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SURVEY

Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review

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ABSTRACT Artificial intelligence (AI) approaches have been used in personalised adaptive education systems to overcome the limitations of statically determined learning styles (LSs). These approaches utilise algorithms from machine learning (ML) to tackle the challenge of personalising e-learning by mapping students' behavioural attributes to a particular LS automatically and dynamically to optimise the individual learning process. Motivated by the many influential studies in this field and the current developments in ML and AI, a comprehensive systematic literature review was conducted from 2015 to 2022. Influential scientific literature was analysed to identify the emerging trends and gaps in the literature in terms of LS models and possible ML techniques employed for personalised adaptive learning platforms. The outcomes of this paper include a review and analysis of the current trends of this emerging field in terms of the applications and developments in using ML approaches to implement more intelligent and adaptive e-learning environments to detect learners' LSs automatically for enhancing learning. In addition, the following issues were also investigated: the platforms that stimulated research; identifying LS models utilised in e-learning; the evaluation methods used; and the learning supports provided. The results indicated an increasing interest in using artificial neural network approaches to identify LSs. However, limited work has been conducted on the comparison of deep learning methods in this context. The findings suggest the need to consider and stimulate further empirical investigation in documenting the adoption and comparison of deep learning algorithms in classifying LSs to provide higher adaptability.

INDEX TERMS Artificial intelligence, e-learning, learning style, machine learning, personalized adaptive learning, systematic literature review.

I. INTRODUCTION

The advent of novel technologies has unlocked new learning opportunities creating a paradigm shift in the education sector [1]. Technological advances compounded by the COVID-19 pandemic have fuelled a rise in the online education paradigm. E-learning has enabled global access to information for learners. This has resulted in generating more data flows contributing to the rise in big data technology [2]. Consequently, e-learning needs to provide for the growing number of users and prolific data [2], [3]. Furthermore, e-learning has led to not only a physical distance between the teacher and learner but also less personal engagement. This amplifies the need to develop a more personalised approach to e-learning for growing student populations to meet the requirements of the heterogeneous needs of individual learners [2], [3].

[4] defines personalised adaptive learning as a "technology-empowered effective pedagogy which can adaptively adjust teaching strategies timely based on real-time monitored (enabled by smart technology) learners' differences and changes in individual characteristics,

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individual performance, and personal development''. Adaptive education systems aim to enhance learning efficiency and performance and reduce cognitive overload issues by providing an optimal learning path and individualised content based on the knowledge, behaviour and profile of each learner [5], [6], [7]. Thus, personalised adaptive educational systems are built based on the fact that the learning process is different for each learner [8], [9]. However, current systems offer the same resources for all learners regardless of individual learner needs and preferences, therefore, these systems lack adaptivity [5].

The formation of an effective student profile and model that represents a learner's characteristics such as *learning styles (LSs)* is important to consider in the implementation of an efficient adaptive *e-learning* system [10]. *Differences inLSs are determined by the different approaches that students use to engage with learning materials and internalise information [10].* Therefore, to 'personalise' *e-learning*, it is important to understand the types of learners and evaluate and classify their *LSs* to adapt the content and learning techniques according to their preferred way of learning to support learners more effectively and efficiently [6], [11]. To determine *LSs*, well-known and used *learning style theory models (LSMs)* have been suggested to identify the initial *LSs* of learners [2].

The efficiency of personalised adaptive education systems depends on the approach used to categorise and collect information regarding the *LSs* of learners according to learner needs and characteristics and how this information is processed to develop an adaptive and intelligent learning context [5]. Therefore, by classifying learners' *LSs* with greater accuracy, adaptive learning systems can utilise *LS* information to provide accurate personalisation. Traditional methods to determine students' *LSs* involve filling in a questionnaire, however, this solution has notable drawbacks [10]. First, filling in questionnaires is time-consuming [10]. Second, results obtained from the questionnaires can be inaccurate in determining the real *LSs* of the students as students are not always conscientious of their *LS* which results in them providing uninformed answers [10]. Third, *LSs* continually change during the learning process and are dynamic whereas results obtained from questionnaires are static [10].

To overcome these limitations, *artificial intelligence (AI)* approaches have been used in personalised adaptive education systems to detect *LSs* automatically [5], [6], [10]. The automatic detection of *LSs* to classify students according to the way they prefer to learn is beneficial as it is not only more efficient than filling in questionnaires, but it is also dynamic and can be changed according to the students' behaviours [10]. These approaches utilise algorithms from the field of *machine learning (ML)* to tackle the challenge of personalising *e-learning* by mapping students' behaviour attributes to a particular *LS* automatically and dynamically to optimise the individual learning process and enhance the *e-learning* experience [9], [10].

After the identification of accurate *LSs*, adaptive learning systems utilise the information to provide accurate personalisation leading to benefits for students, including increased student performance, satisfaction, learner engagement and time efficiency [2], [6], [8], [12], [13]. By students being aware of their *LSs*, they can self-regulate their learning, capitalise on their strengths and understand why they are struggling [14]. Moreover, instructors can use *LS* information to offer accurate guidance to their learners to improve their learning efficiency and support their personalised development [12], [15]. These appealing reasons inspired a growing interest in research investigating the integration of *LS* and *personalised adaptive learning(PAL)* systems to enhance *e-learning*. The graph in Fig. 1 displays the statistical analysis of article publication trends by year across the four databases in this field during the period from 2015 to 2022. Moreover, some of these articles have been recognised and highly cited in research communities.

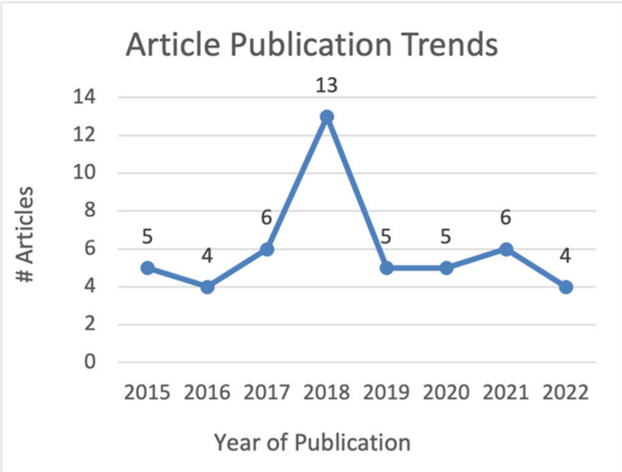

FIGURE 1. Statistical analysis of article publication trends from 2015 to 2022.

Previous studies and recent publications have shown the *application* of *AI* approaches in the automatic *detection* of *LSs* based on various *LS* models [5], [16], [17], [18]. For example, [5] developed an *AI*-based system that provided the facility to compare the performance of multiple *LS* models and *AI*-based classification techniques. These models were developed dynamically, within the same tool [5]. This study is an influential work, receiving a high number citations in Google Scholar. Another highly-cited work [16] investigated four computational intelligence algorithms for their ability to improve the accuracy of automatic *LS* identification. [17] used *LS* to develop a personalised conversational Intelligent Tutoring System (ITS). More recently, [18] proposed a robust classifier to identify the *LS* of the learners in an e-learning system which performed well for several courses tested [18]. This study also attracted attention in research communities with a good number of citations within the last two years. Motivated by the many influential studies in this field and the current development of technologies in the field of *AI*, it is essential to understand the extant literature across this field of study.

Furthermore, *AI* technologies associated with *PAL* can be integrated into *e-learning* to offer efficient and effective ways to address the challenge of personalising *e-learning* – particularly relevant during the COVID-19 pandemic – to optimise individual learning. [19] emphasises the significance of such systems, particularly during a pandemic, due to the ability of these systems to assist educators in rethinking and revising the learning design of their courses to provide enhanced learning experiences. Consequently, the relevance of *PAL* based on *ML* techniques is evident and supports the principal reason for advancing research in this field through this *SLR*.

Although the surveys of recent review studies have addressed research on the global view of *PAL* [20], [21], [22], [23] from perspectives of the use of *AI* techniques [9] and theory of learning styles employed in adaptive *e-learning* [13], [24] environments, these *SLRs* have not considered and delved deeply into the application and integration of *LS* theories and *AI* techniques in adaptive *e-learning* systems to identify *LSs* automatically.

SLRs conducted by [25] and [26] have considered the *application* and *integration* of *LS* theories and *AI* techniques in adaptive *e-learning* systems. These authors reviewed various aspects of *LS* theory selection in the *e-learning* environment, online *LS* predictors/attributes and automatic *LS* classification algorithms for numerous *LS* applications in adaptive learning systems. This paper was based on these two previous reviews in the field of *LS* detection.

The current *SLR* presented here overlaps with the classification of some topics in the *SLRs* presented by [25] and [26]. These *SLRs* have two limitations. First, with the recent rapid advances in technology and innovations, studies that have been published after 2014 have yet to be reviewed. Second, these studies have not considered the different evaluation methods to evaluate and validate the accuracy of the *AI* techniques implemented in their analyses.

The *SLR* presented here differs as it covers the period from 2015 to 2022. Furthermore, this *SLR* aims to augment existing research by reviewing articles that emphasise the *LS applications* in the development of the *PAL* system as well as the papers that provide insights into the *ML* techniques used to *classify* learners' LSs automatically. Lastly, this *SLR* has also considered the different evaluation methods to evaluate and validate the accuracy of the *AI* techniques implemented in their analyses.

In this paper, the survey summarises, quantifies and expands on the current research in the field of *AI* approaches used for personalised adaptive education systems within *e-learning* to classify the type of learners dynamically and automatically to optimise the individual learning process. Furthermore, it probes deeply into the application and integration of *LS* theories and *AI* techniques in adaptive *e-learning* systems to automatically identify an *LS*. A comprehensive search of the scientific literature following a systematic methodology related to this topic will be selected for the review and will be analysed to identify the emerging trends in terms of the *LS* models and possible *AI* techniques used for *PAL* platforms.

The theoretical implications of the findings obtained from this study will certainly help and be of great interest to academicians, practitioners and researchers in providing insight into the potential of how *ML* techniques can be exploited for implementing and supporting *PAL* to identify *LSs*. Furthermore, the practical implications of this research will enhance the understanding of the status and trends of *AI* techniques and LSMs that are adopted to support *PAL e-learning* systems. Moreover, performing the *SLR* through the extraction of relevant studies provides a background for appropriately positioning and identifying relevant lines of new research events [27].

II. SEARCH METHODOLOGY

The *SLR* survey was conducted following the methodological guidelines for literature reviews in software engineering as recommended by Kitchenham and Charters [27]. This methodology has already been used in other systematic reviews for similar fields of applicability in the *SLR* articles by [28] and [29]. Following these guidelines, in this section, the designed review protocol, which includes the research questions, the search process, the selection criteria and the selection process, is described.

The main objective of the current *SLR* entails systematically collecting and analysing studies on *ML* approaches used for personalised adaptive education systems within *e-learning* to implement intelligent and adaptive *e-learning* environments based on classifying learners' LSs automatically and dynamically to enhance learning. To realise this goal, the literature review was guided by the following research questions:

- What platforms are frequently investigated in *PAL* environments to determine learners' *LSs*?
- Which LSMs are frequently investigated in *PAL* environments to classify learners' LSs?
- Which *ML* techniques are frequently employed for adaptive education systems to automatically identify learners' *LSs*?
- What evaluation methods are used to determine the performance and accuracy of the *ML* techniques implemented to predict a new learner's *LS*?
- What learning supports are provided in the current literature to provide personalised learning according to the learners' LSs?

The search strategy defined was used to search for primary studies and included search terms and generating search strings to be searched. The reviewers identified keywords, paying particular attention to words to answer the research questions. The main keywords that were used to identify the articles were 'personalized learning' OR 'personalised learning' and 'adaptive learning', '*e-Learning*' OR *ELearning*'

OR '*online learning*', '*machine learning*', '*artificial intelligence'* and '*learning styles*'.

An *SLR* was implemented covering papers published in journals and at conferences and available in the four identified electronic databases, namely, IEEE, Springer, Science Direct (Elsevier) and ACM. To make this research contemporary and well-intentioned in *AI* technologies employed in adaptive education systems, the literature search covered contributions from 2015 to 2022. Relevant studies that were not found following this search appear in the referenced bibliography of the searched results and were also included in the second and third analysis iterations.

Screening of the literature for the selection process reported the most appropriate papers for the mapping study through the inclusion and exclusion criteria provided by the protocol. Specifically, articles from the preliminary search were included if they met the following main inclusion criteria:

- Current application and integration of *LS* theory/theories in the development of *PAL* systems.
- Techniques based on automatic and dynamic approaches using *ML* approaches applied in the area of education to obtain *LS* information and patterns. Therefore, the focus is on data-driven approaches.
- Articles applicable to technology-supported adaptive/personalised learning such as adaptive/personalised interfaces, learning contents and learning paths for administering teaching and learning activities.
- Empirical studies that have investigated the usage, evaluated and or implemented a *PAL* system based on *ML* techniques to identify LS for use in educational institutions.

The following main exclusion criteria were applied in this *SLR*:

- Articles that emphasise the application of *LSs* and only use traditional measurement methods such as questionnaires and rule-based approaches such as the study by [30]. However, the study by [31] was included as it combined a literature-based method with *ML* techniques to detect learners' *LSs*.
- Research that deals with learner modelling in the context of adaptive learning using an ontology approach and recommender systems.
- Studies relevant to personalised adaptive learning but with NO references to education, such as health care.

Once the potentially relevant primary studies were obtained, they were assessed for their actual relevance. Articles were selected based on the research questions, keywords, search strings, databases and screening of inclusion and exclusion criteria identified above. The study selection process involved a multistage process, involving five stages: the search of the digital databases; pre-screening by assessing title and key words; examination of the complete text of the abstract for relevance; examination of the introduction and conclusion; and the full-text screening of the primary studies to determine compliance with the inclusion and exclusion criteria. The final number of articles included from the selected databases in this *SLR* was narrowed down to 48 during the period of investigation.

III. ANALYSIS, RESULTS AND DISCUSSION

In this literature survey, the selected articles focus on *AI* approaches used for personalised adaptive education systems within *e-learning* to classify the type of learners dynamically and automatically (by identifying *LSs*). These articles were analysed, synthesised and categorised using similar themes to answer the research questions. They provide insight into current practices, identify the emerging trends in terms of the LSMs and potential *AI* techniques to be employed for *PAL* platforms and suggest areas for further investigation. In this section, the results and discussion of the research articles surveyed and the studies addressing the five research sub-questions are presented. Based on the research questions, the taxonomy outlined in Fig. 2 was used in the current research. The taxonomy will be elaborated on in this section.

Classification and recommendation are the two foremost tasks needed in *e-learning* personalisation [2]. Thus, the articles reviewed herein present both the tasks of the development process and how they are interrelated. All the studies selected in the review adhered to a similar integration and development process so the results of the analysis will be presented accordingly.

The classification task entails classifying and predicting a learner's LS using LSM and ML algorithms [25], [30]. The development begins by selecting the LS framework and then selecting and collecting data using the data sources and the corresponding LS attributes to build the learner model [25], [30]. This is followed by the selection, training, testing and evaluation of the classification models to detect and recognise a new learner's LS [25], [30]. Thereafter, in the recommendation task, the application of this model into an adaptive learning system according to learner preferences is implemented [26], [31]. An illustration of the process/method used to personalise e-learning through the automatic and dynamic detection of LSs is depicted in Fig 3.

A. WHAT PLATFORMS ARE FREQUENTLY INVESTIGATED IN PERSONALISED ADAPTIVE LEARNING ENVIRONMENTS TO DETERMINE LEARNERS' LEARNING STYLES?

This question investigated the different platforms that stimulated research on applicable learning scenarios found across the literature to automatically detect LSs. These platforms for each of the selected studies in this *SLR* are detailed in Table 1 and are depicted in Fig. 4.

Among the 48 papers that have addressed this topic, *e-learning* is still the platform that has received the most interest at 73%. Massive Open Online Course (MOOC) platforms to address attrition and the high dropout rate have also been implemented. Only 7% of the papers have invested MOOC platforms in personalised adaptive learning platforms to identify LSs. Notable examples include papers by [6], [8],

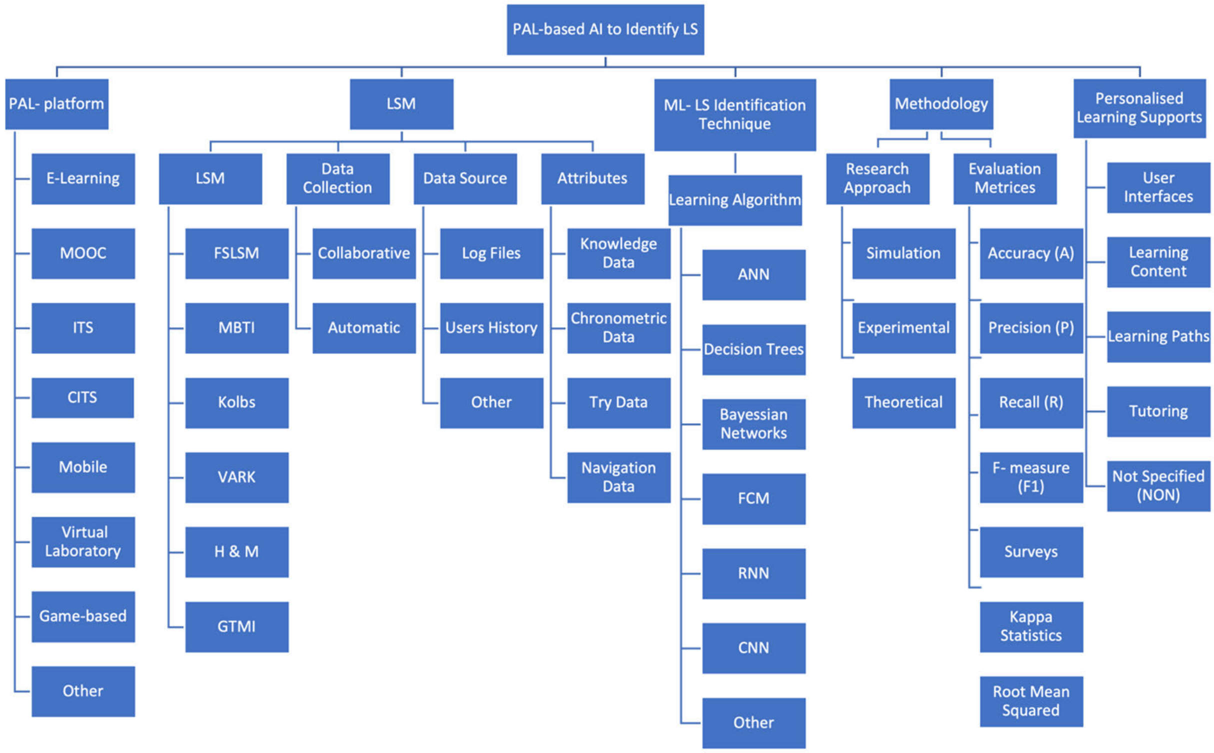

FIGURE 2. Taxonomy – PAL based on ML techniques to automatically identify LSs.

and [32], which investigated solutions to integrate adaptive recommendation systems with MOOC.

PAL platforms based on *LS* have also been applied to various platforms such as the ITS [33], [34]; the Conversational Intelligent Tutoring System (CITS) [17] and online mobile applications [35], [36]. In [35], the proposed approach enabled elementary students to learn materials in an online mobile application and adjust the delivery method according to their preferred *LS*. Other platforms found through the review contain a virtual laboratory; [37] proposed a complete personalised learning solution for *LS* identification, learning performance assessment and adaptive learning content delivery for virtual hands-on laboratory-based education solutions. On the other hand, [38] investigated LSs to determine their relevance in problem-solving abilities in a game-based environment.

Platforms categorised as 'other', such as the research frameworks proposed by [5], [39], and [40], are representative of the studies that presented a proposed approach and framework (or were evaluated using simulated data) where no particular platform was specified in their work.

B. WHICH LEARNING STYLE MODELS ARE FREQUENTLY INVESTIGATED IN PERSONALISED ADAPTIVE LEARNING ENVIRONMENTS TO CLASSIFY LEARNERS' LEARNING STYLES?

This question addressed the first step of the integration process. This section analyses and reviews the current literature to determine which LSM theories are used in *PAL* platforms to evaluate and understand e-learners' *LSs*. Furthermore, this analysis also identifies which of the LSMs are better adapted to the online learning environment. The *LS* framework selection includes the selection of the LSM, how the information model is built (data collection procedure) with respect to the data source and the corresponding attributes (predictors) used for identifying learners' *LSs* [25], [26]. In addition to the LSM, the types of data collection methods, data sources and variables that can be tracked for each of the selected studies in this *SLR* are detailed in Table 1.

1) LEARNING STYLES THEORY MODEL

In the area of the automatic detection of *LSs*, the *LS* model plays a vital role in directing researchers during that process [26]. Identifying and examining these models are important as these approaches can be applied to sustain learners' *LSs* and subsequently improve learners' learning performances by engaging and motivating them [2], [6], [13], [41]. To determine LSs, well-known and tested learning models have been suggested to identify the initial *LS* of each learner [2]. Among the prominent models identified in the selected studies are the VARK model, Kolb model, Felder and Silverman model (FSLSM), Myer-Briggs Type Indicator Theory (MBTI), Gardner Theory of Multiple Intelligence (GTMI) and the Honey and Mumford model [2], [5]. These theories suggest that individuals can be classified according to their 'style' of learning and postulate different views on defining and categorising LSs [5].

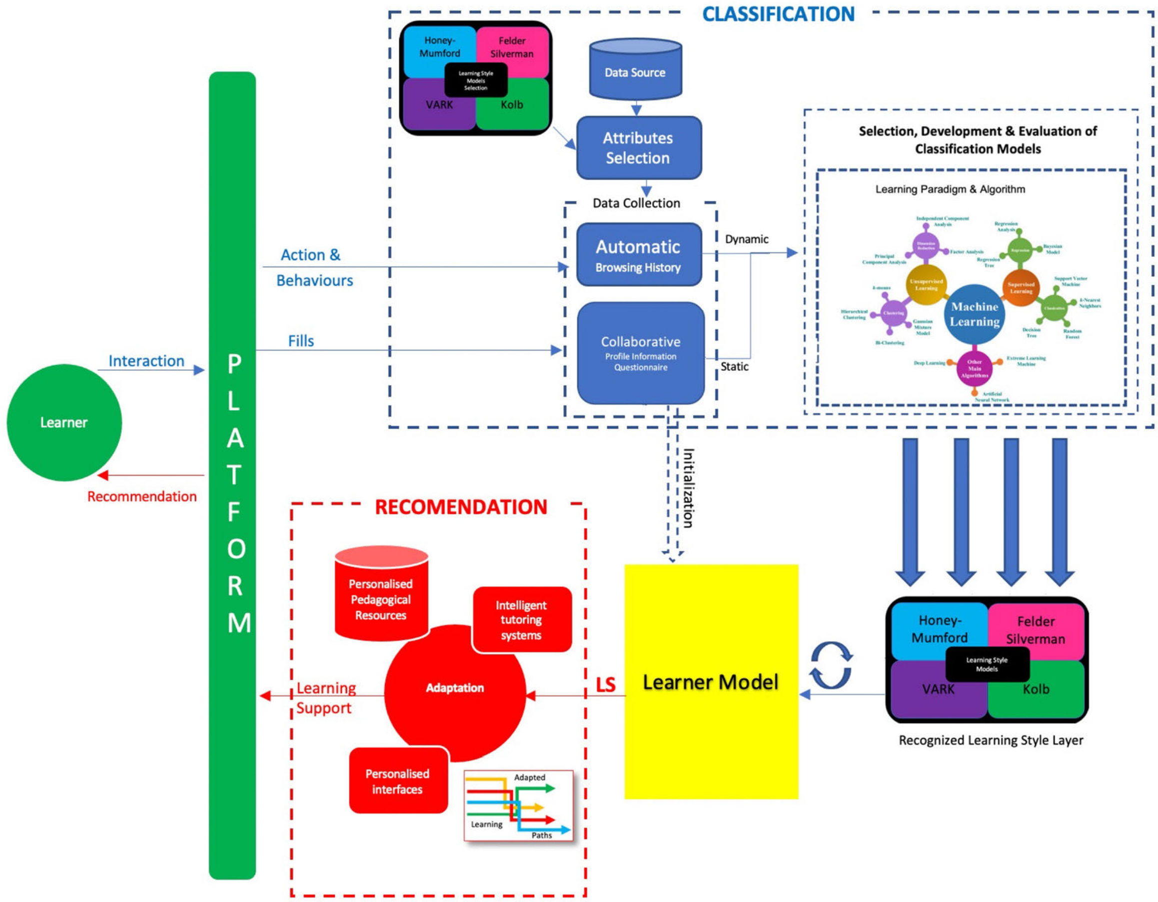

FIGURE 3. Research development process of PAL based on ML techniques to classify LS automatically and dynamically [6].

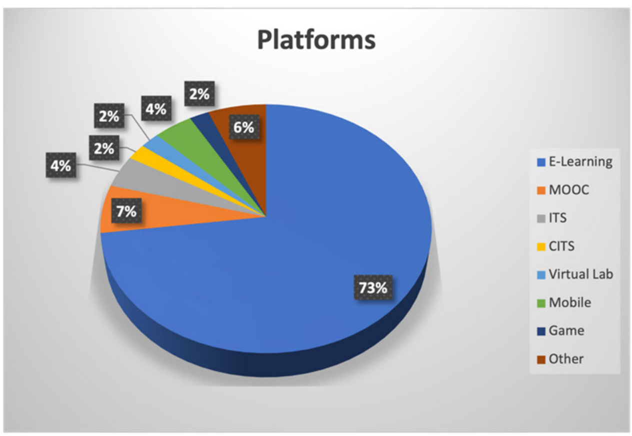

FIGURE 4. Platforms that stimulated research on PAL based on ML to identify LSs.

The FSLSM for engineering education classifies learners according to their position on several scales to evaluate how students *"perceive and process information"* [42]. Their model categorises learners based on the different levels of the learning process [2]. The model describes *LS* in more detail by characterising each learner according to four aspects – called dimensions – which each cover a stage in the course of receiving and processing information, namely Perception, Input, Processing And Understanding [42], [43]. Within each dimension, there are two opposite LS preferences and each learner has a dominant preference in each dimension [42], [43]. In the Information Processing dimension, learners prefer to process information actively through active engagement with information or reflectively through introspection [42], [43]. In the Information Perception dimension, the learner prefers to perceive or take in information through sensing or intuitive LS preferences [42], [43]. In the Information Reception dimension, the learner prefers information to be presented either through visual or verbal sensory channels [42], [43]. In the Information Understanding dimension, learners prefer to progress towards understanding sequentially in continual steps or globally in a holistic way [42], [43].

The FSLSM rates the learner's *LS* on a scale of four dimensions to define 16 distinct *LSs*. Felder and Solomon developed the *Index of Learning Styles (ILS), a 44-item online questionnaire for identifying the LS according to FSLSM* [42], [43]. The ILS questionnaire is structured so that students are required to complete a sentence by choosing one of two options representing opposite ends of one of the *LS* scales [42], [43].

On the contrary, Kolb defines learning *"as the process whereby knowledge is created through the transformation of experience"* [44]. Kolb's *LS* model is based on the Experiential Learning Theory and has four distinct *LSs*, which are based on a four-stage learning cycle [44]. The four stages are Concrete Experience (CE), Reflective Observation(RO), Abstract Conceptualisation (AC) and Active Experimentation (AE). The combinations of learning cycles produce four *LSs* namely Accommodating: (CE/AE); Diverging: (CE/RO); Assimilating: (AC/RO); Converging: (AC/AE). The instrument developed by Kolb for identifying *LSs* based on Kolb's LSM is the learning style inventory (LSI) [44]. It is a 12-item forced-choice ranking questionnaire [6], [13], [44].

The results of the content analysis according to the frequency with which LSMs have been applied in the *PAL* system to identify learners' *LSs* automatically are depicted in Fig. 5. Although there exist many *LS* models, the FSLSM appears to be the most frequently used in the selected articles.

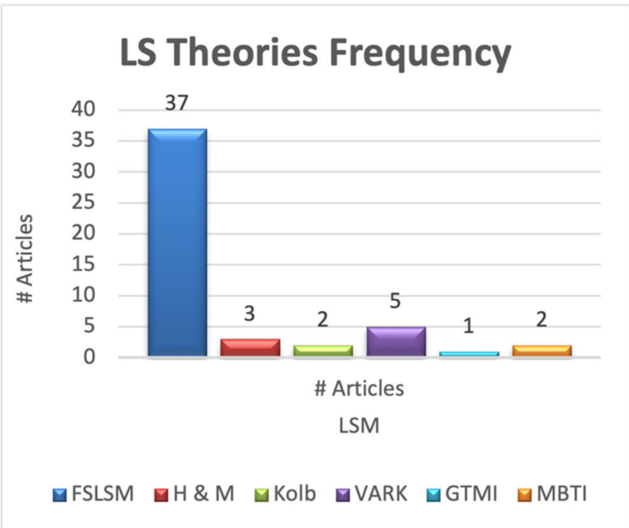

FIGURE 5. **Frequency of learning style theories used in PAL to classify learners' LSs.**

Researchers have selected the FSLSM due to several advantages of this model which include the following:

- FSLSM describes *LSs* in greater detail by characterising each learner's preference according to four dimensions and using scales to represent the strength of the *LS* preferences [12], [13].
- Furthermore, the descriptions indicate the types of learning objects (LO) that can be included in each *LS* preference and this is beneficial as knowing the *LS* preferences of LOs assists in identifying the *LS* of learner sequences [10]. For example, visual learners remember, understand and assimilate information more effectively when it is presented in a visual way. Visual learners prefer LOs such as videos and pictures [42] whereas verbal learners prefer to learn from textual representations, which may be written or spoken [42]. Verbal learners prefer textual and audio explanations [42]. Active learners prefer to learn and understand information best by working actively in the external world and applying the information [42]. They prefer LO which entails for example practical problem solving [42]. Reflective learners prefer to learn by thinking things through and working individually [42]. Thus, this group of learners prefer introspective examination and manipulation of information [42]. They prefer LO such as examples and exercises [42].
- The ILS instrument has been effectively used in several studies for instruction and design in determining *LSs* as the number of dimensions can be controlled and can be easily interpreted and implemented [13].

2) DATA COLLECTION

A learner model can be statically initialised collaboratively by asking learners to fill in a questionnaire. This approach is the simplest method; it is static, and its accuracy is dependent on learners providing explicit feedback and attention in completing the questionnaire [45]. The automatic approach on the other hand is dynamic and more accurate than the collaborative approach [45]. The learner's adaptable model is built automatically by the adaptive system through intelligent and *ML* approaches that use the learner's interactions and behaviours while they are learning and interacting with the system [30].

a: DATA SOURCE AND CORRESPONDING ATTRIBUTES

According to [25], the possible sources of data and corresponding attributes can be categorised as follows:

- Log files (LFs): According to Reference [25] the measurable input data related to 'learning activities and behaviours' are analysed and interpreted based on output LF data. The corresponding attributes used for the classification of this source varied. Some of the corresponding attributes include tracking learner activities, using forums, performances, characteristics and the type of objects chosen. Studies differ on the different attributes used for detecting LSs [25]. For example, the study by [12] employed generic behaviour patterns investigated by [11] to automatically identify LSs. These included content objects, outlines, examples, self-assessment tests, exercises and discussion forums. On the other hand, [37] detected LSs using attributes related to assessments such as quiz grades, chats, mouse click counts and keyboard input counts within the virtual machine window. Reference [34] used online reactions on an e-learning platform to predict LSs. All three studies ([12], [34], [37]) used Felder-Silverman's LSM.
- Users' history and background data: This source includes static information (SI) [25]. It includes corresponding information such as gender, education majors, demographic data and culture [25]. Reference [40]

utilised both SI (demographic data) and LFs (learner behaviours) in their study. Other studies that used both SI and LFs are the studies by [46], [47], [48], and [49]. One of the studies that used only SI was the study conducted by [50].
- Others (O): Besides those directly associated with LSs, as indicated above, other personalisation sources that were considered together with LS in some cases include background knowledge, language and motivation level. An example is the study by [51] where the LS was identified using various parameters such as image streaming and cognitive and sensory abilities. In [52], the learners' skills (level of knowledge) and their prior knowledge were the key characteristics that were used in the automatic detection of LSs. One of the studies that used LFs and O was the study conducted by [33]. Other studies that used both SI and O are the studies by [36] and [53]. Reference [36] took as input a minimum number of personal (age and gender) and cognitive characteristics (prior academic performance) and only four questions about the FSLSM dimensions to identify the LS. Reference [51] includes all three sources in their study.

b: VARIABLES/ATTRIBUTES

According to [54], the types of variables on which personalised learning can be tracked and provided in an education system can be classified as the following:
- Knowledge data (KD): This refers to, for example, the number of correct or incorrect answers in a test.
- Chronometric data (CD): This refers to, for example, the time spent on reading the material, time spent reviewing quizzes and the total task time.
- Try data (TD): This refers to, for example, the number of attempts to determine the correct answer and the review attempts for each question.
- Navigation data (ND): This refers to, for example, the frequency of a topic or exercise that has been selected, the 'number of watched videos' and the 'number of posts in the forum'.

It is important to note that the study conducted by [5] and [55] are the only two studies documented in this *SLR* that utilised and compared two LSMs. Reference [5] used attributes from Kolb's model and the FSLSM and compared the two models to determine the most appropriate model based on the performance of different models in identifying *LSs* whereas [55] attempted to identify attributes from GTMI and FSLSM. This is important to consider for enhancing the performance and efficacy of the different prediction and classification models [25].

C. WHICH MACHINE LEARNING TECHNIQUES ARE FREQUENTLY EMPLOYED FOR ADAPTIVE EDUCATION SYSTEMS TO AUTOMATICALLY IDENTIFY LEARNERS' LEARNING STYLES?

The first step of the integration process entails selecting the correct *LS* framework (see Section III-B). This is followed by the selection, training, testing and evaluation of the *AI* classification models to detect and recognise a new learner's *LS*. This section provides an overview and the frequency of the *AI* techniques employed in the current literature for adaptive education systems to identify LSs automatically, as summarised in Table 1. The evaluation methods of the *AI* classification models are discussed in Section III-D.

1) FREQUENCY OF MACHINE LEARNING USED TO DETECT LEARNING STYLES

To learn the associations between e-learners' actions in *e-learning* environments and their corresponding *LSs* based on the LSM implemented, the *ML* technique for detection and recognition of *LSs* is firstly trained with the user model and or the results of the *LS* identification instrument collected from the learners [26]. After the training, the *ML* technique can automatically and dynamically classify a new learner's *LS* using their updated user model [6], [26]. Fig. 6 indicates the frequency of the *ML* algorithms used in the detection of *LS* in the current studies. Table 1 shows an overview and related references of *ML* methods listed in column *AI* techniques for all the studies reviewed in the current *SLR*. The three most popular methods implemented are decision trees, followed by artificial neural networks (ANNs) and Bayesian networks.

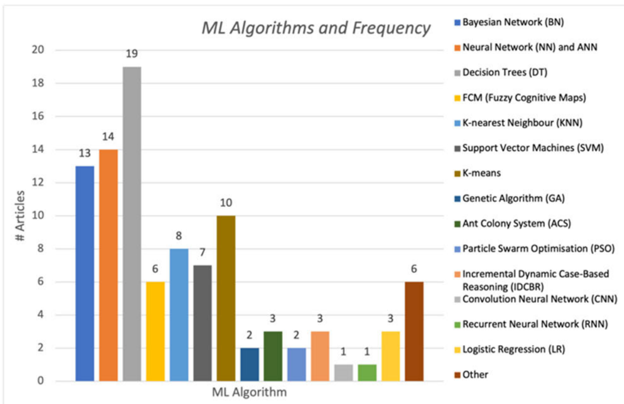

FIGURE 6. Frequency of learning style classification (ML) algorithms.

The decision tree structure is a tree in which each branch node denotes the selection between various alternatives and each leaf node represents a decision. Statistical metrics are used to determine the branching of the nodes [2], [26], [56]. There are numerous algorithms within decision trees used to classify learners based on their LSs. A few of these decision tree-based algorithms include ID3, C4.5, J48, NBTree, random forests and RandomTree. These differ based on the order in which the attributes are selected and the splitting criterion used to build the tree [2], [26], [56]. Nineteen articles (Fig. 6) documented in this review have used this approach to automatically identify an *LS*.

Artificial neural network (ANN) consists of several interlocked neurons which work together to process information and solve problems [9]. The learning process in an ANN entails updating the network architecture and connection weights [57], [58]. Backpropagation is a supervised learning algorithm for determining weights in a multilayer perceptron and is prevalent among researchers and users of ANN [57], [58]. Fourteen articles (Fig. 6) documented in this review used this approach.

Deep learning (DL) is an extension of classical NN in that it combines computing power and NN with more hidden layers so that the algorithms can handle complex data with various structures [59]. Besides ANN, a few popular DL algorithms include convolutional neural networks (CNN) and recurrent neural networks (RNN) [2], [60]. The study by [51] is the only study documented in this *SLR* that utilised CNN and RNN.

Among the prominent *AI* techniques identified in the selected studies of this *SLR* are Fuzzy Cognitive Maps (FCM); K-nearest Neighbour (KNN); Support Vector Machines (SVMs); K-means; Genetic Algorithm (GA); Ant Colony System (ACS); Particle Swarm Optimisation (PSO); Incremental Dynamic Case-Based Reasoning (IDCBR); and Logistic Regression (LR).

Other classification algorithms not so commonly used were classified as Others. These include Linear Discriminant Analysis [55], semantic clustering [29], simple logistics [61], Kstar, OneR, JRIP and Decision Table [62]. In Reference [34], three different classification methods namely Classifier Chains, Binary Relevance, and Label Powerset were applied to make a model for *LS* prediction. Reference [53] modified a collaborative filtering model, which is typically used for recommendation tasks, to also predict the learners' LSs.

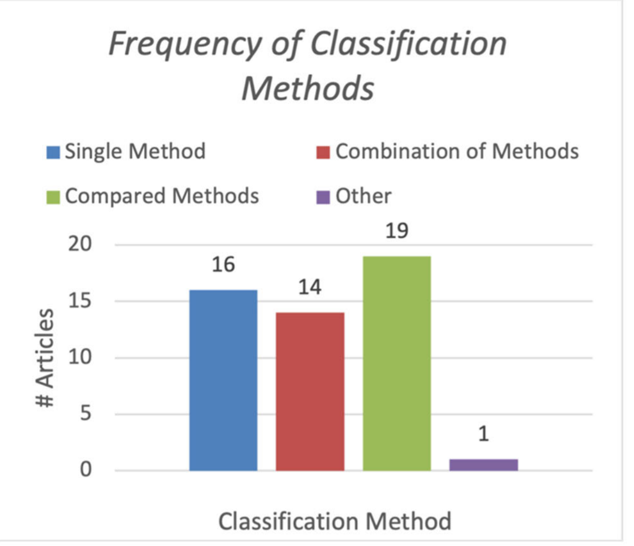

FIGURE 7. Frequency of classification methods, combinations and comparisons.

2) FREQUENCY OF CLASSIFICATION METHODS COMBINATIONS AND COMPARISONS

Of the 48 articles reviewed, 16 used a single method to determine *LSs* (Fig. 7). Advanced algorithms combining single algorithms in various ways to produce greater accuracy, such as hybrid or ensemble classification, have shown positive results in determining *LS* automatically and dynamically [25], [63], [64]. Table 1 shows an overview and related references of *ML* methods combination and comparison listed in column *AI* techniques for all the studies reviewed in the current *SLR*.

In hybrid (combined) learning, the first approach produces the initial output which will be processed by the second approach to acquiring the final output [63]. References [10], [14], [46], [50], [51], and [65] are some examples identified in this *SLR* that used a combination of techniques to determine the *LS*.

The approach presented by [10] used a 2-step process: learners' sequences were extracted from the LFs and then, they were transformed into an input of the K-means algorithm where each cluster was labelled with an LS combination. Thereafter, the Naïve Bayes algorithm was used to predict the LS for a new sequence.

Reference [14] designed a loosely coupled multi-step hybrid architecture where the main feature was the computation of additional information at each step to feed forward into the next step of the architecture. To detect LSs, the architecture was broken down into three steps [14]. The first step produced an initial prediction of the LS preference, which was then combined with the behaviour data in the second step to compute a confidence value in the initial prediction [14]. Thereafter, the data were split into high and low confidence [14]. Lastly, two identification algorithms for high and low-confidence data were used [14].

In [50], clustering (K-means) and two classification algorithms were used to predict LS combinations in the study. An SVM was used to predict the individual LSs and a DT was used to predict the LS combination. The study by [51] is the only study documented in this SLR that proposed a personalised e-learning system based on a combination of DL and ML algorithms that could be adapted to the LS and level of a learner in creating an enhanced understanding of the course [51]. NNs have been combined with fuzzy logic to identify the LSs of learners as per FSLSM categories, for example, in the approach proposed by [46] and [65].

Ensemble learning (comparison) entails combining multiple models into one that is usually more accurate than the best of its components [64]. Notable examples include the studies by [5], [37], and [66] took into consideration multiple *AI* techniques for determining students' *LSs*. Their tool provided the facility to compare *AI*-based classification techniques with the performance of developed models. Besides applying ANN, Reference [5] also employed DT on the sequences of learner actions. The results of the simulation data indicated that NNs displayed higher performance in comparison to DT based on kappa statistics (KS) values. Reference [37], on the other hand, in their ensemble algorithm constructed the constituent SVMs and DT models to predict *LSs* automatically. The testing data was classified by both algorithms independently. Reference [66] compared J48, BN, Naïve Bayes and random forest using experimental data; the J48 algorithm performed the best.

Studies by [8] and [61] used both hybrid and ensemble classification. Research by [61] focused on developing dynamic methods for the search and identification of a learner's preferred *LS* using case-based reasoning (CBR) and NN. The efficiency of the algorithm for the selection of *LSs* via CBR combined with NN was compared with the results obtained by other *LS* selection algorithms: simple logistic, Naïve Bayes, tree J48 and NN [61].

The study by [53] proposed an innovative *AI* approach that enabled collaborative filtering-based *AI* models driven by *LS* prediction to provide content recommendations personalised specifically to the *LS* of each learner. A single model was designed that performed both prediction and recommendation.

D. WHAT EVALUATION METHODS ARE USED TO DETERMINE THE PERFORMANCE AND ACCURACY OF THE ARTIFICIAL INTELLIGENCE TECHNIQUES IMPLEMENTED TO PREDICT A NEW LEARNER's LEARNING STYLE?

In this section, the research approach and evaluation methods used in the current literature to determine the effectiveness and measure the performance and accuracy of the *AI* technologies implemented to predict a new learner's *LS* are discussed. Table 1 specifies a summary of the research approach and evaluation methods for all the studies reviewed in the current *SLR*.

The research approach in data-driven approaches requires collecting relevant information for the user model (see 3.2); thereafter, AI classification algorithms (see 3.3) are used to identify *LS* preferences automatically [26]. The research approach of the works was classified into three groups based on the categories by [26]:

- Simulation (S): these researchers evaluate the proposed approach through simulations. Notable examples include those in [5], [35], and [46].
- Theoretical (T): the authors present a new framework or approach where there are no experiments or empirical evaluations. Typically, these articles describe an initial approach that will be discussed comprehensively in future works. Notable examples include those in [6], [29], [39], [40], and [51].
- Experiment (E): these researchers evaluate the proposed method through empirical evaluations. Typically, the experimental setting comprises an LS instrument, an education system where the proposed method is tested and learners who interact with the system [26]. The majority of the studies fall into this category.

ML architectures that perform well in mapping students' actions in the system and identifying learners' LSs that 'best fit' can capture learners' LSs accurately and so can provide more accurate adaptivity. Therefore, it is important to investigate the evaluation methods in the current literature to determine the efficacy, accuracy and performance of the *AI* techniques implemented in predicting a new learner's *LS*.

The efficacy and performance of the *AI*-based *PAL* platform in predicting a new learner's *LS* were evaluated by a few of the studies. The evaluation methods included surveys and statistical evaluation matrices that included accuracy (A), precision (P), recall (R) and F-measure (F1). Other methods for evaluating models include Receiver Operating Characteristics (ROC), Area Under the Curve (AUC) among others. In the research presented by [67], these evaluation matrices were used to evaluate the models.

In the work of [5], simulations were generated with two *AI* techniques and two *LS* theories. A simulation first generated a model structure and, thereafter, measured the model's performance. Statistical evaluation was used to establish the most appropriate model for implementation in a specific learning environment. The model with the highest kappa statistics (KS) value and the least root mean square error (RMSE) value indicated the most appropriate one. After the model/s were selected and trained for a particular learner's environment, these were used to identify learners and determine their *LS* accordingly.

A variety of other statistical evaluation tests were compared between adaptive and non-adaptive (A&NA) systems, such as learning rate and process (learning objects, tests and sessions), performance (tests, satisfaction and popularity) [46] and pre- and post-test performance (Pre&P) and t-tests [68].

E. WHAT LEARNING SUPPORTS ARE PROVIDED IN THE CURRENT LITERATURE TO PROVIDE PERSONALISED LEARNING ACCORDING TO THE LEARNERS' LEARNING STYLES?

This question deals with the second step of the integration process which corresponds to the *recommendation*. To understand how the adaptive/personalised learning processes are provided by systems in the selected studies in this review, various kinds of learning support require examination [20]. This section explores and discusses the learning support and applications that are provided in *PAL* to identify *LSs* in the current literature. Five applicable categories of learning support for the learning processes of adaptive/personalised systems are classified in this *SLR* based on the previous review studies by [20] and [25]:

- Personalised interfaces (UI)
- Personalised learning contents and resources (LC)
- Personalised learning paths (LP)
- Adaptation general not specified (NON)
- Intelligent tutoring and recommendation systems (TUT).

The distribution of learning support types provided by adaptive/personalised systems to facilitate the learning processes based on *LSs* in the selected studies is indicated in Table 1 and depicted in Fig. 8.

The most frequently adopted learning support type used in 17 of the 48 selected studies on adaptive/personalised systems was personalised learning content. Notable examples of systems presented in the work by [37] and [66] provide

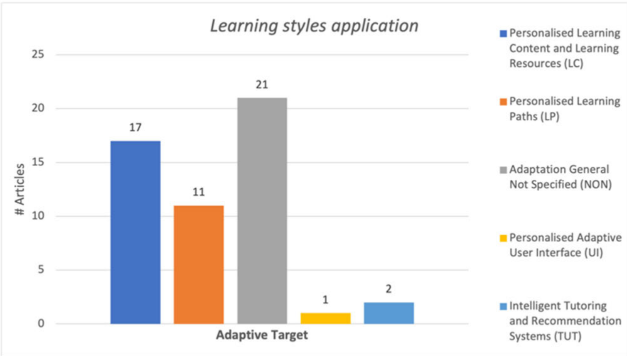

FIGURE 8. **Learning styles application in developing adaptive learning systems.**

a presentation of adaptive learning resources according to learners' *LSs*. In [37], after the dynamic identification of *LSs*, the adaptive lab learning content manager updated the lab content on the web user interface by choosing and constructing a suitable format of lab materials from the lab content repository.

The second most frequent type of *LS* support – 11 out of 48 – provides each user of the system with a personalised learning path. For example, the architecture proposed by [40] is based on the FSLSM to detect the initial learning profile to adapt the learning path according to the learners' *LSs*. Other types of support included personalised interfaces. Only one study identified in this review – [68] – provided an adaptive personalised interface. Applications such as TUT systems that personalise learning for students with different backgrounds, abilities, behaviours and knowledge were also supported [17].

Some studies mention the general adaptation of *LSs* but do not specify any particular learning support. It is also worth noting that the papers identified in this review may also have more than one target for the adaptation of *LSs*. The model developed by [5], for example, can be used to classify learners and identify their *LSs* which can then be mapped to learning content and learning paths to provide personalised education.

IV. CONCLUSION

In this *SLR*, influential scientific literature was analysed to identify any emerging trends and gaps in current research in terms of the LSM and possible *AI* methods to be used for *PAL* platforms. In particular, four databases were systematically searched and the reference lists of relevant studies were screened, ultimately resulting in the 48 studies involved in this review. The following references were the studies involved: [5], [6], [8], [10], [12], [14], [15], [16], [17], [18], [29], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [46], [47], [48], [49], [50], [51], [52], [53], [55], [61], [62], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79].

The analysis presented in this paper has allowed an enhanced understanding of the trends and characteristics of how *PAL* based on *ML* approaches has been used to identify *LSs* automatically and dynamically from 2015 to 2022.

Additionally, research issues across the literature that were investigated and discussed included the platforms that stimulated research, identifying which of the *LS* models was more adapted to the online learning environment, the evaluation methods and learning supports provided. A summary of recent developments and open issues, recommendations and future research opportunities and limitations of the *SLR* are specified in the following subsections.

A. SUMMARY OF CURRENT DEVELOPMENTS AND OPEN ISSUES

E-learning has gained significant attention in recent times as it has enabled global access to information for learners due to rapid advances in technologies compounded by the global pandemic. The findings of this study reveal the positive results of this emerging field in terms of its applications and developments using *AI* approaches to implement intelligent and adaptive *e-learning* environments based on learners' *LSs* in enhancing *e-learning* to optimise individual learning.

The research development process entailed the classification that was responsible for detecting the *LSs* and storing them in the learners' profiles which are used by the recommendation step to provide the desired adaptability [25], [30]. The articles reviewed in this paper emphasise the application of LSMs in the development of adaptive learning systems and provide insights into *ML* algorithms used to *classify* learners' *LSs* in the current literature. Through this study, several interesting developments and opportunities for further research were identified.

Various platforms with relevant learning scenarios that adapt to learners' *LSs* and that have been implemented in the *PAL* system have been found in the literature. *E-learning* and MOOC platforms have received the most interest. *PAL* platforms based on *LS* have also been applied to various other platforms such as ITS, mobile applications, game-based environments and virtual laboratories.

Although many LSMs based on the automatic identification of *LSs* are used in *PAL* in the current literature, the FSLSM appears to be the most frequently used in technology-enhanced learning and is regarded as one of the best models to use in adaptive systems to identify learners' *LSs* in *e-learning* environments [13], [21]. Articles also differed on the number of FSLSM dimensions to consider for *LS* detection. For example, the study by [40] used only two dimensions for *LS* detection whereas [18] considered using all 4 FSLSM dimensions in their study.

The information that was utilised to construct the user model and the variables for predicting *LS* preferences were also analysed in each article. The potential data sources identified predominately entailed tracking learner behaviours through interactions and behaviours with the system interface [25]. The types of variables that can be traced in an education system in this review were classified as KD, CD, TD and ND. The identification of these sources shows a "dynamic picture of potential attributes and behaviours'' that can be considered in identifying learners' *LSs* automatically and dynamically [25]. Even with similar *LS* frameworks, the variables used in former studies can be diverse [25].

This SLR focuses on the automatic and dynamic identification of *LSs* in the current literature using a data-driven approach. Through reviewing the current literature, the emerging trends of potential *AI* techniques employed for *PAL* platforms, as well as the methods and algorithms used to predict LS, were analysed. *AI* approaches receive significant attention and are used in several applications to personalise and adapt e-learning experiences to classify students based on their *LSs* to enhance their *e-learning* experience.

Among the *ML* algorithms employed for the adaptive education systems included in this review are NNs, DT, the KNN, the K-means, BN, FCM, SVM, ACS, GA, CBR, PSO, LR, CNN and RNN. Each of the methods has its own strengths. The most popular methods implemented were DT followed by ANN. The study by [51] is the only study documented in this *SLR* that proposed a personalised *e-learning* system based on DL and *ML* algorithms that could be adapted to the *LS* and level of the learner.

Many of the articles used a single *AI* technique, where a single algorithm was constructed on the dataset mostly observed for automatically determining the LS. Furthermore, there is growing interest in considering multiple *AI* techniques, either by combining and/or comparing techniques, for determining students' *LSs* [25]. This leaves an opportunity – still less explored – for more advanced algorithms to be combined in various ways to produce higher accuracy.

Moreover, a significant number of researchers have used NNs in the context of adaptive education systems to enhance learning. Limited work has been documented to include more advanced student behaviour classification models such as combining deep neural networks in various ways to produce higher accuracy with more meaningful behaviour features.

The fourth question analysed articles concerning the research approach implemented and the evaluation methods to determine the efficacy and performance of the *AI*-based *PAL* platforms in predicting a new learner's *LS*. The research approach of the works was classified into theoretical, experimental and simulation studies. Among the selected studies, certain studies presented a new framework or approach that could be extended in future works. Studies that provided empirical evaluation methods and testing on the system indicated positive initial results. The evaluation methods included surveys, statistical evaluation tests and statistical evaluation matrices.

The findings indicated promising results for the application of the learner model into an adaptive learning system according to the learner preferences implemented in the selected studies in this review. In the current *SLR*, the learning support and applications that are provided in *PAL* learning to identify *LSs* are classified as follows: UI, LC, LP and TUT. Adaptive LC and resources received the most interest. Some of the studies may also have had more than one target for the adaptation of *LSs*.

B. RECOMMENDATIONS AND FUTURE RESEARCH OPPORTUNITIES

According to [25], the integration of IT-, psychology- and pedagogy-related areas has gained significant attention over the past few years. The results of the current *SLR* indicate an increasing interest in the impact of LSM and the potential *AI* techniques employed for *PAL* platform research. DL using *AI* is gaining popularity and impacts *e-learning* by providing intuitive algorithms and automated delivery of *e-learning* content through modern learning management system (LMS) platforms [59]. ANNs using back propagation are commonly used, however, limited work has been conducted on the comparison of DL technologies in this context.

The findings suggest the need to consider and stimulate further empirical investigation in considering the adoption of advanced DL algorithms, such as deep neural networks, and opportunities for comparing DL architectures as they support and add value to each other, which can result in higher adaptability and recommendation ability [25].

Thus, what remains under-researched based on the aforementioned recommendations is how advanced classification models such as DL architectures can be combined in different ways. To support ongoing advancement, personalised learning requires research across the continuum of *PAL* based on *ML* to automatically and dynamically determine the identification of *LSs* to optimise individual learning. That said, research on the comparison of DL architectures incorporated with LSM to adapt and personalise learning strategies for each learner is needed. In addition, an investigation of the evaluation of the performance of these approaches in classifying learners' *LSs* is equally important.

C. LIMITATIONS

Although this research provides insight into the impact of LSMs and potential *AI* techniques employed for PAL platforms, it is important to specify the limitations. A possibility that the *SLR* process may have missed some relevant published papers due to several reasons exists. First, this review only included research articles published from 2015 to 2022 because previous publications by [25] and [26] had reviewed the automatic detection of *LSs* before 2015. Second, although the keywords used in the search process are documented in the methodology section of this *SLR*, various other search strings that can be constructed and synonyms that could be used relevant to the area being investigated are possible. Third, many search engines, besides the search systems that were considered in this *SLR* and documented in the methodology section, exist; consequently, papers in these databases might not have been considered.

However, the authors believe that the papers chosen for this *SLR* are representative of the entire literature and that any papers not identified in this study would not significantly

TABLE 1. Platforms, LS theories, AI techniques, evaluation methods and adaptation implemented in PAL to automatically identify LS.

Author	Platform	LSM	Data collection	Data source	Attributes	AI techniques	Research approach	Evaluation method	Learning support
[5]	Other	FSLSM Kolb	A	LF	CD, ND, TD, KD	NN, DT compared	Simulation	KS, RMSE	LC, LP
[6]	MOOC	FSLSM	A & C	LF	ND	NN	Framework	None specified	LC, LP
[8]	MOOC	FSLSM	A	LF	ND, CD, KD	K-means, DT, KNN, NN-combined & compared	Experiment	A, P, R, F1, Macro & Micro-precision, Calinski-Harabasz, Silhouette index	NON
[10]	E-learning	FSLSM	A	LF	ND	K-means, BN-combined	Experiment	P, A, R, Negative Predictive Value, Specificity	NON
[12]	E-learning	FSLSM	A & C	LF	CD, ND	ANN	Experiment	SIM (similarity), ACC (accuracy)	NON
[14]	E-learning	FSLSM	A & C	LF	ND, CD, KD, TD	ANN, ACS-combined	Experiment	SIM, ACC, Compared – related works	NON
[15]	E-learning	FSLSM	A & C	LF	ND, CD	KNN	Experiment	Effectiveness of A&NA, Performance	LC, LP
[16]	E-learning	FSLSM	A & C	LF	ND, KD, TD	ANN, GA, ACS, PSO – compared	Experiment	SIM, ACC, Compared – related works	NON
[17]	CITS	FSLSM	C & A	LF	KD, ND	DT	Experiment	Pre- & P-test, Survey	TUT
[18]	E-learning	FSLSM	C & A	LF	ND, CD	FCM	Experiment	A	NON
[29]	E-learning	FSLSM	C & A	LF	ND, CD, KD	Other, ANN - combined	Framework	–	LP
[31]	E-learning	FSLSM	C & A	LF	ND	Literature Based, SVM, BN – compared	Experiment	A	NON
[32]	MOOC	FSLSM	A	LF	ND, KD, TD	ANN	Experiment	P, R, F1, A, Sensitivity, Specificity, positive & negative, predictive value, Detection rate & prevalence, Balanced accuracy	NON
[33]	ITS	H & M	A & C	LF, O	ND, KD	ANN; FCM - combined	Experiment	Compared A&NA, Survey, T-tests	LC, TUT
[34]	ITS	FSLSM	A	LF	ND, KD	Other – compared	Experiment	P, R, F1, A,	NON
[35]	Mobile	VAK	C & A	LF	KD	BN	Simulation	Survey	LC
[36]	Mobile for tutoring	FSLSM	C	SI, O	KD	SVM, BN, KNN – compared	Experiment	Survey, T-tests, A, P, R, F1, ROC, KS, RMSE, Mean	LC

TABLE 1. *(Continued.)* **Platforms, LS theories, AI techniques, evaluation methods and adaptation implemented in PAL to automatically identify LS.**

Author	Platform	LSM	Data collection	Data source	Attributes	AI techniques	Research approach	Evaluation method	Learning support
								Absolute Error, Relative Absolute Error, Root Relative Squared Error	
[37]	Cloud-based virtual lab	FSLSM	A & C	LF	ND, CD, KD	SVM, DT – compared	Experiment	None specified	LC
[38]	Game-based	FSLSM	C & A	LF	KD	K-means	Experiment	Survey	NON
[39]	Other	FSLSM	A & C	LF	ND, CD	BN, IDCBR – combined	Framework	–	LP
[40]	Other	FSLSM	A & C	LF, SI	KD, ND, CD	IDCBR, KNN – combined	Framework	–	LP
[41]	E-learning	FSLSM	C & A	LF	ND, CD, KD	DT	Experiment	ML compared questionnaire, P, Survey, A&NA comparison, Performance	LC, NS
[46]	E-learning	FSLSM	A & C	LF, SI	ND, CD, KD	FCM, NN – combined	Simulation & Experiment	Learning rate and process A&NA, Performance A&NA	LP
[47]	E-learning	MBTI	A & C	LF & SI	CD, ND, TD, KD	K-means	Experiment	P, R, F1, A,	NON
[48]	E-learning	Kolb	C & A	LF, SI	ND, KD	DT	Experiment	P, F1	NON
[49]	E-learning	VAK	A & C	LF, SI	KD, CD	DT, K-means – combined	Experiment	None specified	LP
[50]	E-learning	VAK	C	SI	–	K-means, SVM, DT – combined	Experiment	Not specified	LP
[51]	E-learning	FSLSM	A & C	LF, SI, O	ND, KD	RNN, CNN, DT – combined	Framework	–	LC
[52]	E-learning	VARK	C	O	KD	ANN	Experiment	Compared A - previous research	NON
[53]	E-learning	VAK	C	SI, O	-	Other	Experiment	Pre&P - test, RMSE, Compared AI model & teacher's prediction, t-test	LC
[55]	E-learning	GTMI FSLSM	C & A	LF	CD, ND, KD	SVM, KNN, BN, DT, Linear Discriminant Analysis, LR – compared	Experiment	P, R, F1, A, cross-validation score, AUC, Consistency Compared – related works	NON
[61]	E-learning	H & M	A & C	LF	ND	CBR and NN, Other, BN, DT,	Experiment	T-test, Confusion	LC

TABLE 1. *(Continued.)* Platforms, LS theories, AI techniques, evaluation methods and adaptation implemented in PAL to automatically identify LS.

Author	Platform	LSM	Data collection	Data source	Attributes	AI techniques	Research approach	Evaluation method	Learning support
						NN – combined & compared		matrix – A & errors	
[62]	E-learning	MBTI	C & A	LF	CD, ND	BN, DT, Other, KNN – compared	Experiment	P, R, F1, A,	NON
[65]	E-learning	FSLSM	A	LF	ND, CD	FCM, NN - combined	Experiment	Jaccard Index, Xie-Beni Index, A, P, R, F1	NON
[66]	E-learning	FSLSM	A & C	LF	ND, KD, CD	BN, DT, compared	Experiment	Precision, ROC, Compared P – previous studies	LC
[67]	E-learning	FSLSM	C & A	LF	ND	SVM, BN, KNN, DT, LR – compared	Experiment	A, P, R, F1, ROC, AUC, ML, Cross-validated accuracy scores compared questionnaire	LC
[68]	E-learning	FSLSM	A	LF	ND, CD, KD	FCM	Experiment	T-test, Pre- & P-tests	UI, LC
[69]	E-learning	FSLSM	A & C	LF	KD, ND	DT, BN – compared	Experiment	Performance, Mean Absolute Error, False Positive Rate, ROC	LC
[70]	E-learning	FSLSM	A	LF	ND, TD, KD	GA, PSO – compared	Experiment	Test scores	LC
[71]	E-learning	FSLSM	A & C	LF	ND, CD	K-means	Experiment	A, P, R, F1	NON
[72]	E-learning	FSLSM	A & C	LF	ND, KD, CD	FCM, K-means – compared	Experiment	A, P, R, F1, Time complexity	NON
[73]	E-learning	FSLSM	C & A	LF	ND, CD, KD	BN, NN, DT, KNN – compared	Experiment	P, R, F1, Compared – related works	NON
[74]	E-learning	FSLSM	A	LF	ND; KD	K-means	Experiment	-	NON
[75]	E-learning	FSLSM	C & A	LF	ND	DTs – compared	Experiment	A, P	NON
[76]	E-learning	H&M	A & C	LF	ND	ACS	Experiment	T-tests	LP
[77]	E-learning	FSLSM	A	LF	ND, KD	DTs – compared	Experiment	A, P, R	LC
[78]	E-learning	FSLSM	A & C	LF	ND, TD	BN, DT – combined	Experiment	P	NON
[79]	E-learning	FSLSM	A & C	LF	KD, CD, ND	K-means, SVM, DT, LR combined	Experiment	Pre- & P-test, Survey	LP

change the results, even if the study were to be replicated at a low cost and rapidly.

APPENDICES

See Table 1.

REFERENCES

[1] K. Bijlani, K. R. Jayahari, and A. Mathew, "A-view: Real-time collaborative multimedia e-learning," in *Proc. 3rd Int. ACM Workshop Multimedia Technol. Distance Learn.*, Scottsdale, AZ, USA, Dec. 2011, pp. 13–18.

[2] A. Moubayed, M. Injadat, A. B. Nassif, H. Lutfiyya, and A. Shami, ''E-learning: Challenges and research opportunities using machine learning & data analytics,'' *IEEE Access*, vol. 6, pp. 39117–39138, 2018, doi: 10.1109/ACCESS.2018.2851790.

[3] A. El Mhouti, M. Erradi, and A. Nasseh, ''Using cloud computing services in e-learning process: Benefits and challenges,'' *Educ. Inf. Technol.*, vol. 23, no. 2, pp. 893–909, Mar. 2018.

[4] H. Peng, ''Personalized adaptive learning: An emerging pedagogical approach enabled by a smart learning environment,'' in *Foundations and Trends in Smart Learning*, M. Chang, Eds. Singapore: Springer, 2019, pp. 171–176, doi: 10.1007/978-981-13-6908-7_24.

[5] R. Bajaj and V. Sharma, ''Smart education with artificial intelligence based determination of learning styles,'' *Proc. Comput. Sci.*, vol. 132, pp. 834–842, Jan. 2018, doi: 10.1016/j.procs.2018.05.095.

[6] B. Hmedna, A. El Mezouary, and O. Baz, ''Identifying and tracking learning styles in MOOCs: A neural networks approach,'' *Adv. Intell. Syst. Comput.*, vol. 520, no. 2, pp. 125–134, 2017, doi: 10.1007/978-3-319-46568-5_13.

[7] P. Brusilovsky, ''Adaptive and intelligent technologies for web-based education web-based educational systems: A review of technologies,'' *Künstl. Intell., Special Issue Intell. Syst. Teleteaching*, vol. 13, no. 4, pp. 19–25, 1999.

[8] B. Hmedna, A. El Mezouary, and O. Baz, ''A predictive model for the identification of learning styles in MOOC environments,'' *Cluster Comput.*, vol. 23, no. 2, pp. 1303–1328, Jun. 2020, doi: 10.1007/s10586-019-02992-4.

[9] K. Colchester, H. Hagras, D. Alghazzawi, and G. Aldabbagh, ''A survey of artificial intelligence techniques employed for adaptive educational systems within e-learning platforms,'' *J. Artif. Intell. Soft Comput. Res.*, vol. 7, no. 1, pp. 47–64, Jan. 2017, doi: 10.1515/jaiscr-2017-0004.

[10] O. E. Aissaoui, Y. E. A. El Madani, L. Oughdir, and Y. E. Allioui, ''Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles,'' *Proc. Comput. Sci.*, vol. 148, pp. 87–96, Jan. 2019, doi: 10.1016/j.procs.2019.01.012.

[11] S. Graf, Kinshuk, and T. Liu, ''Supporting teachers in identifying students' learning styles in learning management systems: an automatic student modelling approach,'' *Educ. Technol. Soc.*, vol. 12, no. 4, pp. 3–14, 2009.

[12] J. Bernard, T.-W. Chang, E. Popescu, and S. Graf, ''Using artificial neural networks to identify learning styles,'' in *Proc. Int. Conf. Artif. Intell. Educ.*, Madrid, Spain, 2015, pp. 541–544, doi: 10.1007/978-3-319-19773-9.

[13] O. Zine, A. Derouich, and A. Talbi, ''A comparative study of the most influential learning styles used in adaptive educational environments,'' *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 11, pp. 520–528, 2019.

[14] J. Bernard, E. Popescu, and S. Graf, ''Improving online education through automatic learning style identification using a multi-step architecture with ant colony system and artificial neural networks,'' *Appl. Soft Comput.*, vol. 131, Dec. 2022, Art. no. 109779.

[15] R. Xue-Jun, Z. Ya-Ni, Z. Wei-Hu, and W. Xiao-Shuang, ''Research and practice of user learning style model recognition based on big data,'' in *Proc. Int. Conf. Internet, Educ. Inf. Technol. (IEIT)*, Suzhou, China, Apr. 2021, pp. 270–273, doi: 10.1109/IEIT53597.2021.00066.

[16] J. Bernard, T.-W. Chang, E. Popescu, and S. Graf, ''Learning style identifier: Improving the precision of learning style identification through computational intelligence algorithms,'' *Exp. Syst. Appl.*, vol. 75, pp. 94–108, Jun. 2017, doi: 10.1016/j.eswa.2017.01.021.

[17] K. Crockett, A. Latham, and N. Whitton, ''On predicting learning styles in conversational intelligent tutoring systems using fuzzy decision trees,'' *Int. J. Hum. Comp. Stud.*, vol. 97, pp. 98–115, Jan. 2017, doi: 10.1016/j.ijhcs.2016.08.005.

[18] I. Azzi, A. Jeghal, A. Radouane, A. Yahyaouy, and H. Tairi, ''A robust classification to predict learning styles in adaptive e-learning systems,'' *Educ. Inf. Technol.*, vol. 25, pp. 437–448, Aug. 2020, doi: 10.1007/s10639-019-09956-6.

[19] I. O. Pappas and M. N. Giannakos, ''Rethinking learning design in IT education during a pandemic,'' *Frontiers Educ.*, vol. 6, pp. 1–8, Apr. 2021, doi: 10.3389/feduc.2021.652856.

[20] H. Xie, H.-C. Chu, G.-J. Hwang, and C.-C. Wang, ''Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017,'' *Comput. Educ.*, vol. 140, Oct. 2019, Art. no. 103599, doi: 10.1016/j.compedu.2019.103599.

[21] E. Jando, Meyliana, A. N. Hidayanto, H. Prabowo, H. L. H. S. Warnars, and Sasmoko, ''Personalized e-learning model: A systematic literature review,'' in *Proc. Int. Conf. Inf. Manage. Technol. (ICIMTech)*, Yogyakarta, Indonesia, Nov. 2017, pp. 238–243.

[22] A. A. Kardan, M. Aziz, and M. Shahpasand, ''Adaptive systems: A content analysis on technical side for e-learning environments,'' *Artif. Intell. Rev.*, vol. 44, no. 3, pp. 365–391, Oct. 2015.

[23] J. Talaghzi, A. Bennane, M. M. Himmi, M. Bellafkih, and A. Benomar, ''Online adaptive learning: A review of literature,'' in *Proc. 13th Int. Conf. Intell. Syst., Theories Appl.*, Rabat, Morocco, Sep. 2020, pp. 1–6.

[24] Ö. Özyurt and H. Özyurt, ''Learning style based individualized adaptive e-learning environments: Content analysis of the articles published from 2005 to 2014,'' *Comput. Hum. Behav.*, vol. 52, pp. 349–358, Nov. 2015.

[25] H. M. Truong, ''Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities,'' *Comput. Hum. Behav.*, vol. 55, pp. 1185–1193, Feb. 2016, doi: 10.1016/j.chb.2015.02.014.

[26] J. Feldman, A. Monteserin, and A. Amandi, ''Automatic detection of learning styles: State of the art,'' *Artif. Intell. Rev.*, vol. 44, no. 2, pp. 157–186, Aug. 2015, doi: 10.1007/s10462-014-9422-6.

[27] B. Kitchenham and S. Charters, ''Guidelines for performing systematic literature reviews in software engineering version 2.3,'' *Engineering*, vol. 45, no. 4, p. 1051, 2007, doi: 10.1145/1134285.1134500.

[28] S. A. Ochukut and R. Oboko, ''A learner model for adaptive e-learning based on learning theories,'' in *Proc. IST-Africa Week Conf.*, Nairobi, Kenya, 2019, pp. 1–8, doi: 10.23919/ISTAFRICA.2019.8764826.

[29] J. Melesko and E. Kurilovas, ''Semantic technologies in e-learning: Learning analytics and artificial neural networks in personalised learning systems,'' in *Proc. 8th Int. Conf. Web Intell., Mining Semantics*, Novi Sad, Serbia, Jun. 2018, pp. 1–7, doi: 10.1145/3227609.3227669.

[30] H. Fasihuddin, G. Skinner, and R. Athauda, ''A framework to personalise open learning environments by adapting to learning styles,'' in *Proc. 7th Int. Conf. Comput. Supported Educ.*, Lisbon, Portugal, 2015, pp. 296–305, doi: 10.5220/0005443502960305.

[31] E. S. Amir, M. Sumadyo, D. I. Sensuse, Y. G. Sucahyo, and H. B. Santoso, ''Automatic detection of learning styles in learning management system by using literature-based method and support vector machine,'' in *Proc. Int. Conf. Adv. Comput. Sci. Inf. Syst. (ICACSIS)*, Malang, Indonesia, Oct. 2016, pp. 141–144.

[32] E. Gomede, R. Miranda de Barros, and L. de Souza Mendes, ''Use of deep multi-target prediction to identify learning styles,'' *Appl. Sci.*, vol. 10, no. 5, p. 1756, Mar. 2020, doi: 10.3390/app10051756.

[33] C. Troussas, A. Krouska, and M. Virvou, ''A multilayer inference engine for individualized tutoring model: Adapting learning material and its granularity,'' *Neural Comput. Appl.*, vol. 35, no. 1, pp. 61–75, Jan. 2023.

[34] K. A. H. Assiry and A. Muniasamy, ''Predicting learning styles using machine learning classifiers,'' in *Proc. Int. Conf. Electr., Comput. Energy Technol. (ICECET)*, Prague, Czechia, Jul. 2022, pp. 1–7.

[35] A. F. Nurzaman, R. T. Tedja, L. Kusuma, Y. Kurniawan, G. Bhutkar, and J. Johan, ''LAISES—Learning AI integrating system for elementary students,'' in *Proc. 5th Int. Conf. Graph. Signal Process.*, Nagoya, Japan, 2021, pp. 65–71, doi: 10.1145/3474906.3474913.

[36] C. Troussas, A. Krouska, C. Sgouropoulou, and I. Voyiatzis, ''Ensemble learning using fuzzy weights to improve learning style identification for adapted instructional routines,'' *Entropy*, vol. 22, no. 7, p. 735, Jul. 2020.

[37] Y. Deng, D. Lu, C. Chung, D. Huang, and Z. Zeng, ''Personalized learning in a virtual hands-on lab platform for computer science education,'' in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, San Jose, CA, USA, Oct. 2018, pp. 1–8, doi: 10.1109/FIE.2018.8659291.

[38] Y. H. Hung, R. I. Chang, and C. F. Lin, ''Hybrid learning style identification and developing adaptive problem-solving learning activities,'' *Comput. Hum. Behav.*, vol. 55, pp. 552–561, Feb. 2016, doi: 10.1016/j.chb.2015.07.004.

[39] N. El Ghouch, E. M. En-Naimi, A. Zouhair, and M. Al Achhab, "Our architecture of an adaptive learning system based on the dynamic case-based reasoning and the learner traces," in *Proc. 2nd Int. Conf. Comput. Wireless Commun. Syst.*, Larache, Morocco, Nov. 2017, pp. 1–5, doi: 10.1145/3167486.3167497.

[40] N. El Ghouch, E. M. En-Naimi, A. Zouhair, and M. Al Achhab, "Guided retrieve through the K-nearest neighbors method in adaptive learning system using the dynamic case based reasoning approach," in *Proc. ACM Int. Conf.*, Tetouan, Morocco, 2018, pp. 1–6, doi: 10.1145/3286606.3286852.

[41] I. Karagiannis and M. Satratzemi, "An adaptive mechanism for moodle based on automatic detection of learning styles," *Educ. Inf. Technol.*, vol. 23, no. 3, pp. 1331–1357, May 2018, doi: 10.1007/s10639-017-9663-5.

[42] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Eng. Educ.*, vol. 78, no. 7, pp. 674–681, 1988.

[43] T. A. Litzinger, S. H. Lee, J. C. Wise, and R. M. Felder, "A psychometric study of the index of learning styles," *J. Eng. Educ.*, vol. 96, no. 4, pp. 309–319, Oct. 2007.

[44] D. A. Kolb, *Experiential Learning: Experience as the Source of Learning and Development*, vol. 1. Englewood Cliffs, NJ, USA: Prentice-Hall, 1984.

[45] A. Latham, K. Crockett, and D. Mclean, "Profiling student learning styles with multilayer perceptron neural networks," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Manchester, U.K., Oct. 2013, pp. 2510–2515, doi: 10.1109/SMC.2013.428.

[46] S. Sweta and K. Lal, "Personalized adaptive learner model in e-learning system using FCM and fuzzy inference system," *Int. J. Fuzzy Syst.*, vol. 19, no. 4, pp. 1249–1260, Aug. 2017, doi: 10.1007/s40815-017-0309-y.

[47] S. Fatahi, H. Moradi, and E. Farmad, "Behavioral feature extraction to determine learning styles in e-learning environments," in *Proc. Int. Conf. E-Learning, Multi Conf. Comput. Sci. Inform. Syst.*, 2015, pp. 66–72.

[48] A. A. Kalhoro, S. Rajper, and G. A. Mallah, "Detection of e-learners' learning styles: An automatic approach using decision tree," *Int. J. Comput. Sci. Syst. Anal.*, vol. 14, no. 8, pp. 420–425, 2016.

[49] M. Sogy, H. Kaur, A. Garg, M. Khunger, and R. Sehgal, "Assessing dynamic learners' behaviour using open ended tasks," in *Proc. 4th Int. Conf. Inform. Syst. Comput. Netw.*, Mathura, India, 2019, pp. 234–239, doi: 10.1109/ISCON47742.2019.9036258.

[50] A. S. Kuttattu, G. S. Gokul, H. Prasad, J. Murali, and L. S. Nair, "Analysing the learning style of an individual and suggesting field of study using machine learning techniques," in *Proc. 4th Int. Conf. Commun. Electron. Syst.*, Coimbatore, India, 2019, pp. 1671–1675, doi: 10.1109/ICCES45898.2019.9002051.

[51] H. Anantharaman, A. Mubarak, and B. T. Shobana, "Modelling an adaptive e-learning system using LSTM and random forest classification," in *Proc. IEEE Conf. e-Learning, e-Management e-Services (ICe)*, Langkawi, Malaysia, Nov. 2018, pp. 29–34, doi: 10.1109/IC3e.2018.8632646.

[52] M. S. Hasibuan, L. E. Nugroho, and P. Santosa, "Detecting learning style based on level of knowledge," in *Proc. 3rd Int. Conf. Informat. Comput. (ICIC)*, Palembang, Indonesia, Oct. 2018, pp. 1–5, doi: 10.1109/IAC.2018.8780435.

[53] B. Pardamean, T. Suparyanto, T. W. Cenggoro, D. Sudigyo, and A. Anugrahana, "AI-based learning style prediction in online learning for primary education," *IEEE Access*, vol. 10, pp. 35725–35735, 2022, doi: 10.1109/ACCESS.2022.3160177.

[54] R. Stathacopoulou, G. D. Magoulas, M. Grigoriadou, and M. Samarakou, "Neuro-fuzzy knowledge processing in intelligent learning environments for improved student diagnosis," *Inf. Sci.*, vol. 170, nos. 2–4, pp. 273–307, 2005.

[55] F. Rasheed and A. Wahid, "Learning style detection in E-learning systems using machine learning techniques," *Exp. Syst. Appl.*, vol. 174, Jul. 2021, Art. no. 114774.

[56] A. L. Symeonidis and P. A. Mitkas, *Agent Intelligence Through Artificial Intelligence*. Cham, Switzerland: Springer, 2006.

[57] A. K. Jain, J. Mao, and K. M. Mohiuddin, "Artificial neural networks: A tutorial," *Computer*, vol. 29, pp. 31–44, Mar. 1996.

[58] J. E. Villaverde, D. Godoy, and A. Amandi, "Learning styles' recognition in e-learning environments with feed-forward neural networks," *J. Comput. Assist. Learn.*, vol. 22, no. 3, pp. 197–206, May 2006, doi: 10.1111/j.1365-2729.2006.00169.x.

[59] A. Muniasamy and A. Alasiry, "Deep learning: The impact on future elearning," *Int. J. Emerg. Technol. Learn.*, vol. 15, no. 1, pp. 188–199, 2020, doi: 10.3991/IJET.V15I01.11435.

[60] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Comput. Surv.*, vol. 1, pp. 1–35, Jul. 2019, doi: 10.1145/3285029.

[61] B. Maraza-Quispe, O. Alejandro-Oviedo, B. Cisneros-Chavez, M. Cuentas-Toledo, L. Cuadros-Paz, W. Fernandez-Gambarini, L. Quispe-Flores, and N. Caytuiro-Silva, "Model to personalize the teaching-learning process in virtual environments using case-based reasoning," in *Proc. ACM Int. Conf.*, Amsterdam, The Netherlands, 2019, pp. 105–110, doi: 10.1145/3369255.3369264.

[62] M. S. Halawa, M. E. Shehab, and E. M. R. Hamed, "Predicting student personality based on a data-driven model from student behavior on LMS and social networks," in *Proc. 5th Int. Conf. Digit. Inf. Process. Commun. (ICDIPC)*, Sierre, Switzerland, Oct. 2015, pp. 294–299, doi: 10.1109/ICDIPC.2015.7323044.

[63] C.-F. Tsai, Y.-F. Hsu, C.-Y. Lin, and W.-Y. Lin, "Intrusion detection by machine learning: A review," *Exp. Syst. Appl.*, vol. 36, no. 10, pp. 11994–12000, 2009, doi: 10.1016/j.eswa.2009.05.029.

[64] G. Seni and J. F. Elder, *Ensemble Methods in Data Mining: Improving Accuracy Through Combining Predictions* (Synthesis Lectures on Data Mining and Knowledge Discovery). San Rafael, CA, USA: Morgan and Claypool, 2010.

[65] V. K. Sucheta, M. P. Radhika, and P. M. M. Manohara, "Prediction of learner's profile based on learning styles in adaptive e-learning system," *Int. J. Emerg. Technol. Learn.*, vol. 12, no. 6, pp. 31–51, 2917, doi: 10.3991/ijet.v12i06.6579.

[66] M. P. P. Liyanage, K. S. L. Gunawardena, and M. Hirakawa, "Detecting learning styles in learning management systems using data mining," *J. Inf. Process.*, vol. 24, no. 4, pp. 740–749, 2016, doi: 10.2197/ipsjjip.24.740.

[67] R. R. Maaliw, "A personalized virtual learning environment using multiple modeling techniques," in *Proc. IEEE 12th Annu. Ubiquitous Comput., Electron. Mobile Commun. Conf. (UEMCON)*, New York, NY, USA, Dec. 2021, pp. 8–15, doi: 10.1109/UEMCON53757.2021.9666645.

[68] S. V. Kolekar, R. M. Pai, and M. Pai M. M., "Adaptive user interface for moodle based e-learning system using learning styles," *Procedia Comput. Sci.*, vol. 135, pp. 606–615, 2018, doi: 10.1016/j.procs.2018.08.226.

[69] M. Abdullah, W. H. Daffa, R. M. Bashmail, M. Alzahrani, and M. Sadik, "The impact of learning styles on learner's performance in e-learning environment," *Int. J. Adv. Comput. Sci. Appl.*, vol. 6, no. 9, pp. 24–31, 2015, doi: 10.14569/ijacsa.2015.060903.

[70] B. C. L. Christudas, E. Kirubakaran, and P. R. J. Thangaiah, "An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials," *Telematics Informat.*, vol. 35, no. 3, pp. 520–533, Jun. 2018, doi: 10.1016/j.tele.2017.02.004.

[71] O. El Aissaoui, Y. El Madani El Alami, L. Oughdir, and Y. El Allioui, "Integrating Web usage mining for an automatic learner profile detection: A learning styles-based approach," in *Proc. Int. Conf. Intell. Syst. Comput. Vis. (ISCV)*, Fez, Morocco, Apr. 2018, pp. 1–6, doi: 10.1109/ISACV.2018.8354021.

[72] O. El Aissaoui, Y. El Alami El Madani, L. Oughdir, and Y. El Allioui, "A fuzzy classification approach for learning style prediction based on web mining technique in e-learning environments," *Educ. Inf. Technol.*, vol. 24, pp. 1943–1959, Sep. 2019, doi: 10.1007/s10639-018-9820-5.

[73] L. D. Ferreira, G. Spadon, A. C. Carvalho, and J. F. Rodrigues, "A comparative analysis of the automatic modeling of learning styles through machine learning techniques," in *Proc. IEEE Frontiers Edu. Conf. (FIE)*, San Jose, CA, USA, Oct. 2018, pp. 1–8, doi: 10.1109/FIE.2018.8659191.

[74] A. Hidayat, K. Adi, and B. Surarso, "Determine Felder Silverman learning style model using literature based and K-means clustering," in *Proc. 6th Int. Conf. Informat. Comput.*, Jakarta, Indonesia, vol. 2021, pp. 1–6, doi: 10.1109/ICIC54025.2021.9633010.

[75] Y. Ikawati, M. U. H. Al Rasyid, and I. Winarno, "Student behavior analysis to detect learning styles in moodle learning management system," in *Proc. Int. Electron. Symp. (IES)*, Surabaya, Indonesia, Sep. 2020, pp. 501–506, doi: 10.1109/IES50839.2020.9231567.

[76] E. Kurilovas, I. Zilinskiene, and V. Dagiene, "Recommending suitable learning paths according to learners' preferences: Experimental research results," *Comput. Hum. Behav.*, vol. 51, pp. 945–951, Oct. 2015, doi: 10.1016/j.chb.2014.10.027.

[77] T. Sheeba and R. Krishnan, "Prediction of student learning style using modified decision tree algorithm in e-learning system," in *Proc. Int. Conf. Data Sci. Inf. Technol.*, Singapore, Jul. 2018, pp. 85–90, doi: 10.1145/3239283.3239319.

[78] L. X. Li and S. S. A. Rahman, "Students' learning style detection using tree augmented naive Bayes," *Roy. Soc. Open Sci.*, vol. 5, no. 7, Jul. 2018, Art. no. 172108, doi: 10.1098/rsos.172108.

[79] M. A. M. Rishard, S. L. Jayasekara, E. M. P. U. Ekanayake, K. M. J. S. Wickramathilake, S. Reyal, K. Manathunga, and J. Wickramarathne, "Adaptivo: A personalized adaptive e-learning system based on learning styles and prior knowledge," in *Proc. 7th Int. Conf. Informat. Comput. (ICIC)*, Dec. 2022, pp. 1–9.

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