Journal of Multimedia Processing and Technologies

DLINE JOURNALS

Print ISSN: 0976-4127
Online ISSN: 0976-4135

JMPT 2025: 16 (2)
https://doi.org/10.6025/jmpt/2025/16/2/57-82

A Survey of Personalization in E-learning and Adaptive Content According to Learner Profile

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ABSTRACT

With the proliferation of technology, the field of adaptive e-learning has garnered significant attention in recent years. This is because it has allowed users to learn at their own pace and to define personal learning paths based on their individual interests and needs. Using several different devices and sensors around the world can provide to generate massive amounts of data. The analysis of this collected data will provide a basic solid information to ensure adaptive e-learning. Machine learning and data analytics are today very common techniques that can help extract information and find valuable patterns within the collected data. In this work, the field of adaptive e-learning is investigated in terms of definitions and characteristics. Moreover, a taxonomy of various challenges, used machine learning algorithms, the data used in this process are discussed. Also, some of the works proposed in the literature, which tackle these challenges are presented. Our study shows that, despite attempts made by these works to improve the adaptive e-learning. Data processing is generally performed in deferred time, which does not reflect the current state and needs of learners. Likewise, the learner's behavior is often unpredictable, it can be influenced by several mental and environmental factors and it changes rapidly over time. Data stream mining is very important in adaptive e-learning which originated many main research directions for this area that merit further exploration and investigation.

Keywords: E-learning, Personalized learning, Machine Learning, Real-time, Data Stream Mining

Received: 13 December 2024, Revised: 11 February 2025, Accepted: 20 March 2025

1. Introduction

With the proliferation of technology throughout the world and with the boom in information access, e-learning has become more popular as it allows individuals to learn new skills without having a mentor physically present teaching them. In this context, several e-learning systems exist like Learning Management Systems (LMSs: Blackboard, Claroline) and Massive Open Online Courses (MooCs:edx, Coursera). These E-learning systems offer multiple and diverse online courses/learning activities open to all learners. They facilitate access to information and continuity of the learning process for everyone, and this is especially noticeable in this hypersensitive period of COVID-19 which has compelled decision education officials across the world to close school.

Noting that an effective learning system involves three main types of actors which are: establishment, teacher and learner which are heterogeneous, and each of them may have different needs. Figure 1 expresses the needs of each of these actors.

As shown in Figure 1, all actors in a learning process seek personalization. In this present work, we focus on the study of personalization in LMSs which is directed for the learner. Real-time personalization in LMS system is a complex and challenging task, since the communication with learner can be synchronous. This can learn and predict the learner behavior in real-time.

In this context, we notice that most courses on current LMS barely offer any information about which didactical techniques and learner models they utilize (Jagadeesan & Subbiah, 2020; Oneto & al., 2009). Generally, LMSs offer the same kind of course structure and Learning Objects to each learner (Brusilovsky & Moller, 2002; Shishehci & al., 2011). This is called the "one size fits all" approach ((Imran & al., 2014). But each learner has different characteristics/needs, and therefore, a "one size fits all" approach does not support most learners particularly well. Studies in (Paneva, 2005) have shown the existence of a significant effort to support the learner in the learning process. However, we could find a lot more possibilities for personalization to the learner than this.

One of the possible ways to support each learner individually based on his/her characteristics is the use of personalization. Personalization in LMS refers to the functionality which enables the system to uniquely address a learner's needs and characteristics such as levels of expertise, prior knowledge, cognitive abilities, skills, interests, preferences and learning styles (Huang & al., 2007) so as to improve a learner's satisfaction and performance within the course and therefore minimize the dropout rate of students in e-learning.

Adaptive E-learning System enhances the efficiency of online education by providing personalized contents and user interfaces. The personalized environment should be adaptive and should change according to the learner's requirements. Learners are free to learn at their own pace and to define personal learning paths

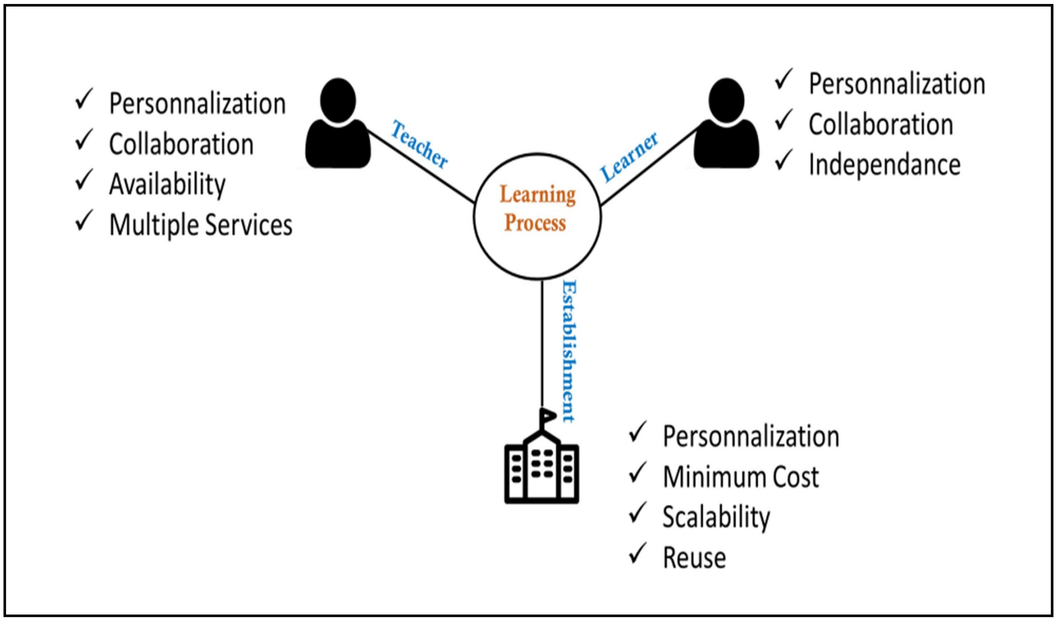

Figure 1. Learning Process Actors and needs

based on their individual interests and needs. Authors in (Doukhi, 2014) defined three types of adaptation: i) Content adaptation involves selecting information that depends on the current state of the user model. For an expert, the content of the pages will be different from that of a beginner for a specific subject, ii) Presentation adaptation involves adjusting the layout and visual appearance of the elements (fragments) that will be presented, to the preferences and expectations of the user, iii) Navigation adaptation which consists in easily orienting the learner to the information he needs and providing good navigation.

These different types of adaptation are carried out according to the needs and requirements of the learner. These learner requirements can be captured through their: i) learner models such as *Personal and Private Information* (PAPI) Standard (LTSC Learner Model Working Group of the IEEE, 2000), *Educational Modelling language* (EMLs) (Rawlings & al., 2002). ii) learning style model such as (Moubayad & al., 2018; Clark, 2011; Felder & Soloma, 2000): *Honey*, *Mumford*, *Kolbs*, *Felder Silverman Learning Style Model* (FSLSM), *VAK*, *Gregorc'c*, *Riding Cognitive Style and Myer-Briggs Type indicator*. Recently, research is directed towards the exploitation of the growing amount of collected data that is already being generated through different devices and sensors employed around the world to predict other's important data and valuable patterns in multiple fields such as spam filtering, and autonomous driving and house pricing prediction (Kearns & al.,1994).

E-learning is one of the most recent fields that is contributing to the great amount of generated data. Statistics show that LMSs such as Moodle, Blackboard, and Sakai have more than 78 million students combined with around 10000 courses being offered by more than 600 universities (Shah, 2016). Moreover, there are almost 1000 event log entries per student every month and around 60,000 course visits every month for online courses (Eichhorn & Matkin, 2016). The analysis and extraction of useful information from these log files can help the personalization and adaptation of e-learning.

To this end, machine learning (ML) and data analytics (DA) have been proposed to perform these tasks. ML techniques aim to "train" computers to complete specific tasks without being explicitly programmed using the collected data (Moubayed & al., 2018). On the other hand, DA aims to analyze and draw conclusions from the raw collected data to be able to make better decisions (Jagadeesan & Subbiah, 2020). Hence, such techniques can become crucial and useful tools for researchers to tackle the challenges found in the adaptive e-learning field. They can be used to get better insights into the performance and the behavior of students in different e-learning environments, classify students based on their learning style. Therefore, ML and DA can play a crucial role in the adaptive e-learning and improvement of the learning experience.

This paper aims to provide a comprehensive view of the field of adaptive e-learning and the challenges it is facing based on a scoping review of the literature. The rest of this paper is organized as follows: In Section 2, we presented the review methodology adopted in this work by providing the information sources and the research questions. Section 3 presents the background containing the important concepts related to our study. Section 4 describes the personalization in industrial LMS. Section 5 presents the data types used to determinate the learner profile. Section 6 present the different challenges in adaptive e-learning as well as some of the previous works that tackled these challenges. Section 7 discusses the existing work. In section 8, some of the research opportunities that can be explored facing the field of adaptive e-learning. Finally, Section 9 concludes this paper.

2. Review Methodology, Information Sources and Research Questions

In this section, we introduces the review methodology adopted we relied on to perform the following study. We provide the different types of studied information sources together with the search and selection criterion we used to select the final set of papers.

2.1 Review Methodology

We presented the review methodology adopted in this work by providing the information sources and the research questions.

To elaborate this current study on personalization in e-learning, we used a review methodology inspired by Kitchenham and Charters (2007), Herari and Omri (2021). This approach, is a set of processes that make up a validation protocol. First, we provide various sources of information, and second, search and select criteria for the main references used in this study. Next, we present the questions that we have to answer in this survey work.

According to our objective, we introduce some important work and targeted.

In this context, we performed three search iterations. In the first one, we used the following keywords: personalization in e-learning, adaptive e-learning, learner behavior. In the second iteration, we tried to look to the related research areas and we used the following keys words: learner behavior and big data, adaptive e-learning and machine learning, student engagement predictions. In the third iteration, we used others keys words such as: learner behavior in real time, adaptive e-learning and data streams, multimodal Data Stream Mining for e-Learner's Emotion.

To select the articles, we based on selective criteria such as:

- Peer-reviewed and written in English language.
- Published in reputable journals, conferences, and magazines
- Written by academic or industrial researchers.
- Have a high number of citations in case it is not published in reputable journals, conferences, and magazines.
- recent articles
- Articles which propose methodologies, methods or approaches for adaptive e-learning.
- Articles which supply models, uses cases and relevant results

2.2 Source of Articles Studied

To find relevant articles, we used the following databases in our search: Springer[1], ScienceDirect[2], Scopus[3], ACM Digital Library[4], IEEE explore[5], TaylorFrancis[6], Google Scholar[7]. Thus, we selected research articles from journals, conference proceedings, books, and magazines. In Figure 2, the percentage of papers reviewed from different types of resources is provided.

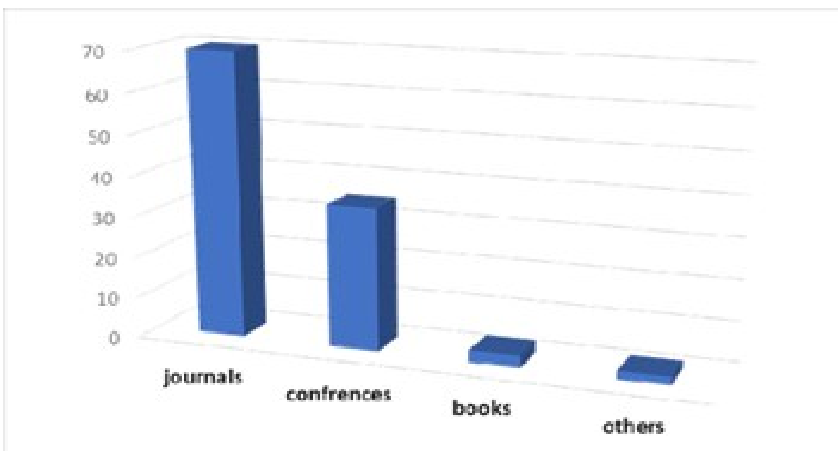

Figure 2. Percentage of articles from different types of resources

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[1]https://link.springer.com

[2]http://www.sciencedirect.com

[3]https://www.scopus.com

[4]https://www.acm.org/digital-library

[5]http://ieeexplore.ieee.org

[6]https://www.taylorandfrancis.com

[7]https://scholar.google.co.in

2.3 Research questions

The research done in this article aims to answer some research questions. This part is devoted to identifying survey questions and our goal is to answer these questions by conducting a review of existing surveys.
RQ1: What is adaptive e-learning and what is its importance in e-learning?
RQ2: What are the main reasons and motivations to apply adaptive learning.
RQ3: How can we define the behavior of a learner?
RQ4: What are the methods adopted to achieve adaptive e-learning?
RQ5: What resources and metrics have been considered in the adaptive e-learning?
RQ6: What algorithms are being exploited?
RQ7: What are the evaluation methods used in existing approaches?
RQ8: What is the processing mode of collected data (in real time or in deferred time)?
RQ9: What should be the future research challenges and orientations behind personalization in e-learning?

3. Background

3.1 Adaptive e-learning system

E-learning is a training method that eliminates the physical presence in the classroom of the teacher and the learner. So, each learner will learn according to their needs and their preferences. Therefore, an e-learning course should match students' needs and desires as closely as possible, and adapt during course progression. This requires creating learning content that meets their needs. This is called personalized adaptive e-learning (Vagale & al., 2020). Adaptation and personalization are two key words for a learning environment able to motivate, engage and inspire learners. These two words are strongly related: adaptation is based on personalization (Oneto & al., 2009). They allow the learner to access the most appropriate, interesting and challenging learning activities, and to avoid learning material already acquired by the learner, and then not any more necessary to him. Personalization and related adaptation are possible through adaptive learning technology (Adaptive Learning Environment).

Authors in (Graf, 2007; Ahmad, 2014) defined the personalized e-learning as the ability of the e-learning system to detect differences in individual learning approaches, in terms of knowledge level, preference of learning styles, cognitive ability, goals etc. Adaptivity means adapting the e-learning environment or e-learning process to facilitate and accelerate individual learning performance in a dynamic way (Alkhuraiji, 2016). Another definition of personalized learning is that it is a form of on-line learning where the presentation and content learning material can vary according to an individual preferred learning style. The material may be available in different formats such as text, graphics, audio or video, and an adaptive learning system would then be able to automatically select the most appropriate style for a given learner. The potential of adaptive learning is to accelerate learners' performance in achieving their goals, reduce time spent in learning, facilitate instructions, or improve learners' scores or knowledge.

One of the most relevant characteristics of a personalized learning system is the ability to interact with change in the learner behavior in real time in order to adapt the learning content.

From the historical viewpoint on adaptive learning theories, three main approaches can be identified (García-Barrios, 2006; Mödritscher & García-Barrios, 2005; Park & Lee, 2008): The Macro-adaptive Approach (MaA), the Aptitude- Treatment Interaction approach (ATI), and the Micro-adaptive Approach (MiA).

In MaA theory, on behalf of learning goals as well as general abilities and achievement levels of learners, the instructional alternatives are selected.

In the ATI approach, instructional alternatives are adapted according to specific learner traits, such as intellectual abilities, cognitive or learning styles, expertise level, and achievement motivation.

The MiA approach is based on the diagnostics of the specific learning needs during instruction, and consequently provides instructional alternatives for these needs.

The use of adaptive learning can realize various benefits (Jagadeesan & Subbiah, 2020) such as:

- **Flexibility:** By adopting adaptive aspect, content its generated in various formats, for example, pdf, word, clips of videos, sound, etc. Learners have typical learning styles; some prefer learning by verdicting out on subjects, some may watch videos, and others may listen. All students can work at their own pace to achieve the most perfect academic result (Ennouamani & Mahani, 2017; Jagadeesan & Subbiah, 2020).

- **Engaging:** Adaptive learning used the interactive exercises and tutorials for exhibiting information, which make students active and engaged to learn and consequently achieving higher course rates completion.

- **Efficient:** Adaptive learning methods used analytics of data to express learning gaps among class, authorizing instructors to modify discourses to discuss the shortcoming or see where exercises can better be made.

- **Behavioral Learning:** It is important to know how people learn and what are all the factors

3.2 Learner profile model

3.2.1 Educational Modelling language (EMLs)

influencing the learning style of the learner, what motivates the learner. The learning model can be updated based on the preferred learning content, time spent on learning that content and answers obtained from quiz and tests. The offer of adaptive learning content to learner requires a profile to be stored for each learner and for each group of learners (where a group of learners here means a set of individual users who work on some activities in collaboration, for example a class of learners all studying the same topic, and who use a single 'group profile' for the collaborative activity).

In order to build an adaptative e-learning, an efficient modeling of the user profile is needed.

In literature multiple schemes to describe the learner profiles have been proposed. In this section we briefly consider some of these models, and whether they can provide the information necessary for the personalization.

The *CEN's Information Society Standardization System* (CEN/ISSS) defines an EML as " a semantic information model and binding, describing the content and process within a 'unit of learning' from a pedagogical perspective in order to support reuse and interoperability" (Rawlings & al., 2002). EMLs are dedicated to describe both the content of learning units and the interactions and activities of students and teachers when connecting to e-learning system. However, studies have shown that all of the proposals have so far concentrated on the description of learning content (a 'unit of learning' - e.g. a course), and they neglect the description of the actors involved in the learning process (Paneva, 2005).

Only some proposals such as OUNL-EML[8] and PALO (Rodriguez-Artacho, 2002) considered the user model as well as course content. In these works, users are defined in terms of the roles they play (what activities they participate in) for workflow modelling. This type of user modelling doesn't directly concern the personalization. The most important information for personalization realization is the learner's current goals, experience and preferences, which are not covered by workflow modelling.

3.2.2 Personal and Private Information (PAPI)

The *IEEE LTSC's Personal and Private Information (PAPI)* Standard (LTSC, 2000) defines the syntax and semantics of a "learner model", which characterizes a learner and his or her knowledge/abilities. This standard includes elements for recording knowledge acquisition, learning styles, skills, abilities, records, and personal information. This standard allows these elements to be represented in multiple levels of granularity, from a coarse overview, down to the smallest conceivable sub-element.

PAPI distinguishes personal, relations, security, preferences, performance, and portfolio information.

3.2.3 IMS Learner Information Package (IMSLIP)

The IMS LIP standard provides a means for recording information about a learner in a database (LMS-LIPIMS, 2001). This standard represents a data model that makes it possible to describe the characteristics of a learner necessary for the management of his learning history. This model is richer and more detailed compared to the other previous models. It offers eleven categories of information that define a data structure that can be imported or exported between interoperable systems. These categories are represented by Figure 3.

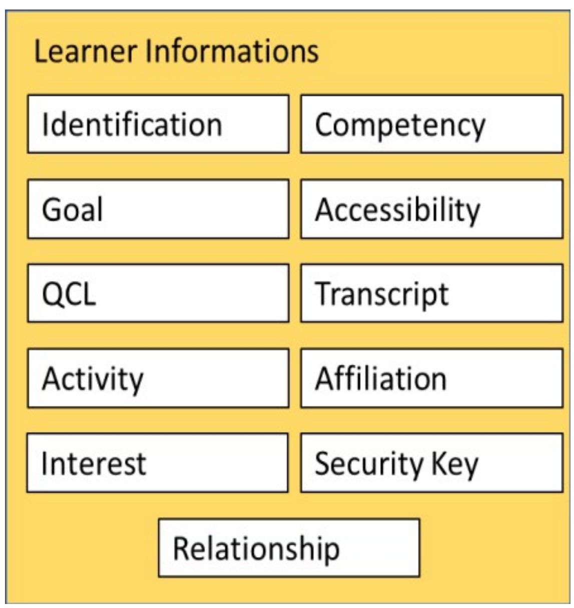

Figure 3. Categories of IMSLIP model

[8]https://www.ou.nl/web/blurred-lives/contact

We notice that IMS-LIP improves on PAPI slightly by providing a string field for learning goals. However, these informations are not sufficient knowing that learner behavior changes over time and the personalization in LMSs requires schemas to be developed, allowing spaces in the profile for descriptions of learner behavior (facial expressions, head pose, eye gaze, learner reaction, etc.). All of these data elements should have a place in the learner profile model in order to facilitate the communication between teacher and learner in real time, improve the personalization and ensure continuity of the learning process. In this context, various challenges in personalized e-learning and some works proposed in the literature to tackle these challenges are presented in the next section.

4. Personalization in industrial LMSs

Personalization in industrial LMSs consist to be concerned with remembering which courses the user is allowed to view and how they like their content to be presented. Sometimes, users (learners, teacher and administrators) are able to edit their own profile; to maintain their personal calendar (monthly and weekly) which keeps track of their event transactions; to subscribe to forums, etc. Observing the educational process as a whole in LMSs, learners are very rarely allowed to get access to learning objects which are conditioned on a wide range of personal data including achievement, date/time and class code. In what follows (Table 1), we study seme existing LMSs in term of personalization.

LMS	Personalization type
WebCT	- Personalization mainly at the institutional, rather than individual level. The 'look and feel' of the system can be tailored to reflect the institution logo.
Blackboard	- Allowing users to set individual bookmarks and providing a single-sign-on system - Provide "a total e-education infrastructure" for schools, colleges, universities, and other education providers. -Provides various facilities including a bulletin board, calendar, active conferencing and quiz tools. -Users can pick and choose which features they want in their system from existing building blocks, or can build their own if a suitable one is not available.
Xtensis	- Combine the learner history with the Learning Object metadata to make 'intelligent suggestions' about the next LOs. -Consider some factors to personalization such as the language of the LO, the intended age range of the LO, prerequisites of a LO, nearness in a taxonomy of subjects, the preferred learning style.
Class Server 3.0	-Provides personalized pages for different user types - teachers, students and administrators.

	-Learners can adjust the colors, the font size, and the interface view. -The teacher gives the learning material (lessons, tests, etc.) to the student during the learning process, who sees them in his/her personal page. -The teacher can monitor how the student deals with the learning material and provides student-specific materials.
Future Learning Environment (Fel3)	- The system is open source, so the interface and functionality can be customized by users.
Moodle	-The navigation through the learning units will be system-guided and personalized. -Users (learners, teacher and administrators) are able to edit their own profile. -The learner can restore and continue the learning process and allows more flexible schedule for learning on the work place, necessarily intermixed with work tasks.
.LRN	-The teachers are able to manage their classes and groups and fully personalize the layout of the course. -The students can join forums, courses or news groups that they are interested in, request change notification, store their personal files and maintain their personal calendar, which keeps track of their event transactions

Table 1. Personalization in existing LMSs

From our study of personalization in LMSs existing, we notice the existence of a significant effort to support the teacher, learner and institution in the learning process. However, there would seem to be a lot more scope for personalization to the learner than this, as these learning systems records quite a massive amount of information on the behavior of the users (which documents they visit, how long they spend viewing them, test results and grades, discussion in forum). At present this information seems to be used solely for the production of reports, but could be used towards providing for learners a truly personalized educational experience.

In recent years, research is directed towards the exploitation of this data for the learning content personalization in real-time according to the behavior of the learner which is changing over time. In this context, various challenges in personalized e-learning and some works proposed in the literature to tackle these challenges is presented in section 6. But before that, we present in the following section the types of data used to adapt the learning content according to the profile and preferences of each learner.

5. Data Types used

Visiting websites online produce a massive amount of data. Also, our environment allows us to give indicators that we can exploit for the detection of the learner behavior learner. In this section, we present the types of used data (Table 2).

6. Personalized E-learning Challenges

Personalization in e-learning is a topic that is garnering significant attention in recent years and there are many challenges related to this aspect. Some of these challenges are related to learners, others are related to teachers and others related to both. Figure 4 summarizes some of these challenges, the classification type, the used data for personalization, ML algorithms and the adaptation type. In what follows, a more detailed discussion about these challenges that were identified by leading experts within the field as well as some related work is presented.

6.1 Reduce the Student's Dropout Rate

Along with the rapid growth of E-learning, its problem of having a much higher student dropout rate than traditional learning has also become more prominent. In this context, several studies assert that the student's dropout rate for E-learning is 10-20% higher than traditional learning (Allen & Seaman, 2011). This is due to several factors:

• E-learners leave courses without completion due to the processing of all learners with uniform teaching strategies and the lack of interaction with teacher. Adaptive e-learning systems should be used that provide learning material according to the student's requirements. Learning styles are helpful to understand the learning needs of the learners and improve the interaction between learner and teacher.

• Lack of self-motivation among learners.

• Lack in support and orientation of learners in online courses.

Tan & Shao (2015) use the ML method for constructing a prediction model for dropping out to achieve the objective of identifying potential dropouts before the behavior happens. For this, they use input attributes for the predictive model such as personal characteristics and academic performance of students. Then, three machine learning methods namely *Artificial Neural Network* (ANN), *Decision Tree* (DT) and *Bayesian Networks* (BN) for predicting students' dropout factors are tested. The DT had relatively better prediction results.

In the same context, Mourdi & al., (2019) assert that, despite the success and the growth in the number of courses offered by the MOOCs platforms, a very appropriate problem that cannot be neglected: the huge number of learners' dropout. This is due to lack of self-motivation among learners, the low quality of learner/instructor interaction and lack in support and orientation of learners in MOOCs causes a very high dropout rate.

To resolve this problem, authors develop a prediction model to track learners in a MOOC on a weekly basis (per week) and classify them into three broad classes: the admitted; the non-admitted and those at risk of dropping

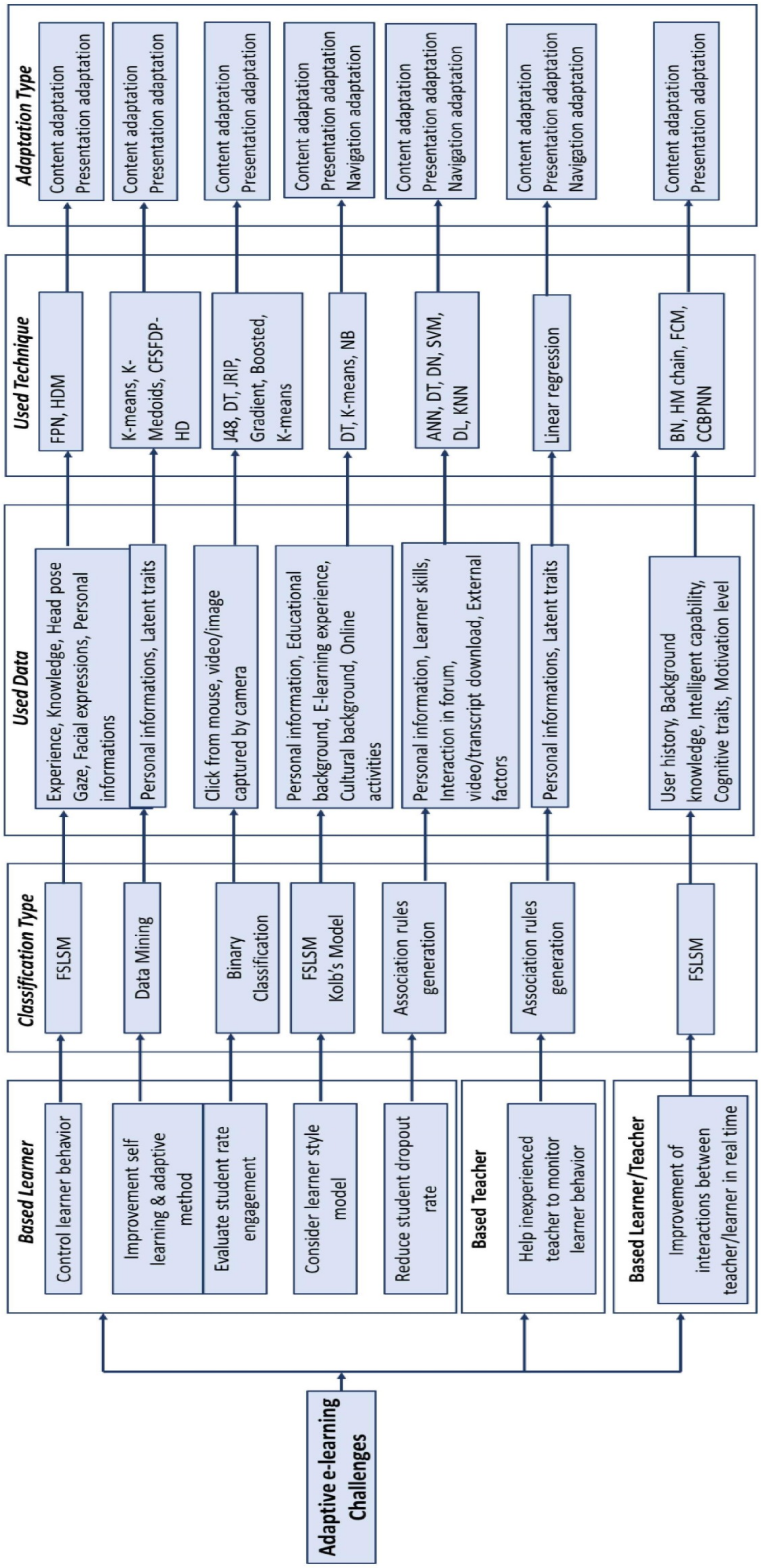

Figure 4. Taxonomy of adaptive e-learning challenges

Data type	**Example**	**Description**
Log Files	Navigation	-Number of distinct units (pages) visited -Number of concrete resources visited -Number of sequences visited -Total time spent on sequences -Number of times the learner advances to the next unit in a sequence -Number of times the learner returns to the previous unit in a sequence - Number of course overview page visits
External data	Discussion on forums and social networks	-Number of messages posted on the forum -Number of messages viewed in the forum - status shared on social networks - Time spent on social networks
	Quiz	-Number of quizzes visited -Total time spent on quizzes -Number of quiz answers visited -Total time spent reading quiz answers
	Video	-Number of videos watched -Number of times the learner reviews a part of the video -Total time spent watching videos -Number of clicks on the play button -Number of subtitle deactivations -Number of subtitle activations -Number of video playback speed changes
	Camera	- Non-verbal communication (or body language), - body posture -The pose of the head -The look. - Learner facial expressions
	Eye tracker	Eye Movement Behaviors
	Microphone	Vocal expressions (voice intonations)
	Physiological sensors, bracelet, Epoc helmet	-Respiratory rate -Skin temperature or sweating -Blood pressure -Heart rate -Breathing

Table 2. Data types used

out the MOOC. To do this, authors select features serving as characteristics for each class of learners such as learners' performance, interaction with the forum, their personal information, their platform behaviors, their engagement, and their interactions with problems, videos and even the download files. Then they adopted many ML algorithms such as DTs, *support vector machines* (SVM), *deep learning* (DL) and *k-nearest neighbor* (KNN).

6.2 Consider the Student Learning Style Model

The major limit of existing e-learning systems is to provide a personalized interface with personalized contents which adapts to the learning styles of the learners. This should be possible if the learning style of the learner is known. So, this solves the problem of procedural learning like static and general-purpose content delivery for all learners and improvises it with adaptive and personalized content delivery. In this context, several authors consider the learner style model to develop the adaptive e-learning system. Kalhoro & al., (2016) affirmed that e-learners leave courses without completion due to the lack of teachers' interaction and diversity of students dealt with uniform teaching strategies. Adaptive e-learning systems that provide learning material according to the student's requirements should be used. Hence, learning styles are helpful to understand the learning needs of the learners. They use Kolb's model and the decision tree to detect the learning styles of e-learners on LMS.

Hidayat & al., (2020) proposed a detection model of student's learning styles by utilizing information from log file data and FSLSM model (Felder Silverman Learning Style Model). This model consists of four processes: The first process is pre-processing to get 29 features that are used as the input in the clustering process. The second process is clustering using a modified *K-Means* algorithm to get a label from each test data set before the classification process is carried out. The third process is detecting learning styles from each data set using the *Naive Bayesian* classification algorithm, and finally, the analysis of the performance of the proposed model.

Authors (Joseph & Abraham, 2019), developed an *adaptive e-learning system* (AeLS) to support slow learners, to provide an efficient learning mechanism. It is an instruction design-based course module, developed using Lesson activity in Moodle. The Felder- Silverman Learning Style Model was also employed with the intention of integrating diverse learning styles of students. The learning paths of all learners were identified using activity logs obtained from the Moodle weblog data.

6.3 Evaluate the Student Rate Engagement

It is necessary to identify the students' engagement level during the e-learning course and determine the components that encourage students that are not engaged. Hussain & al., (2018) have Resolved the lack of student motivation in various course activities and for various course materials to evaluate the rate engagement of students to finish a course in VLE (Virtual Learning Environment). They used ML algorithms such as: the *J48*, *decision tree*, *JRIP* and *gradient-boosted classifiers* to identify low engagement students to assess the effect of engagement on student performance. Based on these algorithms, trained models were obtained and a dashboard is developed to facilitate the control to instructors at the VLE. These models can easily be incorporated into VLE systems to help instructors evaluate student engagement during VLE courses.

Moubayed & al., (2020) identify the students' engagement level during the e-learning course and determine the components that encouraged students that are not engaged. They use the machine learning technique, *K-means* algorithm to cluster students based into categories of engagement metrics.

Authors (Yue & al., 2019) have identified learner engagement in VLE from three facets: affect, behavior and cognitive state, which are conveyed by learner's facial expressions, eye movement behaviors and the overall performance during short video learning sessions. For this, authors used three supervised classifiers such as: *CART (Classification and Regression Trees)*, *Random Forest*, and *GBDT (Gradient Boosted Decision Tree)* to classify eye movements.

In the same context, authors (Paul & al., 2019) consider that the *eye gaze tracking-based adaptive e-learning system* can make the work of teachers easier to identify the students rate engagement. They used an *Eye Tribe Tracker Pro* which uses a camera to track the learners eye movement. This data in the form of images is run through a data analysis tool *Open Gaze and Mouse Analyzer (OGAMA)*. The tool reads the "on-screen gaze coordinates" and determines the exact location on the screen where the user is looking. The gaze data is then fed into analysis tools. Several kinds of analysis such as *Area of Interest (AOI)* and fixation ratio are done. In this way, the nature of the students' concentration on the on-screen learning content can be analyzed and the corresponding changes can be introduced and like that, we can determine the learners rate engagement.

6.4 Improvement of Self learning and Adaptive Methods

The traditional approach to find learning styles depends on asking learners to self-evaluate their own attitudes and behaviors through surveys and questionnaires. This approach presents several weaknesses including the lack of self-awareness of learners of their own preferences. Besides that, the traditional approach assumes that learning styles are fixed, and cannot change over time. It is important to develop an adaptive learning system that estimates learners' abilities using measurement models in order to provide them with most appropriate materials for further improvements. Li & al., (2020) developed a systematic method to enable the adaptive learning system to discover an optimal learning policy from the data that has been collected, which include historical learning materials, test responses, and estimated latent traits, etc. For this, an *MMP (Markov Model Process)* formulation for the adaptive learning problem by representing latent traits in a continuum is developed. Second, a *model-free DRL algorithm*, the *deep Q learning algorithm* is applied.

Kausar & al., (2018) proposed a clustering approach based on the educational data mining principle to partition students into different groups or clusters based on their learning behavior. Many clustering methods such as *K-Means*, *K-Medoids*, *Density-based Spatial Clustering of Applications with Noise*, *Agglomerative Hierarchical Cluster Tree and Clustering by Fast Search and Finding of Density Peaks via Heat Diffusion (CFSFDP-HD)* are analyzed.

6.5 Control the Learner's Behavior

Control the learner's behavior help teachers to identify valid cues in order to draw conclusions about students' actual engagement in e-learning Courses/activities. Also, support teachers (inexperienced) in developing these skills by using videotaped teaching to highlight which indicators should be considered to surveil the learner's behavior. For this, the study of learner behavior attracts the attention of some researchers. Goldberg & al., (2021) proposed a machine vision approach to help teachers to monitor students' behavior and identify valid cues in order to draw conclusions about students' actual engagement in learning activities. This approach is based on machine learning to help teachers to predict the behavior and engagement of students in the classroom. This approach used two types of indicators: i) indicators collected manually such as: age, competence, gender, school type, etc. ii) indicators collected by using classroom video such as: gaze, head pose, and facial expressions.

Rani & al., (2017) have considered the control of learner's behavior as an important factor that participates in resolving the problem of procedural learning like static and general-purpose content delivery for all learners and improvises it with adaptive and personalized content delivery. They Proposed an Ontology-based Personalized Adaptive E-learning system using *FPN (Fuzzy Petri Net)* for modeling e-learning course content, *HMM (Hidden Markov Model)* algorithm for adaptability of course content according to the learner's performance and the *Felder-Silverman learning style model*.

In the same context, the authors (Megahed & Mohammed, 2020) adopted the *convolutional neural network (CNN)* and a *fuzzy system* to determine the learner behavior. For this, the CNN is used to detect a learner's facial expressions; and the fuzzy system is used to determine the next learning level based on the extracted facial expression states from the CNN and several response factors by the learner. Also, they introduced methods whereby a group of facial expressions is aggregated into a single representative.

6.6 Improvement of the interaction between teacher and learner in real-time

The learner behavior is changeable. It is necessary to identify it in real time to help teachers determine the difficulties facing the learner, understand their learning style, improve the interaction with him and make the learning portal dynamic and interactive. In this context, Truong (2016) has discussed the problem of real-time learning style predictors. He listed the main sources of data and the corresponding attributes in real-time learning style predictors, such as log files, user history, background knowledge, intelligent capability, cognitive traits, motivation level etc. In learning style classification, the author has explained about *rule-based*, *Bayesian Network* and *hidden Markov Chain*.

Kolekar & al., (2017) have considered the real time captured usage data factor of learning behavior of learners to develop an adaptive e-learning system. For this, in a first step, they identified the learning styles of the learner, by capturing the learning behavior of the learner using Web Log Mining. Then the learning styles are mapped to *Felder-Silverman Learning Style Model (FSLSM)* classes. *Fuzzy C Means (FCM)* algorithm is used to cluster the captured learning behavioral data into FSLSM categories. Finally, the *Gravitational Search based Back Propagation Neural Network (GSBPNN)* algorithm is used to predict the learning styles of the learner in real-time.

6.7 Help inexperienced teacher to monitor learner's behavior

Providing a method to help inexperienced teachers to control their student's behavior has become a major challenge in adaptive learning. Specifically, in the case of students who have a special character and change following an illness. In this context, the authors (Chu & al., 2018), assert that students with *high-functioning autism (HFA)*, negative emotions such as anxiety and anger can impair the learning process due to the inability of these individuals to control their emotions. Hence, detecting emotional transitions and providing adaptive emotional regulation strategies in a time manner to regulate negative emotions can be especially important for students with HFA in an e-learning environment. Authors proposed a facial expression-based emotion recognition method with transition detection. The proposed method used sliding window technique and *support vector machine (SVM)* to build classifiers in order to recognize emotions.

The authors (Fatahi, 2019) proposed an adaptive e-learning system based on personality and emotion designed. They used the *Myers-Briggs Type Indicator (MBTI)* model for personality module and Ortony, Clore & Collins (OCC) model for emotion module. The results showed the human characteristics such as emotion and personality which help teacher to improves the learning process.

Authors (Gombolay & al., 2017), used unsupervised learning techniques such as Hidden-Markov Model (HMM) to discover what types of learner behaviors exist and assist teachers to automatically predicting learner performance, identifying learner disengagement, and recommending personalized lesson plans. Their proposed approach potentially allows providing teachers with insights to assist them in developing better lesson plans and tailored instruction for each individual student.

7. Evaluation and limits of the existing literature

Table 3 summarizes the different challenges, previous works, used algorithms, adaptation types, processing time and data source when:

• Challenges: present the different challenges defined in the previous section.

• Previous works: related work for each challenge.

• Used algorithms: the used algorithms to classify and predict learner behavior.

• Adaptation type: the adopted type of adaptation (content, presentation or navigation).

• Processing time: the collect and treatment data time (in real time or deferred time).

• Data source: to indicate the used data source.

• Analytic data type: used type of data.

Although, these approaches provide a significant result, many challenges need to be improved. We notice that

- Authors have used one or two sources of data such as log file, camera but that remains insufficient. It will be necessary to use other data sources such as the data obtained by the Internet of Things sensor which give information on the learner environment. For example, the detection of the learner's mobility gives information on the internet network used, the infrastructure used, etc. and this can help to determine their behavior. That way, we can get a detailed view of the learner's behavior.

- In general, based only on historical data to predict learning behavior which is not efficient enough given that learner behavior is fluctuating.

- In the majority of work, customization focuses on the type of learning content (content, presentation, navigation) without taking into consideration the variability of the learning process itself. A learning process is a set of synchronized learning activities. Thus, studying its variability will be required through the identification of all the possible configurations allowing to meet the needs of learners and to ensure personalization.

-The proposed approaches only consider the learning content personalization. Sometimes the execution of a learning activity requires specific hardware and software resources. Exploitation of data about the learner's environment such as mobility, used device can help to deliver SaaS and IaaS cloud services to accomplish these activities.

8. Proposed new research directions

Based on the previously provided discussion on the challenges facing the field of personalized e-learning, Machine learning technique becomes a promising tool to improve the e-learning quality and processes. In what follows, we present a set of possible research opportunities within the field of adaptive e-learning that can benefit from using machine learning algorithms.

8.1 Use multimodal Data

Based on what we have presented previously, we conclude that the major challenge of existing learning systems is the personalization of the learning service; and in this context, much research effort is being targeted towards adapting learning in such a way that it fits each learner. But we notice that most of these studies have focused on using a single data stream source (such as log files or camera) or limited data stream combining (such as self-reported data with user clicks etc.) to measure the learner's engagement rate, reduce the dropout rate and adapt the learning content according to the specific needs of each learner.

According to (Zheng & al., 2018; Nandi & al., 2020), authors have shown combining digital data (such as learner historic, discussion in the forum, etc.) with external behaviors (such as eye movement or facial expressions, etc.) which is a promising approach to capture learner's emotions and learning experience.

With the recent advancements of IT and the internet of things (IoT) devices, e-learning has changed and it takes a new dimension. Today, we find many input devices (such as webcams, fit bands, heart rate sensors, eye trackers, etc.) for interacting with e-Learners.

This interaction between technology and learners offers an opportunity for collecting rich and multimodal data (Giannakos & al., 2018). Recent studies (Zheng & al., 2018; Lee & al., 2017) have shown that combining multimodal data increases the accuracy and generates deeper insights about the learner behavior.

As the multimodal data (multi-source data) has volume, velocity, and variety, and given that the learner's behavior is not stable and changes over time, the traditional ML approaches are incapable of mining those multimodal data. For this, we need to process the data in real-time through data stream mining.

8.2 Processing data in real-time

Learner behavior is changeable over time and it is influenced by several factors coming from the environment of the learner. The use of classic data mining which is based on historical data is not sufficient to determine the exact behavior of the learner.

To remedy these problems, Multimodal Data Stream Mining (MDSM) is a good solution. MDSM allows to perform the mining of multimodal learner-data streams in real-time and utilizes this data to design learner behavior. It aims to extract hidden knowledge/patterns from the data stream. A data stream is considered as a voluminous, continuous, unbounded, ordered sequences of data arriving at a high rate and having a distribution that often changes with time. Examples of this data include web searches, sensor data, computer network traffic and so on (Aggarwal, 2015). MDSM, allows reacting in real-time when a change in learner behavior is detected while dealing with resources in an efficient and low-cost way (Albert & al., 2015). This will be able to handle multimodal data streams by reducing the computational time and disk-space consumption without compromising the accuracy of learner behavior prediction. Also, it allows to ensure that learners are engaged during the whole learning procedure with a positive emotional state.

8.3 Learning Service prediction in cloud computing prediction

According to the previous works studied, we notice that the authors use machine learning for the learning content personalization through learning systems such as LMS, MooC, CMS, etc. However, these learning systems suffer from certain weaknesses as mentioned in (Azouzi & al., 2017; Azouzi & al., 2017; Azouzi & al., 2018; Azouzi & al., 2019; Azouzi & al., 2019): i) lack of elasticity: some learning activities require software and hardware resources that are not offered by the institution, which limits the continuity of learning. ii) this produces another problem that is scalability; existing systems are unable to support a large number of users at the same time.

E-learning in the cloud Computing (CC) can help solve these problems. CC offers resources and applications in the form of services (Infrastructure as a Services, Platform as a service, Software as a service) that can help reduce the necessary investments and promote the quality and efficiency of e-learning.

In this context, we propose to combine CC, Machine Learning, Multimodal Data and Data Stream Mining to:

- Predict the preferences and needs of learners and propose e-learning activities to them.

- Predict the preferences and needs of learners and propose a specific variant of the e-learning process to them.

- Predict the needs of each learning activity in terms of infrastructure and software resources.

- Predict user needs in terms of QoS (cost, level of security, response time, etc.).

- Predict the problems of overloading of infrastructure resources in the cloud and propose other solutions such as change of service providers or use of other similar services.

9. Conclusion

E-learning is a field that has attracted interest in recent times due to the proliferation of technology through

Challenge	References	Algorithms	Adaptation type	Processing time	Data source	Analytic data type
Reduce students dropout rate	Ref. (Tan & Shao, 2015), Ref. (Mourdi & Sadgal & El Kabtane, 2019)	-ANN -DT -BNs -Support Vector -SVM -DL -KNN	- Navigation -Presentation -Navigation	-Deferred	-Comma-Separated Value (CSV) files: (Demographics, Event extract, Activity grade, Forum, All data) -Data from information systems of online education institutions	-Quantitative
Consider learner style model	Ref. (Kalhoro, Rajper & Mallah, 2016), Ref. (Hidayat & al., 2020), Ref. (Joseph & Abraham, 2019)	-DT -K-means -NB	-Navigation -Presentation -Navigation	- Deferred	-Log Files -Web Log	-Quantitative -Qualitative
Evaluate the student rate engagement	Ref. (Moubayed & al., 2020), Ref. (Hussain & al., 2018), Ref. (Yue & al., 2019), Ref. (Paul & al., 2019)	-J48 -DT -JRIP -Gradient-boosted -K-means	-Content -Presentation	- Deferred	-Event log -Log Files	-Quantitative
Improvement of self learning and adaptive methods	Ref. (Li & al., 2020), Ref. (Kausar & al., 2018)	-DQL -K-Means -K-Medoids -CFSFDP-HD	-Content -Presentation	- Deferred	-Tests - Log files	-Quantitative -Qualitative
Control the learner's behavior	Ref. (Goldberg & al., 2021), Ref. (Rani & al., 2017), Ref. (Megahed & Mohammed, 2020)	-FPN -HMM	-Content -Presentation	- Deferred	-Video, Image - Test	-Qualitative -Quantitative
Improvement the interaction between teacher and learner in real-time	Ref. (Truong, 2016), Ref. (Kolekar & al., 2017)	-BN -HMC - Fuzzy K-means - GSBPNN	-Content -Presentation	- Deferred	-Web log -Log files	-Qualitative -Quantitative
Help inexperienced teachers to monitor learner's behavior	Ref. (Goldberg & al., 2021), Ref. (Gombolay & al., 2017), Ref. (Chu & al., 2018), Ref. (Fatahi, 2019)	-LR	-Content -Presentation -Navigation	-Deferred	-Test - Video, Image	-Qualitative -Quantitative

Table 3. Summary of personalized e-learning challenges and previous works

ANN: Artificial Neural Network

DT: Decision tree

BNs: Bayesian Networks

SVM: Support Vector Machine

Q-learning

CFSFDP-HD : Clustering by Fast Search and Finding of Density Peaks via Heat Diffusion

FNP: Fuzzy Petri Net

GSBPNN : Gravitational Search based Back Propagation Neural Network

LR: Linear Regression

out the world and this has been noticed especially in the last two years with the proliferation of COVID19. Despite the ability of e-learning systems to provide access to information, e-learning is facing many challenges such as how to deliver content and how to personalize the e-learning experience.

In this context, the growth of data available from various devices and e-learning systems has led to the need to analyze and extract useful information from it. Machine learning and data analytics techniques have been proposed as means to satisfy this need. From supervised learning and unsupervised learning, these algorithms are proving to be beneficial and essential in the field of personalized e-learning.

In this survey, we provided the definition, characteristics and types of personalized e-learning system. Furthermore, some of the challenges faced within this field have been investigated. Also, some of the works that implemented machine learning in personalized e-learning were discussed.

Finally, a few research opportunities have been proposed to give insights into the areas that need further exploration. In order to invest in this rather interesting field, we are working on the prediction of learner behavior in real time with the use of multimodal data.

Author Contribution Each author contributed evenly to this paper. All authors read and approved the fnal manuscript.

Funding The authors certify that no funding was received to assist with the preparation of this manuscript.

Data Availability Not applicable.

Declarations

Ethics Approval The authors certify that they have followed the ethical and professional conduct standards. **Competing Interests** The authors declare no competing interests.

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