact a student's learning outcomes

Students' learning outcomes for each group of different learning styles were analyzed. The results presented in Table 4 show that the group with learning style A tends to interact the most, followed by learning style C and learning style B with the least amount of systematic interaction. However, students with learning style B had the highest average

Table 4 Average scores of students' learning styles when taking the course "Introduction to information technology"

	1st learning styles (A	2nd learning styles (B)	3rd learning styles (C)
Mid-term average score	9.28	9.23	9.09
Final average score	7.73	7.87	7.13
Average score	8.34	8.42	7.91

Table 5 The average number of learning activities per month

	1st learning styles (A)	2nd learning styles (B)	3rd learning styles (C)
Views in 1st month	198	201	357
Views in 2nd month	233	171	436
Views in 3rd month	24	21	33
Views in 4th month	30	19	38
Posts in 1st month	409	297	705
Posts in 2nd month	257	231	350
Posts in 3rd month	49	35	73
Post in 4th month	13	14	19

Table 6 The average results of the top 5% the highest score

	1st learning styles (A)	2nd learning styles (B)	3rd learning styles (C)
Average score	555.48	112.46	622.12
Mid-term average score	9.82	9.7	9.86

score, and students with the learning style A group had more interactions than those with learning style B, but the learning results were not at the top.

Research of 10% of students (11 students) with the best learning results in this subject showed that nine students, accounting for 82%, used learning style B, while learning styles A and C were used by only one student each. Similarly, of the 10% of students with the worst academic results, learning style B still dominated with 8/11 students accounting for 73%, and 3/11 students (27%) came from learning style C group, whereas no student from learning style A group.

When testing the model with 240 students taking an "advanced programming" course, we calculated the average interaction data of students in each learning style as described in Table 5. Statistical results showed that learning style C has a superior number of learner interactions. Regarding learning style B, the number of views of learning materials is more than other activities.

Additionally, at the end of the course, the average learning outcomes of the students in each group are analyzed. Table 6 presents the average learning results of the top 5% of students having highest scores in each learning style. The result shows that students in the Kinesthetic-oriented learning style group (learning style C) have better learning outcomes than those with other learning styles.

5 Discussion

When testing classification methods and determining learning styles, the SVM classification method yielded the best results with an accuracy of up to 0.95. This result confirms the findings of some previous related studies when comparing learning style detection methods using machine learning techniques (Rasheed & Wahid, 2021). Applying K-means to group learners based on their interaction data is quite adequate. However, choosing the best value of k to determine the number of groups depends on the data. The experimental results show that it is still difficult to automatically determine the correct learning style of learners belonging to a specific learning style in each model.

The analysis of learners' learning outcomes according to different learning styles shows that when learners explore learning materials and participate in learning activities that match their learning styles, the learning outcomes practice better. With the experimental course, which is a course that is more inclined to explore concepts and theories, students with learning styles are ranked in terms of Visual learning styles for better learning results when the highest average score was 8.41.

The statistical data in Table 5 regarding the interaction with the online learning system for different learning style groups showed that the average number of interactions with the system varied significantly among groups in terms of interactive activities. However, the differences between these parameters did not classify learners into specific learning style groups, such as V, A, R, or K, according to the VARK model. This also suggests the need for an approach to determine learners' learning styles as a combination of specific styles that approached in (Hung et al., 2016).

The experimentation of two courses with different orientations on theory and practice showed that for students whose learning styles are compatible with the form of content presentation, learning activities often result in better academic performance. Although specific data show that the difference in learning outcomes between learning style groups is little, it is clear that providing learners with appropriate learning materials and activities has a positive impact on learning outcomes.

It is not a small challenge for the lecturers and the course design team to develop learning resources and learning activities for each content in a course to suit and maximize the support for learners with different and diverse learning styles when participating in an online course.

The experimental results of our model showed that students with learning styles that match the provided learning materials have better learning outcomes at the end of the course. The proposed model is effective in providing content forms that are suitable for each student's learning style. Determining learning styles for each learner is done automatically based on analysis of their interaction data with a system that can classify learners according to different learning styles to help design content—personalized content for each student. To deploy the model, instructors and course designers must build and develop multiple representations of learning materials for each content to accommodate different learning styles.

The results of the experimented model for personalized content creation and learning activities based on learning styles showed that the model still has some limitations.

Firstly, the data collected from completed courses are insufficient. The frequency of learners' interaction with online learning systems depends heavily on the number of learning materials and activities implemented by instructors in each course. This data source may affect the results of building, training, and determining the learning styles of the model. In addition, mapping learners' basic interaction activities when participating in courses into factors to determine learning styles according to models needs to be carefully studied.

Secondly, one of the limitations is that we only used 21 survey questions. While this approach makes it easier for students to begin the course without being overwhelmed by too many questions, it is crucial to ensure the accuracy of determining students' learning styles based on their initial survey responses. This accuracy is vital for effectively tailoring the course content and learning materials from the beginning. One possible solution that has been explored is using multiple survey questions to classify learners based on their learning styles. This limitation is also planned to be enhanced in future studies.

Finally, during the learning process, updating and determining learners' learning styles are periodically performed to adjust learning materials and activities to fit each learner. This leads to some learners being identified by the system as having changing learning styles during the course. Further studies are needed to verify the detection results of the model with these adjustments.

6 Conclusion

In this study, we have proposed a personalized learning model based on the student's learning styles. When experimenting with the LMS system, the model's results showed that students with learning styles that matched the learning materials and learning activities achieved better results when completing the course. In addition, with theoretical-oriented courses, students with a Visual-oriented learning style following the VARK model had better results than other students. When testing the model with the practice-oriented course, students identified with Kinesthetic learning styles had better learning outcomes than other groups. Regard to the method automatically determines the learning style of online learners based on their interactions; the experimental results showed that the use of machine learning techniques identifies students' learning styles based on learning activities. Among the techniques to detect student learning styles, the experimental results indicate that SVM can best detect learners' learning styles. The proposed model efficiently delivers learning materials tailored to the individual learning style of each student, resulting in improved learning outcomes for students enrolled in online courses. Although the results only apply to small class sizes and are not diverse in subject matter, the experimental results show that the model can be applied at a larger scale.

In further research, more focus should be given on identifying students' learning styles at the beginning of the course. In addition, the model should be improved by updating students' learning styles throughout the learning process based on their interactions, which will help select appropriate learning materials for them.

Appendix

Table 7 Questionnaires to detect the students' learning styles when starting the course

No	Questions
Multi choice one answer questions	
1	What are your career plans after completing your studies?
	• Work at a non-governmental organization (NGO)
	• Work at a foreign company
	• Work domestically
	• Work at a school
	• Work in the government
	• Start a business
2	In a research group working on difficult materials, you are likely to
	• Participate and contribute opinions
	• Sit back and listen
3	In the classes you have attended, you usually:
	• Often get to know many students
	• Don't get to know many students
4	When starting to do homework, you tend to:
	• Start working immediately
	• Try to fully understand the problem first
5	You enjoy learning:
	• In a group
	• Alone
6	When working on a long problem, you:
	• Tend to check and redo the steps carefully
	• Feel tired of checking and often feel pressured when checking something unfamiliar
7	When doing something, you usually:
	• Become proficient in a certain way of doing things
	• Come up with a new method (if any)
8	For leisure, you prefer to:
	• Watch TV, videos
	• Read books
9	If you were a teacher, you would teach a course that:
	• Solves real-life problems
	• Addresses ideas and theories
10	How much time do you spend on self-study in a day?
	• 1–2 h
	• 2–3 h
	• 3–4 h
	• More than 4 h
11	Do you prefer online or offline learning?
	• Offline
	• Online

Table 7 (continued)

No	Questions
12	Do you prefer using learning materials in English or Vietnamese? • English • Vietnamese
13	Which factor do you emphasize the most in the learning process? • Theory • Practice • Real-world projects
14	What type of learning materials do you prefer? • Videos • Reading • Hands-on practice • Audio
15	Do you plan to pursue a master's degree? • Yes • No
16	Do you have goals to study abroad or work overseas? • Yes • No
17	When you are learning a new subject, you prefer to • Stay focused on that subject, learning as much about it as I can • Try to make connections between that subject and related subjects
Multi choice multi answer questions	
18	Check the descriptions that accurately describe your learning style: - [] I easily feel bored - [] I am often attracted to new things rather than practical ones - [] I tend to adapt and respond rather than make specific plans - [] I feel very happy when solving new and different problems - [] I am someone who likes to practice or do practical projects - [] I tend to evaluate other people's ideas based on their practicality - [] I like to focus on doing one thing at a time - [] I prefer to get to work rather than just talk about it - [] I am very careful and meticulous in learning and working - [] I often discover things that others overlook

Table 7 (continued)

No	Questions
19	Check the box that describes your learning skills:
	- [] You have difficulty solving complex problems (don't know where to start, don't know how to prioritize tasks, etc.)
	- [] You easily get discouraged when faced with long-term tasks or goals
	- [] You often have difficulty in scheduling and managing time to complete tasks
	- [] Instead of completing homework in advance, you do it during class
Likert questions (1 to 5)	
20	Rate your ability to work in a team
21	Rate your ability to concentrate

Funding The author(s) received no specific funding for this work.

Data availability The datasets generated and/or analyzed during the current study are available from the corresponding authors on reasonable request.

Declarations

Conflict of Interest The author hereby declares that there is no conflict of interest.

References

Adorni, G., & Koceva, F. (2015). Designing a knowledge representation tool for subject matter structuring. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 1–14. https://doi.org/10.1007/978-3-319-28702-7_1

Aguilar, J., Buendia, O., Pinto, A., & Gutiérrez, J. (2022). Social learning analytics for determining learning styles in a smart classroom. *Interactive Learning Environments, 30*(2), 245–261. https://doi.org/10.1080/10494820.2019.1651745

Azzi, I., Jeghal, A., Radouane, A., Yahyaouy, A., & Tairi, H. (2020). A robust classification to predict learning styles in adaptive E-learning systems. *Education and Information Technologies, 25*(1), 437–448. https://doi.org/10.1007/s10639-019-09956-6

Barbara, B., & Kathleen, M. (2013). A Step-by-Step Guide to Personalize Learning. *Learning & Leading with Technology, 40*(7), 12–19.

Bursac, M., Milosevic, D., & Mitrovic, K. (2019). Proposed Model for Automatic Learning Style Detecting Based on Artificial Intelligence. *11th International Scientiic Conference "Science and Higher Education in Function of Sustainable Development,"* 47–54.

Carol, C. (2015). Learning Styles in Higher Education. A Case Study in History Training. *Procedia - Social and Behavioral Sciences, 180*, 256–261. https://doi.org/10.1016/j.sbspro.2015.02.113

Cheung, V. Y. T., Tang, Y. M., & Chan, K. K. L. (2023). Medical students' perception of the application of a virtual reality training model to acquire vaginal examination skills. *International Journal of Gynecology and Obstetrics*, 1–6. https://doi.org/10.1002/ijgo.14670

Chookaew, S., Panjaburee, P., Wanichsan, D., & Laosinchai, P. (2014). A Personalized E-Learning Environment to Promote Student's Conceptual Learning on Basic Computer Programming. *Procedia - Social and Behavioral Sciences, 116*, 815–819. https://doi.org/10.1016/j.sbspro.2014.01.303

Christudas, B. C. L., Kirubakaran, E., & Thangaiah, P. R. J. (2018). An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials. *Telematics and Informatics, 35*(3), 520–533. https://doi.org/10.1016/j.tele.2017.02.004

Dziedzic, M., De Oliveira, F. B., Janissek, P. R., & Dziedzic, R. M. (2013). Comparing learning styles questionnaires. *Proceedings - Frontiers in Education Conference, FIE*. https://doi.org/10.1109/FIE.2013.6684972

El Aissaoui, O., El Alami El Madani, Y., Oughdir, L., & El Allioui, Y. (2019). A fuzzy classification approach for learning style prediction based on web mining technique in e-learning environments. *Education and Information Technologies, 24*, 1943–1959. https://doi.org/10.1007/s10639-018-9820-5

Felder, R. M., & Silverman, L. K. (1988). Learning and Teaching Styles in Engineering Education. *Engineering Education, 78*(7), 674–681.

Felder, R. M., & Soloman, B. A. (2004). *Index of Learning Styles Questionnaire*. https://www.webtools.ncsu.edu/learningstyles/. Accessed 17 Sept 2023.

Hasibuan, M. S., Nugroho, L. E., & Santosa, P. I. (2019). Model detecting learning styles with artificial neural network. *Journal of Technology and Science Education, 9*(1), 85–95. https://doi.org/10.3926/jotse.540

Hmedna, B., Mezouary, A. E., & Baz, O. (2017). An approach for the identification and tracking of learning styles in MOOCs. *Advances in Intelligent Systems and Computing*. https://doi.org/10.1007/978-3-319-46568-5_13

Hung, Y. H., Chang, R. I., & Lin, C. F. (2016). Hybrid learning style identification and developing adaptive problem-solving learning activities. *Computers in Human Behavior, 55*(Part A), 552–561. https://doi.org/10.1016/j.chb.2015.07.004

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers and Education, 56*(3), 885–899. https://doi.org/10.1016/j.compedu.2010.11.001

Kühl, T., & Zander, S. (2017). An inverted personalization effect when learning with multimedia: The case of aversive content. *Computers and Education, 108*, 71–84. https://doi.org/10.1016/j.compedu.2017.01.013

Li, Z., Papaemmanouil, O., & Koutrika, G. (2016). Coursenavigator: Interactive learning path exploration. *3rd International Workshop on Exploratory Search in Databases and the Web, ExploreDB 2016 - Proceedings*, 6–11. https://doi.org/10.1145/2948674.2948676

Liyanage, M. P. P., LasithGunawardena, K. S., & Hirakawa, M. (2016). Detecting learning styles in learning management systems using data mining. *Journal of Information Processing, 24*(4), 740–749. https://doi.org/10.2197/ipsjjip.24.740

Matar, N. (2011). Adaptive Unified E-learning Approach Using Learning Objects Repository Structure. *International Journal for Digital Society*, *2*(4), 579–587. https://doi.org/10.20533/ijds.2040.2570.2011.0070

McKenna, L., Copnell, B., Butler, A. E., & Lau, R. (2018). Learning style preferences of Australian accelerated postgraduate pre-registration nursing students: A cross-sectional survey. *Nurse Education in Practice, 28*, 280–284. https://doi.org/10.1016/j.nepr.2017.10.011

Moutafi, K., Vergeti, P., Alexakos, C., Dimitrakopoulos, C., Giotopoulos, K., Antonopoulou, H., & Likothanassis, S. (2013). Mining student learning behavior and self-assessment for adaptive learning management system. *Communications in Computer and Information Science, 384*, 70–79. https://doi.org/10.1007/978-3-642-41016-1_8

Müller, J., & Christandl, F. (2019). Content is king – But who is the king of kings? The effect of content marketing, sponsored content & user-generated content on brand responses. *Computers in Human Behavior, 96*(July), 46–55. https://doi.org/10.1016/j.chb.2019.02.006

Nabizadeh, A. H., Jorge, A. M., & Leal, J. P. (2017). RUTICO: Recommending Successful Learning Paths under Time Constraints. *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, 153–158. https://doi.org/10.1145/3099023.3099035

Nabizadeh, A. H., Leal, J. P., Rafsanjani, H. N., & Shah, R. R. (2020). Learning path personalization and recommendation methods: A survey of the state-of-the-art. *Expert Systems with Applications*, *159*. https://doi.org/10.1016/j.eswa.2020.113596

Niknam, M., & Thulasiraman, P. (2020). LPR: A bio-inspired intelligent learning path recommendation system based on meaningful learning theory. *Education and Information Technologies, 25*(5), 3797–3819.

Oliveira, A., Teixeira, M. M., & Soares Neto, C. S. (2020). Recommendation of educational content to improve student performance: An approach based on learning styles. *CSEDU 2020 - Proceedings of the 12th International Conference on Computer Supported Education*, 359–365. https://doi.org/10.5220/0009436303590365

Pasina, I., Bayram, G., Labib, W., Abdelhadi, A., & Nurunnabi, M. (2019). Clustering students into groups according to their learning style. *MethodsX, 6*, 2189–2197. https://doi.org/10.1016/j.mex.2019.09.026

Rasheed, F., & Wahid, A. (2021). Learning style detection in E-learning systems using machine learning techniques. *Expert Systems with Applications, 174*(February), 114774. https://doi.org/10.1016/j.eswa.2021.114774

Şahin, Ş., Arseven, Z., & Kiliç, A. (2016). Causes of student absenteeism and school dropouts. *International Journal of Instruction*, *9*(1), 195–210. https://doi.org/10.12973/iji.2016.9115a

Sangvigit, P. (2012). Correlation of Honey & Mumford Learning Styles and Online Learning media preference. *International Journal of Computer Technology and Applications, 3*(3), 1312–1317.

Segal, A., Gal, K., Shani, G., & Shapira, B. (2019). A difficulty ranking approach to personalization in E-learning. *International Journal of Human Computer Studies, 130*, 261–272. https://doi.org/10.1016/j.ijhcs.2019.07.002

Sheeba, T., & Krishnan, R. (2018). Prediction of student learning style using modified decision tree algorithm in E-learning system. *ACM International Conference Proceeding Series*, 85–90. https://doi.org/10.1145/3239283.3239319

Tang, Y. M., Chau, K. Y., Lau, Y., & yip, & Ho, G. T. S. (2022). Impact of mobile learning in engineering mathematics under 4-year undergraduate curriculum. *Asia Pacific Journal of Education*. https://doi.org/10.1080/02188791.2022.2082379

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55*, 1185–1193. https://doi.org/10.1016/j.chb.2015.02.014

VARK learn limited. (2023). *The VARK Questionnaire – How do you learn best?* https://vark-learn.com/the-vark-questionnaire/. Accessed 17 Sept 2023.

Vermunt, J. D. (1998). The regulation of constructive learning processes. *British Journal of Educational Psychology, 68*(2), 149–171. https://doi.org/10.1111/j.2044-8279.1998.tb01281.x

Viloria, A., Gonzalez, I. R. P., & Lezama, O. B. P. (2019). Learning style preferences of college students using big data. *Procedia Computer Science, 160*, 461–466. https://doi.org/10.1016/j.procs.2019.11.064

Yang, M., Tu, W., Qu, Q., Zhao, Z., Chen, X., & Zhu, J. (2018). Personalized response generation by Dual-learning based domain adaptation. *Neural Networks, 103*(July), 72–82. https://doi.org/10.1016/j.neunet.2018.03.009

Ye, X., & Manoharan, S. (2019). Providing automated grading and personalized feedback. *ACM International Conference Proceeding Series*, 1–5. https://doi.org/10.1145/3371425.3371453

Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018). Personalized learning full-path recommendation model based on LSTM neural networks. *Information Sciences, 444*, 135–152. https://doi.org/10.1016/j.ins.2018.02.053

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