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TOPICAL REVIEW

A Comprehensive Study On Personalized Learning Recommendation In E-Learning System

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ABSTRACT The Internet and cloud computing technology have enabled learners to choose courses based on their interests through e-learning systems. E-learning systems such as Massive Open Online Courses (MOOC) offer a comprehensive curriculum and teaching resources, including courseware, teaching videos, exercises, and homework. These systems provide free courses, rich content, and flexible selection. However, the abundance of teaching resources in e-learning systems can lead to information overload, making it challenging for learners to select suitable courses and resources. Personalized learning recommendation is a research field within intelligent learning. Its goal is to automatically and efficiently identify learners' characteristics and recommend matching learning resources to specific learners on e-learning systems to enhance learning motivation and effectiveness. This study examines the research articles on personalized learning recommendation technology and methodology published between 2013 and 2023, and only English articles and conference papers were selected. This study collects articles from five scientific databases: ACM Digital Library, IEEE Xplore, ScienceDirect, SpringerLink, and Worldwide Science. Out of 3413 identified articles, 64 relevant studies were selected for further systematic literature research. Only those with specific recommendation methods or implementation codes are chosen to ensure the quality of the articles. It summarizes the modeling of learners and learning objects and the algorithms used for personalized learning recommendations. Finally, the problems of current personalized learning recommendation methods are outlined, and views on future research opportunities are proposed.

INDEX TERMS E-learning, e-learning system, MOOC, personalized learning, recommendation.

I. INTRODUCTION

An e-learning system is used by learners using Internet technology to achieve specific learning objectives. The learning content in the systems is organized according to the teaching strategies. Compared to traditional teacher-based classroom teaching, e-learning systems offer advantages such as high effectiveness, low cost, and high flexibility. In recent years, an increasing number of learners have chosen to use e-learning systems, especially after the outbreak of COVID-19 in 2020, which made traditional offline teaching impossible.

There are e-learning systems widely used, such as Coursera, Khan Academy, XuetangX Online, China University MOOC, and NetEase Cloud Classroom, as well as many colleges and universities that have built their own Learning Management System (LMS). These systems offer tens of thousands of courses and provide e-learning services to a vast number of learners. E-learning systems can meet learners' urgent needs for acquiring knowledge and skills, bringing changes to online education, and posing relevant challenges. On one hand, learners need help to obtain the necessary

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content from the vast and complex learning resources, which reduces learning efficiency. Numerous low-quality and erroneous learning resources can hinder learners from achieving their goals. On the other hand, e-learning systems have limitations in providing personalized learning resources and predicting the learning progress of individual learners. Therefore, some learners need to adapt to the difficulty of the course, are not interested in the content, and cannot complete the course.

As such, personalized learning recommendation (PLR) has emerged. PLR has become the central focus in online education. PLR extracts the characteristics and preferences of each learner through data analysis and recommends e-learning resources that can meet the personalized needs of different learners. The e-learning resources include exercises, concepts, knowledge points, online courses, learning videos, etc. Learners do not need to spend their energy searching for learning resources but rather devote more time to learning their interested resources to improve the efficiency and effectiveness of learning. Unlike the application of recommendation in other domains, PLR is not intended to predict or cater to the potential behavior of learners. PLR should assist learners in discovering learning resources reasonably matching their personalized parameters during the appropriate learning process, stimulate and cultivate learning motivation, improve learners' motivation and persistence, and achieve the goal of enhancing learning efficiency. Some researchers have researched the problem of personalized learning and tried to propose various solutions. Therefore, in the current research, personalized learning recommendation algorithms for e-learning systems have become a dominant research topic in intelligent learning.

To date, there are many research works in the PLR field. Souabi et al. [1] have reviewed the evolution of e-learning recommendation history since the century and listed each stage of the representative recommendation algorithms. Still, this article does not expand on the advantages and disadvantages of the reviewed algorithms. Similarly, Aberbach et al. [2] described the research on content-based (CB), collaborative filtering-based (CFB), and hybrid recommendation algorithms for e-learning recommendation. However, other recommendation algorithms, such as session-based and deep neural network-based algorithms, are not mentioned. Likewise, Raj and Renumol [3] analyzed and summarized the research on learning content recommendation methods in adaptive and personalized learning environments from 2015 to 2020. The author also counted the adopted recommendation algorithms used in the related research literature. Still, it lacks discussion about the advantages and disadvantages of the recommendation algorithms, the experimental datasets, and the applications domains used. Similarly, the review by George and Lal [4] mainly focused on ontology-based e-learning recommendation algorithms and did not describe other recommendation algorithms. Additionally, Lin et al. [5] summarized the learning recommendation algorithms for online micro-learning in which learners used mobile devices to use their fragmented time. The learning method belongs to one of the types of e-learning, and the mode of learning is different from course-based e-learning. Therefore, such recommendation algorithms are not suitable for e-learning. Lastly, Zhang et al. [6] presented the three main recommendation techniques used in e-learning, i.e., content-based recommendation, CFB recommendation, and knowledge-based recommendation. The author identified new research directions, but the article mainly quantified the research results in 2018 and earlier and lacked an analysis of the relevant research situation in the last three to five years. In addition, the research work also lacks new recommendation algorithms research and application of the analysis of the summary.

Many researchers have summarized and reviewed the research on PLR. However, such review studies highlight only the literature published earlier, analyzing fewer research results in related fields in the last 3-5 years. Moreover, these studies have not carried out an in-depth summary and analysis of new recommendation methods. The highlights and limitations of recommendation methods are also insufficiently summarized in the existing studies. Therefore, it is deemed that further work is still needed to systematically sort and summarize on e-learning recommendation systems. More work is also necessary to grasp the latest research and application dynamics in this field and to provide valuable references and guidelines for researchers. The objective of this study is to analyze previous research in the field of personalized recommendations for e-learning, particularly the literature in the past three years. This study gives a summary of the technical routes and mainstream recommendation ideas and algorithms adopted by the current research in this field. It finds out the problems of the current research on personalized recommendations for e-learning and looks forward to the future direction of research. It also provides new research ideas and research directions for the researchers in the subsequent research. The abbreviations in this study are shown in Table 1.

II. SYSTEMATIC REVIEW METHODOLOGY

A. RESEARCH QUESTION

This study examines the research on personalized learning recommendations in e-learning systems. This study poses the following research questions.

- RQ1: What is the status of research on recommendation techniques based on learner and learning content modeling in Personalized Learning Recommendation Systems (PLRS)?
- RQ2: What types of recommendation algorithms and techniques are used in PLRS?
- RQ3: What datasets are used in PLRS for experimental validation of the recommendations algorithms and techniques proposed in the study?
- RQ4: What are the highlights and limitations of the studies related to PLRS?

TABLE 1. Abbreviations.

Abbreviations	Word	Abbreviations	Word
PLR	Personalised Learning Recommendation	RNN	Recurrent Neural Network
PLRS	Personalized Learning Recommendation Systems	CNN	Convolutional Neural Networks
CF	Collaborative Filtering	DBN	Deep Belief Network
CFB	Collaborative Filtering-Based	DFS	Depth First Search
CB	Content-Based	MF	Matrix Factorization
ML	Machine Learning	LSI	Learning Styles Inventory
LMS	Learning Management System	DRLP	Deep Reinforcement Learning for Programming Problems
SLR	Systematic Literature Review	LDA	Latent Dirichlet Allocation
FSLSM	Felder-Silverman Learning Style Model	LSTM	Long Short-Term Memory
IRT	Item Response Theory	RL	Reinforcement Learning
LSM	Learning Style Model	GCN	Graph Convolutional Network
HLR	Hybrid Learning Recommendation	SVD	Singular Value Decomposition
SWRL	Semantic Web Rule Language	KG	Knowledge Graph
MOOC	Massive Open Online Courses	HIN	Heterogeneous Information Network
ILS	Index of Learning Style	SAA	Spreading Activation algorithm
SPM	Sequential Pattern Mining	ARM	Association rule mining
LTP	The Law of Total Probability	BPR	Bayesian personalized ranking
KNN	K Nearest Neighbors	OPCR	Ontology-based personalized Course Recommendation
DCT	Decision Tree	NCF	Neural Network Based Collaborative Filtering
CPN	Colored Petri Nets	DNN	Depp Neural Networks
CBR	Case Based Reasoning	GNN	Graph neural network
MDP	Markov decision Process		

- RQ5: What are the research trends and future research directions for PLRS?

B. LITERATURE SEARCH STRATEGY

This study was conducted by using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [7] approach. The latest version of PRISMA i.e., PRISMA 2020 Statement was used as the standard reference for this study.

The publication period was limited to January 2013-December 2023, i.e., the articles of relevant research within ten years were selected for Systematic Literature Review (SLR), and the search was limited to full-text works

TABLE 2. Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
1. published between the year 2013 and 2023 2. written in English 3. published in journals, conferences 4. focused on the design or development of a recommendation system for personalized learning 5. focused on personalization and adaptive e-learning recommendation and learning style modeling 6. content contains recommendation algorithms, recommendation systems, architecture, learning model or algorithm design, and related experimental data 7. full text accessible	1. published before 1/1/2013 2. not written in English 3. book, book chapters, keynote, poster, panel, discussion, abstract, course, encyclopedia, editorials, reports, correspondence, others(type of literature except for article) 4. articles of literature review 5. articles in which recommendation meant something else or not in the field of e-learning 6. articles that had insufficient information about recommendations or datasets or lacked detailed explanation and evaluation of the topic 7. duplicate articles that adopted the same or very similar algorithm from different datasets and the articles that content was the same 8. articles whose full text was not accessible

TABLE 3. Articles screening keywords from each scientific database.

Databases	Found articles	Fields	Search string
ACM Digital Library	259	Abstract, Title	("Recommender" OR "recommendation") AND ("personalized learning" OR "E-learning" OR "adaptive learning" OR "MOOC" OR "ontology" OR "Learning Style")
IEEE Xplore	279	Title	("Recommender" OR "recommendation") AND ("personalized learning" OR "E-learning" OR "adaptive learning" OR "MOOC" OR "ontology" OR "Learning Style")
ScienceDirect	90	Title	("Recommender" OR "recommendation") AND ("personalized learning" OR "E-learning" OR "adaptive learning" OR "MOOC" OR "ontology" OR "Learning Style")
SpringerLink	1900	ALL	("Recommender" OR "recommendation") AND (educational e-learning online learning resources MOOC)
Worldwide Science	885	Title	("Recommender" OR "recommendation") AND ("personalized learning" OR "E-learning" OdR "learning" OR "MOOC" OR "ontology" OR "Learning Style" OR "Course")

published in journals or conference proceedings available in English.

This study used five databases, ACM Digital Library, IEEE Xplore, ScienceDirect, SpringerLink, and Worldwide Science, to search the research journals and conference articles related to this study. These five databases are all open for access and contain much literature on computer science and educational information technology. A literature search in these databases allows research in this field to be better understood. In addition, books, dissertations, surveys, literature reviews, news reports, and other documents were not included. Each article retrieved from the databases was reviewed for its relevance to the field of education, especially e-learning. The selected articles must have detailed descriptions of the design of recommendation algorithms or system frameworks to facilitate the understanding of the researchers' research ideas and methods. Moreover, the recommendation systems described in the selected articles must have demonstrated the effectiveness of their algorithms and designs by having been applied in a test dataset or an LMS and having obtained experimental data. Table 2 summarizes all the inclusion and exclusion criteria.

Table 3 shows all the scientific databases, fields, and the initial number of articles found in each database. The keywords in the search string for different databases have been slightly adjusted according to the requirements of the articles to be searched.

The keywords "Recommender" and "recommendation" indicate that the types of algorithms or methods retrieved are related to recommendation systems. The keywords "personalized learning, E-learning online learning, adaptive learning, online learning, educational" are keywords closely related to online education and personalized learning. "MOOC, resources, ontology" are keywords related to learning object modeling. "Learning Style" is a keyword related to learner modeling.

C. QUALITY ASSESSMENT

In addition to applying inclusion and exclusion criteria, quality assessment is also required to ensure that the research articles reflect the current research status in this research field and to obtain more accurate research results from these articles. The quality assessment focused on assessing the extent to which the research of the selected articles addressed the research questions posed in the SLR. By using quality assessment methods, studies that are not relevant to this study

TABLE 4. Quality assessment questionnaire.

QA Number	Quality assessment question	Corresponding research question
QA1	How does the author(s) explain the analysis of the current research and the research questions?	RQ1
QA2	How does the author(s) explain the construction of the learning model or the design of the recommendation framework and algorithm?	RQ2
QA3	How does the author(s) validate the proposed recommendation method or learning model by using a test dataset?	RQ3
QA4	How does the author(s) analyze and summarize the results of the proposed recommendation method or learning model?	RQ4
QA5	What is the value of the research results of the article and the future research directions?	RQ5

can be filtered out. Table 4 shows the five quality assessment questions used to develop the quality assessment criteria and the corresponding research questions.

The 95 articles previously screened were assessed according to the quality assessment criteria in Table 4. Table 5 is the scoring matrix of the articles, which illustrates the evaluation criteria for the scores of all five QA items. The result is that only articles with scores greater than three are considered acceptable and included in this study.

D. ANALYSIS OF SEARCH RESULTS

Fig. 1 shows that 3413 research articles were retrieved from five databases. In the total 3413 articles, duplicate articles, papers written not in English, and articles in non-journals and conferences were excluded, so 2110 articles were rejected. Among the remaining 1303 articles, 764 review articles and articles with titles unrelated to research were rejected. This study focused on 2013 to 2023, so 61 articles were rejected due to publication dates before 2013. Articles were screened according to the relevance of keywords, titles, and abstracts to this study and open access, out of which 383 articles were excluded. The articles whose quality does not meet the requirements of the study, such as no technical details of the study, no recommendation-related technical frameworks or algorithms, and no description of the experimental setting or test dataset used, were also excluded. After screening and quality assessment, the final number of articles obtained was 64, closely related to this study. Fig. 1 illustrates the process of the article retrieval.

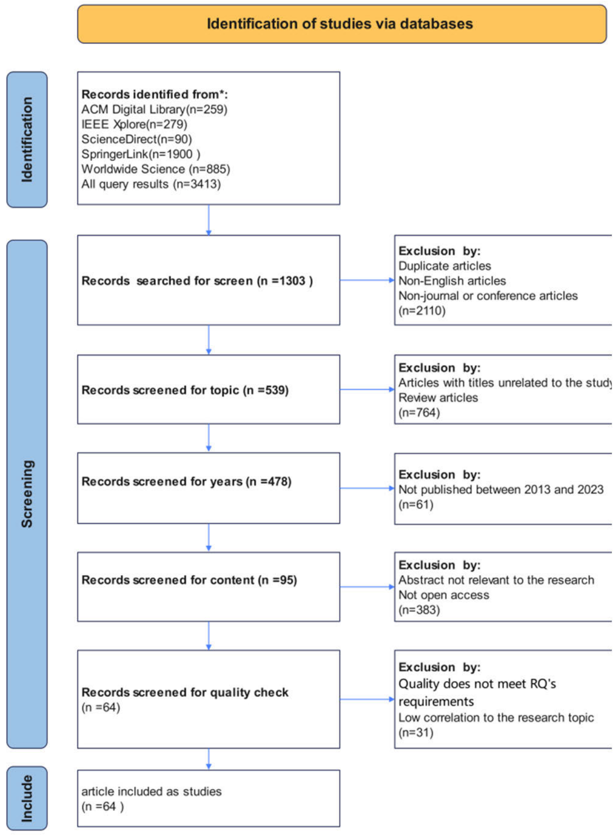

FIGURE 1. Prisma chart.

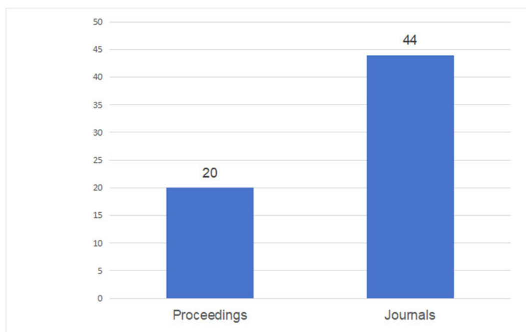

FIGURE 2. Distribution of selected articles.

Among these 64 articles, 20 are conference articles, and 44 are journal articles, as shown in Fig. 2 In this study, the summary statistics of the 64 articles found, according to the databases included, were performed to obtain the research statistics for each database, as shown in Fig. 3.

Fig. 4 shows the statistics of the number of journal and conference articles published in each year during the ten years from 2013 to 2023. It can be seen from the figure that the related research has been increasing yearly since 2013, especially in 2020, due to the impact of COVID-19. The trend indicates that the demand for e-learning learners has surged,

TABLE 5. Quality assessment quantitative evaluation matrix.

QA	Quality assessment scoring criteria	Score
QA1	The article provides an in-depth analysis and explanation of the research, including rich charts and data or quotes from many cited documents.	5
	This article provides a detailed description of the current research, with a certain number of figures or citations.	4
	The article explains the current research briefly and provides a small number of charts or cited literature to support it.	3
	The article provides a relatively simple explanation of the current research without diagrams or cited literature.	2
	The explanation of the current research in the article is very brief or unclear.	1
	The article does not provide any explanation of the current research.	0
QA2	The article provides an in-depth analysis and explanation of the design of learning models or recommendation frameworks and algorithms. It uses various methods, including diagrams and pseudo-code, to explain the underlying mathematical principles or ideas of algorithms and models. In this article, the simulation experiment method is used to obtain the experimental data of the algorithm or framework and carry out quantitative and qualitative analysis of the model performance in detail.	5
	This article proposes a learning model or recommendation framework and algorithm, uses multiple charts or pseudo-code methods to describe the model diagram or explain the principle of these models or framework algorithms in the form of cases, and uses the method of simulation experiments to obtain the experimental data of the algorithm or framework, and carries out a more detailed quantitative or qualitative analysis of the experimental results.	4
	The article explains the learning model or the design of the recommendation framework and algorithm and provides a certain number of charts or reference documents. At the same time, the method of simulation experiment is also used to obtain the experimental data of the algorithm or framework, and the experimental results are only simple quantitative or qualitative analysis.	3
	This article proposes a learning model or recommendation framework and algorithm and also provides a relatively simple diagram or case form to explain the principle of these models or framework algorithms. However, the description of the framework or algorithm is not specific or coherent enough, and it is difficult to understand.	2
	This article proposes a learning model or recommendation framework and algorithm. However, the implementation details of the model or the description of the algorithm are very brief, or the content described is inconsistent or ambiguous.	1
	The article does not explain the learning model or recommendation framework and algorithm.	0
QA3	The recommendation methods or learning models in this article are verified by simulation programs on at least one real data set. It is obtained from the public or a specific e-learning platform. In the validation experiment, the data set is divided into two parts: a training data set and a test data set to verify the model. In the analysis of the experimental results, the differences in the recommendation performance parameters of the model in this article on different data sets are compared, analyzed, and explained.	5
	The recommendation methods or learning models in this article are verified by simulation programs on at least one real data set obtained from the public or a specific e-learning platform. In the validation experiment, the data set is divided into two parts: a training data set and a test data set to verify the model.	4
	The recommendation methods or learning models in this article are verified by simulation programs on at least one real data set obtained from the public or a specific e-learning platform.	3
	The article explains using a test data set to validate the recommendation methods or learning models in this article, but the simulated data set is used.	2
	The article explains how to use the test data set to verify the recommendation methods or learning models but does not explicitly explain its source.	1
	There is no mention of any test dataset.	0
QA4	A dataset and a simulation program are used to validate the proposed recommendation methods or learning models. In analyzing experimental results, the recommendation methods or learning models in this article are compared with similar methods for one or more indicators. The advantages or improvements of this article's recommendation methods or learning models are compared with other methods. In addition, the advantages or improvements of the proposed method or framework over the existing methods or frameworks in design or algorithm are explained in the article.	5
	The recommendation methods or learning models proposed in the article use a dataset and a simulation program to validate the proposed methods and models. In analyzing experimental results, the methods and models in this article are compared with similar methods for one or more indicators.	4
	The advantages and disadvantages of the recommendation methods or learning models proposed in this article are analyzed and summarized. Data sets and simulation programs are proposed to verify the proposed methods and models. The experimental results are also analyzed and summarized.	3
	The advantages and disadvantages of the recommendation methods or learning models proposed in this article are analyzed and summarized, and the data sets and simulation programs are proposed to verify the proposed methods and models. However, the experimental results are not analyzed and summarized.	2

TABLE 5. ***(Continued.)*** **Quality assessment quantitative evaluation matrix.**

	In this article, only the design method and idea of the recommendation methods or learning models are expounded, and their advantages and disadvantages are not clearly explained and expounded.	1
	The methods or learning models recommended in this article do not have any analysis or explanation.	0
QA5	The value of the research results or future research directions are explained in detail. The value statement of the research results is accurate and considerable. The explanation of the future research direction is very valuable and has a good research prospect, which has a high reference value for other researchers' follow-up research.	5
	The value of the research results or future research directions are explained in detail. The value statement of the research results is considerable. The explanation of future research direction has value, good research prospects, and high reference value for other researchers 'follow-up research.	4
	The value of the research results or future research directions is expounded at a certain length. The value of the research results can be expounded from multiple perspectives, such as performance optimization and practical application scenarios in the industry. The content of the future research direction has a specific reference value for the follow-up research of other researchers.	3
QA5	The article briefly expounds on the value of the research results or the future research direction. The value of the research results can be explained from the perspective of performance optimization and practical application scenarios in the industry. The statement of the future research direction needs to be clarified, and the research prospects of this research direction still need to be clarified in the research community.	2
	The article provides a very brief explanation of the value of the research results or future research directions.	1
	The value of the research results and future research directions are not analyzed or explained.	0

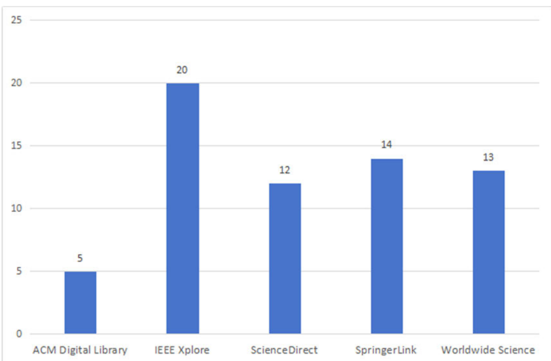

FIGURE 3. **Studies found in scientific databases.**

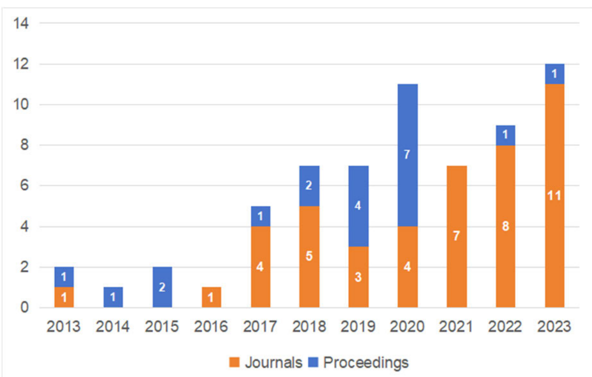

FIGURE 4. **Studies published in journals and proceedings between 2013-2023.**

which in turn triggered the increase in the research intensity of the research on PLRS.

Fig. 5 illustrates that 59 out of 64 studies explicitly mentioned using datasets in the experiments, and the remaining

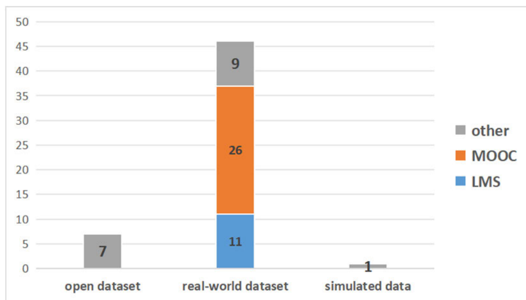

FIGURE 5. **Datasets statistics in studies.**

five studies do not specify the datasets used. Among the 59 studies with datasets, only one used simulated data, seven used open datasets, and MovieLens [8] is the most used open dataset. Another 46 studies used real-world datasets, and most of the data in these datasets were obtained from MOOC or LMS through data export or web crawlers, and some were obtained from student or course data collection.

Fig. 6 shows the statistics of the datasets collected and the e-learning systems on which the experiments were conducted in all the studies. In these studies, the top three e-learning systems chosen by the researchers were XuetangX, Moodle, and Coursera. Except for the studies that did not specify the names of the systems, the researchers rarely chose the remaining systems.

III. RESEARCH RESULTS AND LITERATURE REVIEW

This section discusses about the research questions RQ1 through RQ4, elaborating on the technique used to address the questions.

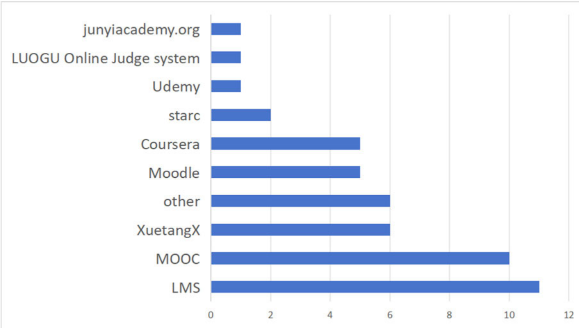

FIGURE 6. Collection systems statistics of datasets.

A. LITERATURE REVIEW OF RECOMMENDATION TECHNOLOGY BASED ON LEARNER AND LEARNING CONTENT MODELING

Given the data diversity of learning resources, learning resource recommendation algorithms vary significantly in structure depending on their recommendation goals. However, the algorithms can be generally divided into two categories: learner modeling and learning resource modeling.

Fig. 7 shows a mind map of modeling approaches for learning recommendation systems, including a learner-based modeling approach and a learning object-based modeling approach.

1) LEARNER MODELING

Learner Modeling refers to the establishment and description of models of learner characteristics, learning history, learning process, and learning outcomes. Learner-based modeling can be divided into knowledge-based modeling approaches and personality trait-based approaches.

Knowledge-based learner modeling refers to forming semantically embedded networks or graph structures by identifying learner feature entities and their relationships based on the domain knowledge background. Subsequently, the learner model is formed by instantiating the graph structure. Knowledge-based learner modeling is mainly based on the ontology technique. An ontology represents domain knowledge based on the concepts, attributes, and conditions involved in the domain and the relationships between them. It supports the formal representation of abstract concepts and attributes and allows for reuse, extension, and updating knowledge when needed. In addition, an ontology is a structured representation that describes concepts and relationships between concepts in terms of rules. In addition, the ontology model is the basis of a learner model, and it typically emphasizes experts' involvement in the domain. Consequently, the ontology model may be affected by subjective bias. As the main body of learning resources recommendation, learner modeling is the most critical part of the PLRS, and only by accurately modeling the learners' preferences can efficient recommendations be achieved.

Approaches to the modeling of learner ontology have been used in many studies [9]. Cheng et al. [10] proposed an ontology-based learning path recommendation solution, which included an ontology-based learning path generation method and a mechanism for updating the learner's ontology. Pereira et al. [11] employed an infrastructure that extracts users' profiles and educational backgrounds from the Facebook social network and recommends educational resources. Grivokostopoulou [12] described the construction of a general ontology based on ontology technology [10], [11]. The ontology contains personal, cognitive, and social information about learners as well as information about learners' performance and skills. Similarly, Jeevamol and Renumol [13] used a hybrid recommendation method based on CF and ontology to solve the cold start problem based on the ontology model used in [11] and [12]. Likewise, Shanshan et al. [14] also proposed a hybrid ontology-based e-learning resource recommendation method combining collaborative filtering (CF) algorithm [13] and adding sequential pattern mining (SPM) technology. Furthermore, Amane et al. [15] proposed an improved ontology-based e-learning resource recommendation method. In addition to the learner ontology modeling method [10], [11], [12], [13], [14], the material resource ontology used by learners in the learning process is combined. The Material Resource Ontology (MRO) and the Learner-Course Relationship Ontology (LCRO) combine learners and courses for recommendation.

In addition, some researchers have modeled ontology in conjunction with learners' learning styles. Petkovič et al. [16] proposed using learning styles to create recommended ontology models. On this basis, Aissaoui and Oughdir et al. [17] used the Felder-Silverman Learning Style Model (FSLSM) to model learner profiles and learning content. Then, learning styles were used as generic data type attributes to match them and generate personalized recommendations.

The recommendation of personalized learning content needs to suggest different content for specific learners' characteristics. Typically, the first stage is to mine the learning style and motivation of the target learners based on their prior knowledge or historical learning data [18]. Learner characteristics parameters are essential for providing basic information about personalized learning content, which describes various characteristics and requirements of learners, e.g., learners' knowledge background, learning goals, and learning styles. Many researchers have studied learners' personalization parameters and have proposed different parameters to describe learners' characteristics. The characteristics of learners can be summarized into five categories: reasons for learning, learning content, learning methods, learning styles, and time constraints of learners.

Three main types of modeling techniques for learners are based on personality traits. First, it is based on the learning ability; second, the knowledge background of the learner; and third, it is based on analyzing the learner's learning style. Learning ability and knowledge background are used to identify candidate learning resources suitable for the target

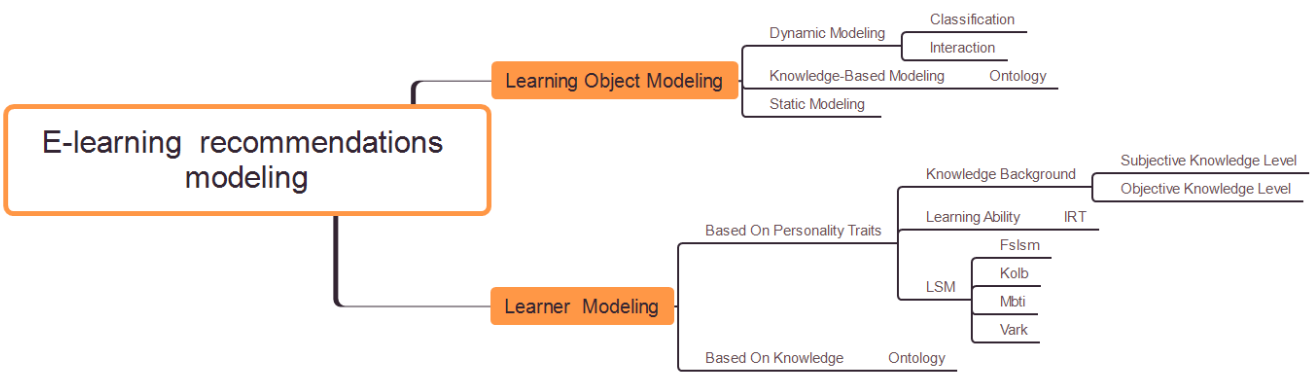

FIGURE 7. Learning recommendations modeling.

learners. Learning style is the key parameter that has received the most attention from researchers [19].

Learning ability refers to the psychological characteristics that learners need to have to engage in learning activities, a combination of various abilities to complete learning activities. It is specifically expressed in the degree of mastery of the learning resource after learning, including perceptual observation ability, memory ability, reading ability, problem-solving ability, and how well learners understand the learning resources [20]. Item Response Theory (IRT) is a prevalent theoretical model in educational measurement. It is based on the relationship between learners' ability and the correctness of test responses.

Intayoad et al. [21] proposed a context-aware recommendation system for personalized e-learning that considered information indicating learning ability, such as learners' majors and test scores. The approach employs K Nearest Neighbors (KNN) and Decision Tree (DCT) algorithms to classify appropriate types of learners based on social context. Many researchers have used IRT to explore learners' learning ability in PLRS. Salahli et al. [22] proposed an Adaptive Personalized Course Learning System (APCL) recommendation scheme based on the student's knowledge level and understanding degree of the course topic. IRT and the Law of Total Probability (LTP) have been used to estimate the degree of understanding. Likewise, Baldiris et al. [23] also used the IRT model and combined it with object quality theory to recommend learning objects to learners.

Usually, the evaluation of learners' learning ability is often unavailable or inaccurate at the initial stage after the PLRS has been put into use. In addition, it needs to be constantly corrected and mined in the process of use through testing, data analysis, and mining. Many studies have proposed solutions to this problem. Dharani and Geetha [24] used Coloured Petri Nets combined with dynamic learner configuration information to learn recommended paths. Additionally, Liu et al. [25] proposed a cognitive structure-enhanced framework for adaptive learning (CSEAL), a new approach to learning the recommended paths. It employs Recurrent Neural Networks (RNN) to track the learner's changing knowledge level at each learning step to ensure that the learning paths are well-designed.

The learner's knowledge background, which refers to the learner's background information, what he or she has learned, and how well he or she has mastered the knowledge, is another standard parameter of the learner's individuality. This parameter is mainly divided into two different types: objective knowledge level and subjective knowledge level. Objective knowledge level refers to the learner's previous performance or learning level data. Meanwhile, subjective knowledge level is the learner's subjective evaluation of his or her learning ability and level [26].

In practical research, many researchers have used learners' knowledge background to generate initial learning paths or candidate learning resources. Xie et al. [26] employed learners' knowledge background as a learner's personalized characteristic for group learner recommendation. Similarly, Zhu et al. [27] used a questionnaire designed by an educational expert, and learners' knowledge background was also considered a dimension of the target learner's personalized characteristic. Similarly, Nabizadeh et al. [28] used learners' knowledge background [26], [27] and recommended learning content and paths based on learners' available time.

Individual differences among learners are considered by the learning style parameter in PLRS processes learning scenarios. Interface and navigation preferences, learning style models, cognitive characteristics, learning resources, and recommending strategies are used to define learners' learning styles and preferences [29].

The Learning Style Model (LSM) refers to a learner's learning knowledge and skills pattern. Statistically, researchers in education and psychology prefer to consider learners' learning styles as a parameter of learners' personalized characteristics. By defining parameters such as single learning time and frequency, researchers can predefine several learning styles and find the LSM that meets the target learners. Learning style is a concept proposed by Herbert Thelen in 1954. Since then, many related theories and models have emerged, among which the following four are common. There are four types of LSM in studies:

1) FSLSM. This model analyses learners from four Dimensions: Sensing/Intuitive Learning, Visual/Verbal Learning, Active/Reflective Learning, and Sequential/Global Learning.
2) The Visual, Aural, Read/write, and Kinesthetic (VARK) model. This model classifies individuals into four types: visual, aural, read/write, and kinesthetic.
3) Kolb model. This model is based on experiential learning theory and classifies learning styles into four types: diverging, assimilating, converging, and accommodating through the two dimensions of Active Experimentation, Reflective Observation, Concrete Experience, and Abstract Conceptualization.
4) Myers-Briggs Type Indicator (MBTI) model. This model is based on the eight types of personality classified by Swiss psychologist Carl Jung and expanded to form four dimensions, i.e., direction of attention, cognitive style, judgemental style, and lifestyle.

FSLSM is the most commonly used model to describe learners. Several researchers have used the model [30], [31], [32] to construct a learner's learning style model and combined it with several recommendation algorithms for personalized learning content recommendation. These algorithms include CF, Ant Colony Systems, Artificial Neural Networks, and Semantic Web Rule Language (SWRL). Riad et al. [18] also proposed a new adaptation technique with improved Felder-Silverman model and motivation scores. They improved the accuracy of adaptive learning by selecting the most appropriate learning objects for learners.

The other three types of models are rarely used in research. Hasibuan et al. [29] used the VARK model to model learners' learning styles. Similarly, Pardamean et al. [33] utilized collaborative filtering and matrix factorization (MF) techniques with a variant of the VARK model to predict learning styles. Likewise, Xu et al. [34] proposed a recommendation algorithm based on Deep Reinforcement Learning for Programming Problems (DRLP). They used the Kolb model to construct learning styles and embedded them into DRLP through the action space to make the recommendation more personalized. In addition, Halawa et al. [35] employed MBTI and Kolb models to construct learners' learning styles to recommend learning courses.

Table 6 summarizes the studies found in this section based on learner modeling.

2) LEARNING OBJECTS MODELING

Recommending learning resources for learners based on the characteristics between learning resource ontology and the interrelationships of resources is a commonly used recommendation method. This approach can effectively solve the CF algorithm's cold-start and learner information sparsity problems when facing new learners without historical information and many learning resources compared to the number of learners.

Learning objects include learning resources and learning paths. Learning resources are the information and data used in learning activities, including practice questions, courseware, videos, references, and test questions. Learning paths are the steps and sequences of learning composed of learning resources according to a particular logical relationship. Learning resources can be divided into two types according to the different sources: the learning resources provided on the e-learning system and the other is the learning resources outside the e-learning system, which are provided through the link on the system [36]. Learning objects modeling is the process of designing learning objects in e-learning systems. There are three general modeling approaches for learning objects: static modeling of learning objects, dynamic modeling of learning objects, and knowledge-based modeling of learning objects.

The static modeling method for learning objects involves extracting the feature information of recommended objects to form a model. Currently, many studies use Convolutional Neural Networks (CNN) to input text learning material information, and then after the neural network training results for recommendation. Zhang et al. [37] proposed a deep belief network (DBN) based high-precision resource recommendation model in the MOOC environment (MOOCRC), the method of deep mining learner characteristics and course content attribute features to complete the task of learning content recommendation.

The static modeling method of learning objects uses the explicit features of the learning objects to model it. The method can achieve the modeling task intuitively and efficiently under the premise of rich feature descriptions, and the distinctive features of the features used are also conducive to improving the interpretability of the recommendations. However, the objects of the learning recommendation system also have fewer text descriptions, such as video, audio, and other multimedia learning resources. Therefore, CB learning recommendation objects modeling also needs to be combined with related technologies in multimedia content analysis, or these non-text resources need to be manually processed by manual tagging or adding text descriptions. Shu et al. [38] proposed a CB recommendation algorithm using CNN. CNN can transform the input textual information into features of learning resources and generate low-dimensional hidden vector representations. The recommendation algorithm can directly use the text information for CB recommendations without labeling. This algorithm solves the problem that some learning resources need labels or have more descriptive information in the resource documents.

The dynamic modeling method of learning objects adopts two dynamic implementation methods: classification and interaction.

Classification is the most commonly used method; that is, the recommended objects are put into different categories and recommended according to the idea that the same kind

TABLE 6. Summary of the studies based on learner modeling.

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR1	2018	Ontology-based learning path generation and learner ontology update mechanism	Ontology,Spreading Activation algorithm (SAA)	The proposed method provides learners with a satisfying and personalized learning path continuously.	Building and maintaining ontologies requires significant resources.	MOOC	China	No description
LR2	2018	Broad-rsi(recommendation system based on social interactions)	Ontology	A method is proposed to extract information from social networks to discover learners' implicit interests and realize personalized recommendations.	It relies on the availability and quality of information from social networks.	University courses	Brazil	Open dataset DBpedia
LR3	2019	Aits(after the artificial intelligence tutoring system)	Ontology,FSLSM,SWRL	The proposed general ontology approach combines the formulation and integration of semantic rules.	It requires complex designing and formulating ontology learner models.	University courses	Greece	Unspecified DataSet
LR4	2021	Learner and learning object similarity and computation generating top-n recommendation list	CF,CB,Ontology	Ontology-based content recommendation solves the cold start problem for new users and can improve the accuracy of recommendations.	It relies on the availability and quality of learning objects and learner feedback.	University courses	India	Real-world dataset from MOOC, which contains 300 students' data
LR5	2021	Data analysis algorithm based on CF, ontology, and SPM	CF,Ontology, SPM	The proposed method alleviates the cold start and data sparsity problems.	Processing ontology and SPM requires more computing resources and cannot adapt to diverse learning resources.	University courses	China	Real-world MOOC dataset, which contains course data
LR6	2022	Ersdo(e-learning recommendation system with dynamic ontology)	Ontology	The proposed method can effectively alleviate the cold start problem and sparsity and improve the quality of e-learning platform recommendations to learners.	Building and maintaining ontologies requires significant resources.	University courses	Morocco	Dataset on Coursera and USMBA university Moodle system
LR7	2017	Ontology-based semantic recommendation with SAA and CF	Index of Learning Style (ILS),ontology,CF,SAA	The proposed method combines the semantic knowledge of the ontology with collaborative user preference information. It not only outperforms the traditional CF regarding prediction accuracy but also improves coverage.	It fails to consider the dynamics and situational factors of the learning process.	MOOC	Serbia	No description
LR8	2020	Combination of ontology-based and Machine Learning-based methods	FSLSM,Machine learning (ML), classification algorithm	The proposed method builds learner and learning object ontologies retrieves the most relevant learning resources, and recommends them to learners.	ML models consume a lot of computational resources.	MOOC	Morocco	No description
LR9	2023	Adaptive learning model based on learning style and motivation scoring	CF,KNN	The proposed new adaptation technique based on learners' learning style and motivation scores selects the most appropriate learning objects for learners to improve the accuracy of adaptation.	Training deep learning models requires large amounts of data.	University courses	Morocco	Open dataset MovieLens100K
LR10	2017	Context-aware recommendation system for personalized e-learning based on KNN and Association rule mining (ARM)	KNN,DCT,ARM	Using KNN and DCT effectively classify learners according to their social background, thereby improving the accuracy of recommendations.	The adaptability of existing methods to different types of learners needs to be improved.	MOOC	Thailand	Unspecified DataSet
LR11	2013	Adaptive and personalized learning based on IRT, The Law of Total Probability (LTP), and concept ontology	IRT,LTP,ontology	The proposed adaptive method improves learning outcomes based on the level of understanding of new concepts in course topics.	Failure to consider the dynamics and situational factors of the learning process.	University courses	Turkey	Dataset on the Moodle system of Canakkale Onsekiz Mart University

TABLE 6. ***(Continued.)*** **Summary of the studies based on learner modeling.**

LR12	2014	Learning object recommendations model based on IRT and logistic functions defined learning object quality	IRT	The proposed IRT-based method recommends high-quality learning content to learners.	Other factors influencing recommendations, such as context, learning goals, and personalization, are not considered.	University courses	Spain	Dataset from the National University of Colombia's MOOC
LR13	2013	Colored Petri Nets-based adaptive e-learning model	Colored Petri Nets (CPN),Case Based Reasoning(CBR)	Generating Adaptive Learning Paths by Dynamically Tracking Learner Behaviors in E-Learning Systems Using Colored Petri Nets.	Ignores the impact of dynamic changes in learner profiles and learning objects on the recommendation effect.	MOOC	India	Unspecified DataSet
LR14	2019	Cseal(cognitive structure enhanced framework for adaptive learning)	Markov decision Process (MDP),Long Short-Term Memory(LSTM),RNN, actor-critic algorithm	The proposed CSEAL method recommends personalized content for learners by treating path recommendation as MDP and applying an actor-critic algorithm.	A clearly defined map of study program prerequisites is required.	MOOC	China	The dataset comes from junyiacademy. org, which contains 39 million learners.
LR15	2017	Profile-based framework for discovering learning paths for a group of learners	Group profile aggregation, learning path discovery	The proposed framework considers factors such as knowledge and preference diversity among group members. It provides learning path recommendations for learner groups.	Data sparsity and cold start problem	University courses	China	A real-world dataset that contains learning data for students
LR16	2018	Multi-constraint learning path recommendation algorithm based on the knowledge map	Edit distance algorithm,Depth First Search (DFS)	Generate recommended learning paths based on knowledge graph and learners' domain knowledge structure and cognitive structure.	The learning scenarios in the study cannot cover all possible situations for learners.	University courses	China	Dataset of basic information about 110 learners from Xi'an Jiaotong University's LMS
LR17	2020	Adaptive learning path recommendation based on DFS and MF algorithm	DFS,MF	The proposed adaptive method adjusts the path according to the learning progress.	Cold start problem	MOOC	USA	Open dataset Mooshak, Enki
LR18	2023	Vark learning style e-learning recommendations based on three clustering algorithms	Vark,K-Means	The proposed mothed recommends personalized learning content based on VARK learning style model.	It requires learners to set the learning path parameters.	University courses	Indonesia	A real-world dataset which contains 276 data records for 138 students

of learning resources are recommended to the same kind of learners. Classification can be performed using classical ML classification methods, such as Naive-Bayes, KNN, and Support Vector Machine (SVM). For example, Li et al. [39] proposed a Bayesian personalized ranking (BPR) based algorithm. Classification operations can also be implemented using deep-learning-based methods.

Interaction is a method modeled using the interaction data between the learner and the recommended objects. Fu et al. [40] proposed a new deep learning method of a feed-forward neural network to learn the low-dimensional vectors of learners and objects, respectively. The method captures the semantic information reflecting the learner-learner and object-object correlations for an intelligent recommendation. The dynamic approach uses the relationship between "resource-resource" and the dynamic relationship between "resource-learner" to form the recommended object's characteristics, making the object model dynamic. It can be adjusted according to the state of the recommended object in the system with the learning process. The dynamic approach is conducive to better matching with the changing learner characteristics.

The Knowledge-based modeling methods of learning objects are also usually implemented by ontology technology. The construction of learning resource ontology is the same as the construction of learner's ontology, which is primarily semi-automated or manual and inseparable from manual participation, and it is challenging to avoid subjective bias.

Bouihi and Bahaj [41] developed a semantic web-based architecture for recommendation systems. The proposed architecture has an additional semantic layer, which contains two semantic subsystems based on ontology and two semantic subsystems based on SWRL rules. Similarly, Sarwar et al. [42] proposed a learner classification model that combines case-based reasoning and neural networks and annotates the learning content using course Ontology. A dynamic rule-based recommendation algorithm for personalized content recommendation was proposed. Likewise, Agbonifo and Akinsete [43] used an ontology-based personalized recommendation system. Learning content is constructed using an ontology [42], and CF is used to collect the preferences of many learners. Then, appropriate learning content is recommended to the learners. Furthermore, Ibrahim et al. [44] employed a new Fog-Based Recommendation System (FBRS). FBRS also uses ontology technology to construct course information [42], retrieve items (courses) based on learner preferences and needs, and make recommendations based on relevance to the learner.

In addition to separating the ontology modeling of learners and learning recommendations, many researchers have used these two types of ontology modeling methods jointly to achieve better recommendation results. For example, Tarus et al. [45] developed a hybrid knowledge recommendation system based on ontology and SPM for recommending e-learning resources to learners. Ontologies model and represent domain knowledge about learners and learning resources, while SPM algorithms discover learners' sequential learning patterns. On this basis [45], Ibrahim et al. [46] proposed a framework for a hybrid ontology-based filtering system called Ontology-based personalized Course Recommendation (OPCR). The approach also uses SPM, integrates information from multiple sources based on hierarchical ontology, combines CF with CB recommendation algorithms, and uses dynamic ontology mapping to link course profiles with student profiles. Similarly, Joy et al. [47] introduced an ontology model encapsulating learner profiles and learning object attributes, which can be used for content recommendation in e-learning systems. Additionally, Wu et al. [48] employed a semantic recommendation framework for educational resources based on the semantic web and pedagogy, using the type of learning content and the learner's learning history as the rules for recommending the learning content. Furthermore, Amane et al. [15] utilized an e-learning Recommendation System based on Dynamic Ontology (ERSDO). This recommendation system uses the CF and CB recommendation algorithms similar to OPCR [46] and integrates them using a clustering method. Lastly, Petkovič et al. [16] also adopted ontology-based semantic recommendation [48] with a propagation activation algorithm and collaborative filtering recommendation model.

The knowledge-based approach is essential to supplement the learning of the description of the recommended object with the help of expert participation and the use of domain knowledge. This approach can enrich the recommended objects' features, and the object model is more suitable for the corresponding recommendation algorithm. Due to the addition of domain knowledge, the learning recommendation object can match a variety of recommendation application scenarios according to the need, and the corresponding recommendation algorithms have a higher degree of interpretability.

Table 7 summarizes the studies based on learning modeling in this section.

B. TYPES OF E-LEARNING RECOMMENDATION ALGORITHMS AND TECHNIQUES

Learning recommendation methods use learner and recommendation object modeling functions. These functions will vary with the differences in application requirements, according to the learner and recommended object model for calculation, matching, screening, sorting, and other algorithms used in the recommendation model. There are four main types of algorithms in e-learning recommendation algorithms: CB learning recommendation algorithm, CFB learning recommendation algorithm, hybrid learning recommendation algorithm, and session-based learning recommendation algorithm. Fig. 8 shows the four types of learning recommendation algorithms.

Many personalized learning recommendation methods refer to product recommendation methods in e-commerce. These methods regard learners as users of e-commerce systems, regarding learning resources as commodities, and use learners' scores on learning resources as training labels for recommendation models. Commonly used methods include CB Recommendation, CF Recommendation, and Hybrid Recommendation. In addition, knowledge-based learning recommendation methods and session-based learning recommendation methods are also hot research topics. The research hotspot in this field is the recommendation system implemented by combining deep learning and other recommendation methods.

1) CB LEARNING RECOMMENDATIONS

The CB learning recommendation method is to find the learning resource that best matches the learner's preference by comparing the attribute features of the learning resource with the learner's preference. The main advantage of the current CB learning recommendation method is that it does not need to consider the data sparsity problem, and the recommended content depends on the learners' preferences. In addition, CB learning recommendations also have disadvantages, e.g., the requirement for a good structure of the feature content, only considering the learner's preferences, ignoring the situation of other learners, and cold start problems. CB learning recommendation methods can be classified into three approaches: similarity calculation, classification, and association rules.

There are significant differences in the application of content-based recommendation algorithms in e-learning and

TABLE 7. Summary of the studies based on learning modeling.

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR6	2022	Ersdo (e-learning recommendation system with dynamic ontology)	Ontology	The proposed method can effectively alleviate the cold start problem and sparsity and improve the quality of e-learning platform recommendations to learners.	Building and maintaining ontologies requires significant resources.	University courses	Morocco	Dataset on Coursera and USMBA university Moodle system
LR7	2017	Ontology-based semantic recommendation with SAA and CF	ILS,ontology,CF,SAA	The proposed method combines the semantic knowledge of the ontology with collaborative user preference information. It not only outperforms the traditional CF regarding prediction accuracy but also improves coverage.	It fails to consider the dynamics and situational factors of the learning process.	MOOC	Serbia	No description
LR25	2019	MOOCrc (a highly accurate MOOC resource recommendation model based on Deep Belief Network)	DBN	The proposed MOOCRC method has higher recommendation accuracy and faster convergence speed than traditional recommendation methods.	It requires large amounts of data and computing resources to train the DL model structure.	University courses	China	Dataset from STARc platform of Central China Normal University
LR26	2018	Cbcnn (content-based learning resources recommendation by CNN)	CNN, CB	The proposed CNN-based content-based recommendation algorithm can directly use text information for content-based recommendations without labeling.	It relies on the availability and quality of text information in learning resources.	MOOC	China	Open dataset Book-crossing
LR27	2020	BPRN (BPR Network)	CF,BPR,neural network	A novel BPRN neural network is proposed that can learn course preferences.	It does not consider the content features of users and items.	MOOC	China	XuetangX dataset
LR28	2018	Deep learning-based CF model for recommendation systems	CF,Feed-forward Neural Networks(FNN)	The proposed method significantly outperforms previous methods using feedforward neural networks.	It does not consider the content features of users and items.	MOOC	China	Open dataset Movielen
LR29	2019	Ontology and SWRL Rule-Based Recommendation System	ontology, SWRL	A recommender system architecture based on ontology SWRL semantic web is proposed.	Significant effort and expertise may be required to build and maintain ontology and SWRL rules for the e-learning domain.	MOOC	Morocco	No description
LR30	2019	Ontology-based and Context-Aware Personalized Learning Model	ontology, CBR,neural network	The proposed framework improves comprehensive attribute selection in learner profiling, dynamic techniques for learner classification, and effective content recommendation while ensuring personalization and adaptability.	Building and maintaining ontology requires significant resources.	University courses	Pakistan	1000 student profile data from real-world
LR31	2020	Ontology-based and CF personalized e-learning recommendation system	ontology,CF	A personalized recommendation system design based on ontology and pre-testing is proposed.	cold start and sparsity problem	MOOC	Nigeria	Real-world learning and learners' dataset

TABLE 7. ***(Continued.)*** **Summary of the studies based on learning modeling.**

LR32	2020	FBRS (Fog-Based Recommendation System)	ontology,Classification algorithm	The FBRS approach is proposed to achieve high response time and security and outperform recent technical solutions in terms of recommendation accuracy.	Building and maintaining ontology requires significant resources.	University courses	Egypt	Open dataset Web KB
LR33	2017	A hybrid e-learning RS with ontology and SPM	Ontology,SPM	The proposed method has improved performance over similar methods and alleviates the cold start and data sparsity problems.	Building and maintaining ontology requires significant resources.	university courses	Kenya	50 students learn data from LMS
LR34	2018	OPCR (ontology-based personalized course recommendation)	ontology,CB,CF,SPM	The proposed method using dynamic ontology mapping is highly flexible and can be adapted to personalized recommendation tasks in different fields.	Building and maintaining ontology requires significant resources.	university courses	UK	Course dataset from the University of Chinese Academy of Sciences' LMS
LR35	2019	Knowledge-based content recommendation in the personalized learning environment	ontology,FSLSM	The proposed FSLSM-based ontology model considers the characteristics of static and dynamic learners and can be used for adaptive content recommendation tasks.	Building and maintaining ontology requires significant resources.	MOOC	India	Unspecified dataset
LR36	2020	A Semantic Web-Based Recommendation Framework with domain ontology	Ontology	A recommendation framework based on semantic web and pedagogy-based reasoning rules is proposed, achieving good experimental results in compatibility and performance.	Building and maintaining ontology requires significant resources.	University courses	China	No description

other fields, especially e-commerce systems, and these differences are mainly reflected in the following aspects.

(1) The differences in the design goals of recommendation systems.

In e-learning systems, users' learning goals and motivation are essential considerations for the design of recommendation systems. In e-commerce systems, the recommendation algorithms need to select and optimize the recommendation strategy according to the user's learning objectives, interest and conversion rate, increase user stackability, increase customer unit price, and other factors.

(2) The differences of recommended objects.

E-learning systems mainly recommend learning resources, such as courses, learning materials, learning communities, etc. These resources are usually closely related to subject knowledge, learning progress, and learner interest. The recommended object of e-commerce systems is products, including physical products and services. These items are closely related to a user's purchase history, browsing history, search behavior, etc.

(3) The differences in feature modeling methods.

The recommendation algorithms of the e-learning systems need to establish feature models for recommended content and users, respectively. Content modeling usually involves extracting characteristics, labels, and other features of learning resources, such as subject, grade, difficulty, etc. User modeling establishes the user's preference feature model by analyzing the user's learning history, interest preference, and knowledge mastery degree. Regarding feature modeling, the recommendation algorithms of e-commerce systems mainly focus on the attributes, categories, labels, and other characteristics of products. User modeling constructs the user's interest preference model by analyzing the user's purchase record, browsing history, search behavior, and other data.

Recommendation method based on similarity calculation. Different researchers have proposed different similarity calculation schemes. There are schemes to calculate the similarity between students and courses. Ibrahim et al. [46] proposed an Ontology-based personalized Course Recommendation approach. The approach integrates information from multiple sources based on hierarchical ontological similarity. It combines collaboration-based filtering with CB filtering and determines the similarity between students and courses by considering relevant concepts familiar to their profiles. Dynamic ontology links course profiles and student profiles. Other schemes use similarity calculations between courses and syllabuses. Ramadhan and Musdholifah [49] constructed a recommendation system that looked for similarities between courses and syllabi, used the cosine similarity method for video annotation, and

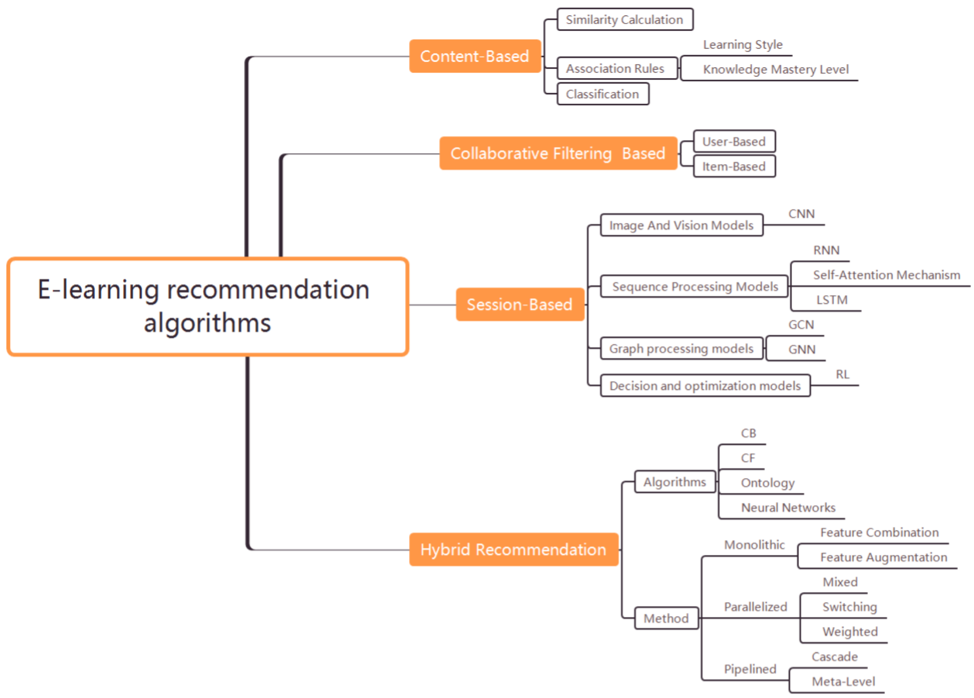

FIGURE 8. **E-learning recommendation algorithms.**

recommended videos based on the association of courses and syllabi. There are also schemes that use similarity calculation between learners and learning objects. Jeevamol and Renumol [13] used domain knowledge to compute the similarity between learners and learning objects and predict learners' preferences.

Recommendation method based on classification. Shu et al. [38] proposed a recommendation algorithm based on the CNN classification, which can transform the input textual information into the features of learning resources. Similarly, Joy et al. [50] used the K-Means clustering algorithm to recommend the course materials in the e-learning system to the learners.

Recommendation method based on association rules. There are two association rules: learners' learning style models and knowledge mastery level. Some researchers use learning resource features to associate with learners' learning style models. Raj and V G [51] proposed custom recommendation rules to associate the features of learning resources with learners' learning style models, calculated the relevance of learning resources to learners and then ranked the recommendations. Other studies adapted the method of learning resources to correlate with learners' knowledge mastery level. Zhou [52] proposed a method based on the convolutional model of the joint probability matrix decomposition method (CUPMF) for recommending and combining teaching resources. This method combines the students' question-answering history, cognitive ability, knowledge mastery, and forgetting influencing factors.

Due to the cold start problem in CB recommendations, many researchers have also solved the problem in CB learning recommendation methods. Bhatt et al. [53] described a video recommendation system that combines topic-based video representation with sequential pattern mining of inter-topic relationships and combines the resulting sequential information with content-level similarity to provide relevant and diverse recommendations. Furthermore, Joy et al. [50] used a recommendation system that used learner parameters and clustering algorithms to solve the pure cold-start problem, and experiments confirmed that this method generates better recommendations under pure cold-start conditions. Other researchers [13], [14], [15] introduced ontology-based e-learning content recommendations for solving the cold-start problem for new learners and used ontology domain knowledge to provide more reliable and personalized learning content.

Table 8. shows the summary of the studies found based on CB learning recommendations in this section.

2) CFB LEARNING RECOMMENDATION

Collaborative filtering is a classic algorithm in recommendation systems; its implementation process is based on the "user-user" similarity matrix or "item-item" similarity matrix comparison to find the most similar user or item. Therefore, it can be further divided into User-Based CF and Item-Based CF. In the learning recommendation scenario, the CF method mainly uses the learners' ratings of learning resources to construct the "learner-learner" similarity matrix or "learning resource-learning resource" similarity

TABLE 8. Summary of the studies based on CB learning recommendations.

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR4	2021	Learner and learning object similarity and computation generating top-n recommendation list	CF,CB,ontology	Ontology-based content recommendation solves the cold start problem for new users and can improve the accuracy of recommendations.	It relies on the availability and quality of learning objects and learner feedback.	University courses	India	Real-world dataset from MOOC, which contains 300 students' data
LR5	2021	Data analysis algorithm based on CF, ontology, and SPM	CF,ontology,SPM	The proposed method alleviates the cold start and data sparsity problems.	Processing ontology and SPM requires more computing resources and cannot adapt to diverse learning resources.	University courses	China	Real-world MOOC dataset, which contains course data
LR6	2022	Ersdo (e-learning recommendation system with dynamic ontology)	Ontology	The proposed method can effectively alleviate the cold start problem and sparsity and improve the quality of e-learning platform recommendations to learners.	Building and maintaining ontologies requires significant resources.	University courses	Morocco	Dataset on Coursera and USMBA university Moodle system
LR26	2018	Cbcnn (content-based learning resources recommendation by CNN)	CNN,CB	The proposed CNN-based content-based recommendation algorithm can directly use text information for content-based recommendations without labeling.	It relies on the availability and quality of text information in learning resources.	MOOC	China	Open dataset Book-crossing
LR34	2018	OPCR (ontology-based personalized course recommendation)	ontology,CB, CF,SPM	The proposed method using dynamic ontology mapping is highly flexible and can be adapted to personalized recommendation tasks in different fields.	Building and maintaining ontology requires significant resources.	University courses	UK	Course dataset from the University of Chinese Academy of Sciences' LMS
LR37	2021	Content-Based Filtering Video RS Based on Course and Outline	CB,term frequency–inverse document frequency (TF-IDF)	The proposed recommendation method uses the cosine similarity method to find similarities between courses and syllabi through video annotations.	Cold start issues	MOOC	Indonesia	Computer Science curriculum in University Gadjah Mada's LMS
LR38	2021	Ontology-based e-learning Content RS	CB,K-Means,Ontology	The proposed ontology-based framework solves the pure cold-start problem by leveraging learner parameters and clustering algorithms.	Building and maintaining ontology requires significant resources.	University courses	India	Learners, learning objects, and learner ratings records from LMS of universities CUSAT and KTU
LR39	2019	rule-based content personalized learning recommendation	CB,FSLSM,rule-based mapping	A recommendation method is proposed to model learners using a probabilistic learning style model, and a defined set of rules is used to recommend the most relevant learning objects to learners.	Failure to consider changes in the learning process and learning environment	MOOC	India	Learning records of 48 learners from LMS
LR40	2022	CUPMF (convolution joint probability matrix factorization) Model	CB,CNN, time-sensitive deterministic input and noise gate	The proposed CUPMF method recommends learning resources by combining learners' answer history, cognitive ability, knowledge mastery, and forgetting factors.	It requires large amounts of data and computing resources to train models and optimize parameters.	University courses	China	Open dataset FrcSub,Math1, Math2 and real-world learning data
LR41	2018	content-based recommendation using Latent Dirichlet Allocation (LDA) and SPM	LDA,CB,SPM	The proposed SeqSense method recommends less redundant video materials than the baseline method.	Learner feedback or behavioral data are not considered in the recommendation approach.	MOOC	USA	A large corpus of 4,186 videos of MOOC

matrix. Then, this method finds similar learners based on the ratings of the learning resource items and finds similar learning resource items according to the ratings on the learning resource items.

The following aspects specifically reflect significant differences in applying collaborative filtering recommendation algorithms in e-learning and other fields, especially e-commerce systems.

(1) Differences in user behavior analysis.

User behavior of e-learning systems mainly focuses on learning activities, such as course selection, video viewing, assignment submission, test completion, forum participation, etc. Behavioral data is usually more fine-grained and involves specific study time, chapter progress, grades, etc. User behavior is relatively stable, and learning progress and points of interest change slowly. The primary purpose of the recommendation is to improve the learning effect, and the recommended content is mostly resources related to the user's learning goals. The user behaviors of e-commerce systems are diverse, including product browsing, clicking, adding to the shopping cart, purchasing, evaluating, collecting, etc. Behaviors are frequent and may occur at any time. User behavior is greatly affected by promotional activities, seasonal changes, and other factors and is highly uncertain. The primary purpose of the recommendation is to promote consumption, and the recommended products are designed to increase users' purchasing intention and transaction volume.

(2) Differences in similarity calculation.

The similarity calculation of e-learning systems is based on the learning content (such as courses and chapters) and the user's learning behavior (such as completion and test scores). It is necessary to consider the correlation between knowledge points and users' learning content order. Feature data involves user learning time, course selection, academic performance, and other data, and calculations focus more on knowledge correlation and learning effects. The similarity calculation of e-commerce systems is mainly based on the user's purchase history, browsing history, and product evaluation. It is necessary to consider the product's attributes (such as price, brand, category) and the user's consumption preferences. Feature data involves users' browsing habits, purchase frequency, product evaluation, and other data, and calculations focus more on the similarity of consumption behavior and the correlation of products.

User-based CF is a recommendation method based on learners' similarity. The method first calculates the similarity between learners. Then, it predicts the degree of interest of target learners in unrated learning resources based on the behaviors and ratings of similar learners. Target learners can be recommended courses and related learning content from learners with the same interests as their own, even if the learning topic is not within their interests. The similarity between learners can be calculated in many ways, including cosine similarity, Pearson's correlation coefficient, and others. However, User-based CF in e-commerce systems recommends products based on users' shopping behaviors and preferences to improve their shopping experience and satisfaction.

Campanella and Impedovo [54] used a clustering algorithm and an improved CF recommendation algorithm to recommend more suitable learning resources for learners. Meanwhile, to further improve the performance of learner-based CF recommendations, Zhao and Liu [55] proposed collecting learners' behavioral logs and analyzing them to form learners' interest model vectors. Then, based on the learners' interest model, the resource characteristics, and learning resources' ratings, the resources that meet the needs were recommended to the target learners. Similarly, Agbonifo and Akinsete [43] presented an ontology-based personalized recommendation system that uses collaborative filtering and ontology to recommend appropriate learning content to learners. On this basis [43], Shanshan et al. [14] introduced SPM in addition to Ontology and CF [43] and designed an improved recommendation of e-learning resources to achieve more accurate recommendations. Furthermore, Agarwal et al. [30] proposed a method of using multiple domain ontologies and combining them with SWRL for recommendation based on the ontology-based and CF recommendation methods [14], [43].

In addition to these approaches, in recent years, many researchers have combined ML and deep learning approaches with user-based CF approaches to improve the effectiveness of CF recommendation methods. One type of method is to calculate the similarity between learners and learning content. Fu et al. [40] proposed an intelligent course video recommendation method based on FNN and CF. Likewise, Pardamean et al. [33] adopted an approach based on the CF algorithm and matrix factorization that could be driven by learning style prediction to recommend personalized learning content based on the material of each student's learning style. Another method is to calculate the similarity between learners and courses. Zhang et al. [56] described a personalized recommendation scheme based on the course feature vectors to mine the learners' interest in the course using the DBN model and CF algorithm. Furthermore, Wu and Liu [57] utilized a personalized hybrid course recommendation algorithm combining K-means and the CF algorithm.

Item-based CF is a recommendation method based on item similarity. The method first calculates the similarity between items and then predicts the interest of the target learners in unrated items based on their ratings of similar items. Similarity between learning resources can also be calculated in various ways, and cosine similarity and Jaccard similarity are widely used methods. The item-based CF of e-commerce systems recommends products to more potential users based on their sales, reviews, and relevance to promote product exposure and sales.

Jeevamol and Renumol [13] and Petkovič et al. [16] both used CF recommendation methods based on ontology technology. Ibrahim et al. [46], on the other hand, proposed a framework for an ontology-based hybrid filtering system called OPCR. The approach aims to integrate information from multiple sources based on hierarchical ontology similarity. OPCR combines CF-based and CB-based algorithms. In addition, there are likewise several studies that combine ML approaches with Item-Based CF recommendation methods to implement recommendation models. Li et al. [39] employed an improved deep Item-Based CF approach using BPR, which learns pairwise course preferences based on the history of courses enrolled by each learner. Furthermore, Jena et al. [58] and Riad et al. [18] both used a combination of KNN and CF to recommend courses and learning resources. Jena et al. [58] adopted a recommendation system for e-learning course recommendation using KNN, Singular Value Decomposition (SVD), and Neural Network Based Collaborative Filtering (NCF) model. Likewise, Riad et al. [18] utilized a recommendation system based on using CF to understand learners' learning styles and motivation scores technique, combining constraints Pearson correlation coefficient, adjusted cosine measure, and KNN algorithm to achieve recommendation.

The advantage of CF over CB recommendation algorithms is that the attributes of similar learners or learning resources are considered without considering the content attributes of courses and learning resources. However, CF still has the following three problems.

The first problem is the sparsity of data because learners' evaluations of courses and learning resources on e-learning systems are usually very few. Therefore, more and more CF-based learning recommendation algorithms, especially learning video recommendation methods, collect learners' preferences through implicit feedback, such as video viewing length and video viewing time. However, these methods often ignore learners' video pause and drag behaviors, which also reflect learners' video preferences.

The second issue is the cold start problem. Any e-learning system has the problem of low usage data from learners at the initial stage of use, which makes it impossible to recommend courses and learning resources.

The third problem is scalability. CF is effective for small datasets, but when the number of datasets increases, the accuracy of the recommendation system decreases.

Table 9 shows the summary of the studies based on CF-based learning recommendations in this section.

3) HYBRID LEARNING RECOMMENDATION

Hybrid Learning Recommendation (HLR) is a method that combines multiple learning recommendation methods by combining the advantages of different algorithms and models to improve the recommendation accuracy. HLR alleviates the problems that may arise from a single recommendation method, such as data sparsity, cold start, etc. Hybrid learning recommendation algorithms use CB, CF, ontology, and neural network methods to achieve learning recommendation functions.

There are some significant differences in applying hybrid recommendation algorithms in e-learning and other fields, especially e-commerce systems. These differences are mainly reflected in the following aspects.

(1) The differences in objectives and evaluation indicators.

The e-learning systems aim to improve the user experience and increase participation in learning activities, the number of courses or modules completed, and user retention time. Evaluation indicators may focus on educational effectiveness-related indicators such as course completion rate, learning duration, interaction frequency, and user feedback satisfaction. The main goal of e-commerce systems is to increase the sales of products, increase the conversion rate of user purchases, increase the amount of user shopping carts, and promote user repurchases. Therefore, the evaluation metrics may include click-through rate, conversion rate, customer unit price, quantity of order, etc.

(2) The differences in user behavior patterns.

The user behavior pattern of e-learning systems may be more long-term and continuous, focusing on personal interest, career development, knowledge system construction, etc., and user interest is relatively stable. However, the learning progress and preference for difficulty will change with the learning process. The user behavior of e-commerce systems is relatively frequent and has a strong purpose, which is often centered on browsing, searching, comparison, purchasing, and other commercial behaviors. User interests may change rapidly with time and are greatly affected by promotional activities, seasons, and other factors.

(3) The differences in recommendation content and algorithm focus.

The recommended content of the e-learning systems includes courses, tutorials, articles, videos, and other learning materials. In addition to considering the user's interest, the algorithm also needs to consider the coherence and difficulty gradient of the learning sequence and may make more use of content-based recommendations and knowledge graphs to ensure the educational quality and logical consistency of the recommended content. The recommended content of e-commerce systems is mainly products, and the algorithm may pay more attention to real-time, popular trends and personal purchase history while dealing with the inventory of products, price fluctuations, and other factors. Hybrid recommendation systems may place more emphasis on item popularity and personalized preferences.

The most common approach to HLR is to use CB or CF as the basis for hybrid recommendation methods and optimize the combination strategy.

There are three hybrid architectures: Monolithic, Parallelised, and Pipelined. Monolithic hybrid recommendation algorithms have two specific implementations: Feature Combination and Feature Augmentation. Parallelized hybrid recommendation algorithms have three specific implementations: Mixed, Weighted, and Switching. Pipelined hybrid recommendation algorithms have the following specific implementations: Cascade and Meta-level.

Monolithic architecture HLR integrates different recommendation techniques into a unified model. Feature

TABLE 9. Summary of the studies based on CFB learning recommendations.

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR4	2021	Learner and learning object similarity and computation generating top-n recommendation list	CF,CB, Ontology	Ontology-based content recommendation solves the cold start problem for new users and can improve the accuracy of recommendations.	It relies on the availability and quality of learning objects and learner feedback.	University courses	India	Real-world dataset from MOOC, which contains 300 students' data
LR5	2021	Data analysis algorithm based on CF, ontology, and SPM	CF,Ontology, SPM	The proposed method alleviates the cold start and data sparsity problems.	Processing ontology and SPM requires more computing resources and cannot adapt to diverse learning resources.	University courses	China	Real-world MOOC dataset, which contains course data
LR7	2017	Ontology-based semantic recommendation with SAA and CF	ILS,ontology,CF,SAA	The proposed method combines the semantic knowledge of the ontology with collaborative user preference information. It not only outperforms the traditional CF regarding prediction accuracy but also improves coverage.	It fails to consider the dynamics and situational factors of the learning process.	MOOC	Serbia	No description
LR9	2023	Adaptive learning model based on learning style and motivation scoring	CF,KNN	The proposed new adaptation technique based on learners' learning style and motivation scores selects the most appropriate learning objects for learners to improve the accuracy of adaptation.	Training deep learning models requires large amounts of data.	University courses	Morocco	Open dataset MovieLens100K
LR19	2022	Hybrid recommendation system based on cluster CF and semantic network rule filtering	FSLSM,CF, SWRL	The proposed method combines cluster-based collaborative filtering and rule-based recommendation using SWRL. FSLSM is incorporated into learner clustering, reducing the processing time and making the algorithm more efficient.	Using one learning style cannot capture all aspects of learner characteristics and preferences.	University courses	India	447 learners' learning data from LMS of the University of California, San Diego
LR22	2022	Modified MF-based learning styles prediction	LSI,ML,CF	The proposed recommendation method based on CF and learning style prediction has achieved satisfactory results in performance testing.	Sufficient scoring data are required to train the model and generate accurate predictions and recommendations.	Primary Education	Indonesia	Real-world data of 322 students
LR27	2020	BPRN (BPR Network)	CF,BPR,neural network	A novel BPRN neural network is proposed that can learn course preferences.	It does not consider the sequential dependence.	MOOC	China	XuetangX dataset
LR28	2018	Deep learning-based CF model for recommendation systems	CF,FNN	The proposed method significantly outperforms previous methods using feedforward neural networks.	It does not consider the content features of users and items.	MOOC	China	Open dataset Movielen
LR31	2020	Ontology-based and CF personalized e-learning recommendation system	ontology, CF	A personalized recommendation system design based on ontology and pre-testing is proposed.	cold start and sparsity problem	MOOC	Nigeria	Real-world learning and learners' dataset
LR34	2018	OPCR (ontology-based personalized course recommendation)	ontology, CB,CF,SPM	The proposed method using dynamic ontology mapping is highly flexible and can be adapted to personalized recommendation tasks in different fields.	Building and maintaining ontology requires significant resources.	university courses	UK	Course dataset from the University of Chinese Academy of Sciences' LMS
LR42	2015	A hybrid recommendation approach based on CF and multi-criteria rating	CF,multi-criteria rating	The proposed method is based on CF and its improvement through tagging systems to find the resources that best meet learners' needs.	Recommendation methods rely on diverse user ratings, tags, and metadata.	MOOC	Italy	42,820 resources and 31,622 tags by 451 users from Moodle

TABLE 9. ***(Continued.)*** **Summary of the studies based on CFB learning recommendations.**

LR43	2020	Personalized MOOC recommendations with user-based CF	CF	The proposed method provides learners with targeted and relevant resources by utilizing learners' interest models and resource features.	Cold start and data sparse problem	MOOC	China	System log file of 100 people's learning behavior data on LMS
LR44	2017	DBNCF (Personalized Courses Recommendation System Based on DBN and CF)	CF,DBN	A personalized recommendation system based on DBN is proposed. The course scores are used as category labels for DBN supervised learning. The training of DBN is achieved through unsupervised pre-training and supervised feedback fine-tuning.	Recommended methods rely on data preprocessing and denoising.	Primary and Secondary School courses	China	Behavior logs of 41321 users on starc MOOC
LR45	2023	A personalized hybrid MOOC recommendation algorithm by integrating clustering and CF	CF,K-means	A personalized hybrid recommendation algorithm combining clustering and CF is proposed. The method is based on multidimensional IRT, learners' course ratings and course attribute preferences, course features, and memory weights to improve the algorithm's accuracy and interpretability.	Cold start problem	University courses	China	Course ratings, attributes, and characteristics data on Coursera
LR46	2023	CF-based e-learning Course Recommender model	CF,KNN, SVD,NCF	A recommendation method for course recommendation using KNN, SVD, and NCF is proposed. Compared with similar methods, the recommendation performance is improved.	Cold start problem	MOOC	India	302 course data from LMS

Combination integrates features from different data sources or recommendation algorithms to form a more comprehensive user profile or item representation, thereby improving the accuracy of recommendations. Feature Augmentation uses the output features of one recommendation algorithm as the input features of another recommendation algorithm to generate the final recommendation results.

Parallelised architecture HLR runs multiple recommendation models simultaneously and combines their outputs in parallel to generate the final recommendation. Mixed Recommendation mixes the outputs of different recommendation technologies, such as collaborative filtering, content-based recommendation, knowledge-based recommendation, etc., to form a unified recommendation framework. Weighted Recommendation assigns different weights to different recommendation algorithms or recommendation results, and then performs weighted summation or weighted sorting based on these weights to form the final recommendation framework. Switching Recommendation dynamically selects different recommendation algorithms or strategies to generate recommendation results based on the current situation or conditions.

Pipelined architecture HLR runs multiple recommendation steps in a certain order, each step may use a different algorithm or model. Cascade uses the recommendation results of one recommendation mechanism as the input of another recommendation mechanism to obtain more refined results. Meta-level combines recommendation models at a higher level of abstraction, usually after all recommendation models generate candidate sets, and then make the final decision.

Among them, CF-based HLR is the solution that attracts the most attention from researchers. Campanella and Impedovo [54] introduced an e-learning recommendation method based on CF and objective features such as learner roles and interests. To improve the accuracy of the recommendation results of MOOC resources, Wang [59] proposed a hybrid recommendation algorithm based on CF and Spark architecture. Furthermore, Agarwal et al. [30] proposed a method to build a knowledge-based Recommendation system that uses cluster-based CF and rules written in SWRL. Lastly, Wu and Liu [57] adopted a personalized hybrid recommendation algorithm that combines clustering and CF.

In addition, several researchers have considered improving the prediction accuracy of recommendation systems based on CF by using ontology techniques in CF-based hybrid recommendation systems. Petkovič et al. [16] proposed a hybrid recommendation approach based on ontology, CF, and spreading Activation algorithm, which effectively combines the semantic knowledge of ontology with the preference information of the collaborative learners. Likewise, Shanshan et al. [14] and Ibrahim et al. [46] both used a hybrid recommendation model based on ontology, CF, and

SPM designed to overcome the problems of cold start and data sparsity. Furthermore, Ibrahim et al. [46] and Jeevamol and Renumol [13] employed ontology-based CB and CF approaches to build hybrid recommendation systems for more reliable and personalized recommendations.

Besides the typical CB and CF-based HLR methods, other methods to build HLR have also received attention from researchers. Wan and Niu [60] used mixed concept mapping and immune algorithm to build HLR systems. Similarly, Tarus et al. [45] proposed a hybrid recommendation method that uses ontology techniques to build recommendation systems. Furthermore, Bhaskaran et al. [61] adopted a hybrid recommendation algorithm based on sequential pattern clustering and pruning.

In recent years, some researchers have implemented HLR by using ML, all of which use clustering methods. EL et al. [17] modeled learner profiles and learning content according to FSLSM and used an ML-based approach to detect learners' learning styles automatically. Similarly, Wu [62] proposed an algorithm for constructing a deep learning-based course resource recommendation technique using Depp Neural Networks (DNN), K-means, and multi-objective optimization function. Furthermore, Riad et al. [18] adopted a new adaptation method by using CF, constrained Pearson correlation coefficients, adapted cosine measure, and KNN. This new method is based on learners' learning styles and motivation scores to improve the accuracy and quality of learning object recommendations in e-learning systems.

Some researchers have also implemented HLR systems using various neural networks. Among these systems, the GNN-based HLR system is the most popular solution among researchers [63], [64], [65]. Gong et al. [63] proposed an end-to-end Graph neural network (GNN) based approach called Attention Heterogeneous Graph Convolutional Deep Knowledge Recommendation (ACKRec) to recommend knowledge concepts in MOOC. Similarly, Alatrash et al. [64] used Concept Graph Convolutional Network (GCN), which combined the knowledge graph (KG) based on the GNN and Transformer models [63] to provide personalized recommendations for knowledge concepts. Likewise, Gong et al. [65] also considered the use of GNN and heterogeneous information networks (HIN) [63] and adopted a reinforcement learning (RL) approach in which interactions between learners, courses, videos, and concepts were formed to better learn semantic learner representations. Furthermore, some researchers [66], [67] described Linear Regression (LR), Machine Forest Regression machine (RFR), and other ML methods to design HLR models.

Although HLR can improve the recommendation performance to a certain extent, the model is more complex due to the use of multiple recommendation algorithms. It will lead to an increase in the time complexity of the recommendation algorithm. Table 10 indicates studies based on hybrid learning recommendations.

4) SESSION-BASED LEARNING RECOMMENDATION

CF and CB recommendation systems are two representative recommendation systems, but these systems still have some shortcomings. The CB recommendation system is based on the static characteristics of users and items. At the same time, the CF algorithm relies on the long-term "user-item" interaction history data. It ignores the short-term transaction patterns of users, which leads to the loss of user preferences over time, which results in the current state of the user being masked by the long-term average situation. Thus, leading to unreliable recommendations. Moreover, these two algorithms usually decompose a basic interaction unit (e.g., ratings, clicks, and other operations) into multiple "user-item" interaction pairs and mix these records. This method is not conducive to retaining the "state transfer" implicit in user interaction events. In practical application scenarios, learners' information is often incomplete, and only their behavior in an ongoing session can better reflect their current state. Therefore, modeling a limited range of behaviors (one session) improves recommendation quality effectively.

It is necessary to consider the transaction structure to capture richer information in recommendations to solve the above problems. Therefore, transferring the learner's transactional behavior patterns and learner preferences from one transaction to another is necessary. In recent years, session-based recommendation methods [68] have become a hot research topic. Session-based recommendation algorithms are used to pay attention to the changes in the learner's state and apply them better to the training of recommendation models. Session-based learning recommendation algorithms mainly use deep neural network models. These models can be divided into four categories. The first category is image and vision models represented by CNN; the second category is sequence processing models, including RNN, LSTM, and Self-Attention Mechanism; the third category is graph processing models, including GNN and GCN; and the last category is decision and optimization models represented by Reinforcement Learning.

There are significant differences in the application of session-based recommendation systems in e-learning and e-commerce systems. These differences are mainly reflected in the following aspects.

(1) The differences in data characteristics and modeling methods.

The learning session of users of e-learning systems usually involves a series of learning activities and resource interactions, such as watching videos, completing exercises, and participating in discussions. These data are time series in nature. Therefore, modeling may focus more on capturing the learning sequence, interests, and preference changes of users. The shopping session of the users of the e-commerce systems is more involved in transaction behaviors such as browsing, adding to the shopping cart, and purchasing. These data not only have time series but also contain rich transaction information. When modeling, we may need to consider both

TABLE 10. Summary of the studies based on hybrid learning recommendation.

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR4	2021	Learner and learning object similarity and computation generating top-n recommendation list	CF,CB, Ontology	Ontology-based content recommendation solves the cold start problem for new users and can improve the accuracy of recommendations.	It relies on the availability and quality of learning objects and learner feedback.	University courses	India	Real-world dataset from MOOC, which contains 300 students' data
LR5	2021	Data analysis algorithm based on CF, ontology, and SPM	CF,Ontology, SPM	The proposed method alleviates the cold start and data sparsity problems.	Processing ontology and SPM requires more computing resources and cannot adapt to diverse learning resources.	University courses	China	Real-world MOOC dataset, which contains course data
LR7	2017	Ontology-based semantic recommendation with SAA and CF	ILS,ontology,CF,SAA	The proposed method combines the semantic knowledge of the ontology with collaborative user preference information. It not only outperforms the traditional CF regarding prediction accuracy but also improves coverage.	It fails to consider the dynamics and situational factors of the learning process.	MOOC	Serbia	No description
LR8	2020	Combination of ontology-based and ML-based methods	FSLSM,ML, classification algorithm	The proposed method builds learner and learning object ontologies retrieves the most relevant learning resources, and recommends them to learners.	ML models consume a lot of computational resources.	MOOC	Morocco	No description
LR9	2023	Adaptive learning model based on learning style and motivation scoring	CF,KNN	The proposed new adaptation technique based on learners' learning style and motivation scores selects the most appropriate learning objects for learners to improve the accuracy of adaptation.	Training deep learning models requires large amounts of data.	University courses	Morocco	Open dataset MovieLens100K
LR19	2022	Hybrid recommendation system based on cluster CF and semantic network rule filtering	FSLSM,CF,SWRL	The proposed method combines cluster-based collaborative filtering and rule-based recommendation using SWRL. FSLSM is incorporated into learner clustering, reducing the processing time and making the algorithm more efficient.	Using one learning style cannot capture all aspects of learner characteristics and preferences.	University courses	India	447 learners' learning data from LMS of the University of California, San Diego
LR33	2017	A hybrid e-learning RS with ontology and SPM	Ontology,SPM	The proposed method has improved performance over similar methods and alleviates the cold start and data sparsity problems.	Building and maintaining ontology requires significant resources.	university courses	Kenya	50 students learn data from LMS
LR34	2018	OPCR (ontology-based personalized course recommendation)	ontology,CB,CF,SPM	The proposed method using dynamic ontology mapping is highly flexible and can be adapted to personalized recommendation tasks in different fields.	Building and maintaining ontology requires significant resources.	university courses	UK	Course dataset from the University of Chinese Academy of Sciences' LMS
LR42	2015	A hybrid recommendation approach based on CF and multi-criteria rating	CF,multi-criteria rating	The proposed method is based on CF and its improvement through tagging systems to find the resources that best meet learners' needs.	Recommendation methods rely on diverse user ratings, tags, and metadata.	MOOC	Italy	42,820 resources and 31,622 tags by 451 users from Moodle
LR45	2023	A personalized hybrid MOOC recommendation algorithm by integrating clustering and CF	CF,K-means	A personalized hybrid recommendation algorithm combining clustering and CF is proposed. The method is based on multidimensional IRT, learners' course ratings and course attribute preferences, course features, and memory weights to improve the algorithm's accuracy and interpretability.	Cold start problem	University courses	China	Course ratings, attributes, and characteristics data on Coursera

TABLE 10. ***(Continued.)*** **Summary of the studies based on hybrid learning recommendation.**

LR47	2022	A mixed CF recommendation algorithm based on Spark architecture for music MOOC resources	CF, XGBoost, frog-jumping algorithm	Compared with existing CF methods, the proposed hybrid CF recommendation algorithm based on Spark architecture achieves higher accuracy.	Cold start problem	MOOC	China	Course selection records and user operation log records for multiple courses in MOOC
LR48	2016	A learner-oriented recommendation method based on hybrid concept mapping and an immune algorithm	Mixed concept mapping,immune algorithm	The proposed method can provide personalized learning resources and paths according to learners' preferences, abilities, attitudes, and goals. The immune algorithm is used to solve the constraint satisfaction problem of recommendation.	Experimental data on recommended methods are not provided when learning resources are enormous and diverse.	MOOC	China	Unspecified Dataset
LR49	2021	A cluster-based intelligent hybrid recommendation system for e-learning	Clustering,linear pattern mining	The proposed method uses a learning style index strategy to analyze learning style preferences, evaluate learner preference changes in different dimensions, reduce the computational complexity of the recommendation process, and improve the accuracy of recommendation list generation.	cold start problem and the sparsity of ratings and feedback data	MOOC	India	Real-world dataset contains primary data for 1000 learners
LR50	2023	deep learning-based online course resource recommendation	DNN,K-means,multi-objective optimization function	The proposed method can use DNN to capture the nonlinear and complex relationship between users and courses, thereby enhancing the accuracy and diversity of recommendations.	Training neural network models require large amounts of data and computing resources.	MOOC	China	A MOOC dataset containing 17,712 users and all 566 courses
LR51	2020	ACKRec (Attentional Heterogeneous Graph Convolutional Deep Knowledge Recommender)	GNN, attention mechanism,HIN	The proposed method can effectively extract and utilize rich contextual information in HIN, alleviating the data sparsity and cold start problems in MOOC.	Cold start problem	MOOC	China	The dataset of XuetangX includes basic learner information and course information.
LR52	2023	Concept GCN (Knowledge concept recommendation in MOOCs based on KG convolutional networks and SBERT)	GNN,KG, GCN	The proposed method captures structural and semantic information from the knowledge graph to enhance the representation of knowledge concepts and learner models, providing personalized and explainable recommendations.	The construction and processing of knowledge graphs require a large amount of data and computing resources.	MOOC	Germany	Open dataset SemEval2017
LR53	2023	HinCRec-RL (Concept Recommendation based on Heterogeneous Information Networks and RL)	HIN,GNN, RL	The proposed method can recommend fine-grained knowledge to users based on their different expertise and interest levels and update the recommendation strategy through reinforcement learning, which can adapt to dynamic environments and user feedback.	RL and GNN require significant computing resources.	MOOC	China	XuetangX dataset
LR54	2023	ML and CF-based personalized e-learning recommender	CF,ML	The proposed method can exploit various features related to learners, courses, and their interactions, such as learning performance, course difficulty, course popularity, and learning sequence, to provide more relevant and diverse recommendation results.	Data sparsity, cold-start, the scalability problem	MOOC	Pakistan	Udemy course dataset and Coursera course dataset
LR55	2023	ICRS (e-learning Intelligent Content-Based Recommendation System)	CB,DL, LSTM	The proposed method captures the latent semantic relationships between knowledge points and learning resources. It provides more meaningful and personalized recommendations, overcoming the data sparsity and cold start problems.	Vast data and computing resources are required to train and test ML and deep learning models.	MOOC	India	Coursera dataset

the short-term interests of users and long-term purchasing habits and the relevance and complementarity between items.

(2) The differences in recommended goals.

The recommendation algorithms of e-learning systems focus more on recommending learning content sequences and course sequences to help users reasonably complete learning goals. The recommendation algorithms of e-commerce systems focus on predicting the items a user may purchase, usually based on the user's browsing and clicking behavior during the session.

(3) The differences between realtime and dynamic.

E-learning systems have realtime learning sessions, but users' learning interests and preferences may change relatively slowly, so the realtime requirements of recommendations may not be as high as those of e-commerce systems. However, with the continuous update and increase of e-learning content, the recommendation algorithms also need to have the ability to update and adjust dynamically. Due to the realtime changes in commodity inventory, prices, promotions, and other information, as well as the rapid changes in user shopping behavior, the recommendation algorithms of e-commerce systems need to be highly realtime and dynamic to adapt to the market changes and quickly adjust the recommendation strategy.

Many researchers have adopted RNN models in session-based recommendation systems. Liu et al. [25] used RNN to track changes in learners' knowledge levels and then used the learners' cognitive structures and learning items to generate personalized learning paths. Thai-Nghe et al. [69] used session-based Neural Attentive Recommendation (NARM) and RNN models. Likewise, Khan and Polyzou [70] introduced session-based recommendation (SBR) to analyze course relationships and relevance by incorporating LSTM networks into RNN for the dynamic representation of learners. In addition, attention models have also been applied in session-based recommendation systems. The NARM model [69] and the STR-SA model [71] both use attention models to design session-based recommendation systems. Other approaches using neural network models, such as Wang et al. [72], developed a hyper edge-based GNN, i.e., HGNN, for course recommendation. A joint probabilistic matrix decomposition method based on CNN was used by Zhou [52] to recommend instructional resources combined with instructional resources. In addition, RL has also attracted the attention of researchers in the design of session-based recommendation systems [25], [73]. Lin et al. [73] adopted a novel course recommendation framework that combines dynamic attention and hierarchical RL to capture users' dynamic preferences and improve recommendation accuracy.

There are also many studies using various neural networks to design recommendation models. Wang et al. [74] proposed an attention-based CNN approach to obtain learner profiles, predict learner ratings, and recommend the top-N courses. Further extending this study, a personalized recommendation scheme [75] was exploited with GNN which can capture learners' general and dynamic preferences for top-N personalized course recommendations (TP-GNN) in MOOC. Amin et al. [76] also adopted a learning framework for intelligent e-personalization based on RL and MDP. Based on the TP-GNN model [75], Klasnja-Milicevic and Milicevic [77] utilized a recommendation model using neural co-attention mode and combining Fusion function, HIN embedding, and Top-N knowledge concepts. This model integrates important heterogeneous data with knowledge-based conceptual recommendations, improves recommendation performance and efficiency, and can deal with data sparsity and cold-start problems in MOOC.

Table 11 summarizes the studies based on session-based learning recommendations in this section.

5) SUMMARY OF PERSONALIZED RECOMMENDATION SYSTEM

In recent years, the research on personalized learning recommendation methods can be summarized into four categories: CB learning recommendation, CFB learning recommendation, hybrid learning recommendation, and session-based learning recommendation.

CB, CFB, and hybrid recommendation belong to traditional recommendation methods, and these three types of recommendation methods are also widely used in other recommendation scenarios. Related research is also relatively affluent. The CB learning recommendation method can directly match the characteristics of the recommended object with the learner's personalized parameters, which is easy to implement and highly efficient. However, it cannot obtain the changes of the learner and the recommended object during the learning process. The CFB learning recommendation method is based on the interaction history of learners and recommended objects from the behavioral data mining learners on the potential evaluation of recommended objects. This method helps to explore the potential interests of learners or new interests, thus improving the quality of the recommendation. However, this recommendation method has problems such as cold-start, data sparsity, etc. Hybrid learning recommendation methods use multiple recommendation algorithms to collaborate and can alleviate the problems of individual algorithms to a certain extent. Different hybrid learning recommendation methods use different hybrid strategies, usually according to the specific application scenarios and data situation.

The above learning recommendation methods focus on the long-term static preferences of learners and ignore the transfer of their preferences over time. On the other hand, session-based learning recommendations comprehensively consider the state transfer of learners between the previous and subsequent sessions. It takes the session as the basic unit of recommendation, which is conducive to acquiring learners' immediate state. Traditional PLRS are relatively simple, straightforward, and easy to understand and implement. In contrast, deep neural network-based methods are usually relatively complex. These methods involve complex

TABLE 11. **Summary of the studies based on session-based learning recommendation.**

Studies	Year	RS Model	Method & algorithms	Highlights	Limitations	Application area	nation	DataSet
LR40	2022	CUPMF(convolution joint probability matrix factorization) Model	CB,CNN, time-sensitive deterministic input and noise gate	The proposed CUPMF method recommends learning resources by combining learners' answer history, cognitive ability, knowledge mastery, and forgetting factors.	It requires large amounts of data and computing resources to train models and optimize parameters.	University courses	China	Open dataset FrcSub,Math1,Math2 and real-world learning data
LR56	2022	NARM(Neural Attentive Session-based Recommendation model)	neural attentive, RNN	A session-based recommendation system is proposed, which uses neural attention session recommendation and the GRU4Rec model based on RNN for training, testing, and comparison. The results show that the proposed model is more effective than the GRU4Rec model in recommending learning resources.	Training the RNN model requires large amounts of session data	MOOC	Vietnam	Dataset of Tra Vinh University book borrowing records and YOOCHOOSE dataset
LR57	2023	Session-based course recommendation models	RNN,LSTM	A session-based approach is proposed for course recommendation model, and experimental results show that the model outperforms all sequential and non-sequential recommendation models.	Enormous data and computing resources are required to train and test DL models.	University courses	USA	Dataset of Florida International University's LMS
LR58	2020	STR-SA (Session-based Thread Recommendation for Online Course Forum with Self-Attention)	self-attention mechanism	A STR-SA model is proposed, using the self-attention mechanism to capture students' global preferences and interests. Experimental results show that the STR-SA model outperforms other MOOC thread recommendation methods.	Data sparsity	University courses	China	Basic data for 82,535 users from LMS
LR59	2022	HGNN (Hyperedge-based graph neural network for MOOC Course Recommendation)	GNN	A hyperedges-based graph neural network (HGNN) is proposed. It can be incorporated into MOOC learners and course representations and handle similar relationships well. From the experimental results, HGNN is significantly better than other recent course recommendation methods.	Enormous data and computing resources are required to train and test GNN models.	MOOC	China	XuetangX datasets and open dataset MovieLens
LR60	2021	DARL (Dynamic Attention and hierarchical Reinforcement Learning)	RL	The proposed algorithm, Dynamic Attention and Hierarchical Reinforcement Learning (DARL) improves the recommendation model's adaptivity by capturing the user's dynamic interests in sequential learning behaviors. It automatically updates the attention weight of corresponding courses at different sessions, enhancing the accuracy of course recommendations.	It relies on the user's history data to recommend causing cold-start problems.	MOOC	China	XuetangX dataset
LR61	2020	Attention-based CNN for personalized course recommendation	CNN	The proposed model provides real-time course recommendations by combining CF with attention-based CNN.	Training attention-based CNN models requires large amounts of data and computing resources.	MOOC	China	Learning behavior logs and course rating data on LMS

TABLE 11. *(Continued.)* **Summary of the studies based on session-based learning recommendation.**

LR62	2021	TP-GNN (a Top-N personalized Recommendation with GNN)	GNN,GCN, attention mechanism, aggregate function	The proposed TP-GNN model captures the high-order connection information between users and courses through GNN while considering users' general preferences and sequential behaviors. It also uses the attention mechanism to screen important features to better adapt to user preferences' dynamic changes.	A large amount of user-item interaction data and course category data are required to train the GNN.	University courses	China	Dataset of XuetangX
LR63	2023	RL-based e-learning Framework for Personalized Adaptive Learning	RL,MDP, Q-learning	The proposed recommendation framework utilizes RL and MDP to provide a personalized and effective learning path for each learner.	Requires large amounts of data and computing resources to train and update Q-learning models.	MOOC	Pakistan	6,000 students of simulation data
LR64	2023	Top-N Knowledge Concept Recommendations	NCF,A neural co-attention model, Fusion function, Rating prediction,HIN	The proposed method exploits the rich contextual information in HIN, learns embeddings of different meta-paths, and fuses them with nonlinear and personalized functions, which can capture learners' complex and heterogeneous preferences.	Scalability and efficiency issues of HIN	University courses	Serbia	DSAS, SNESS and SP datasets from Coursera

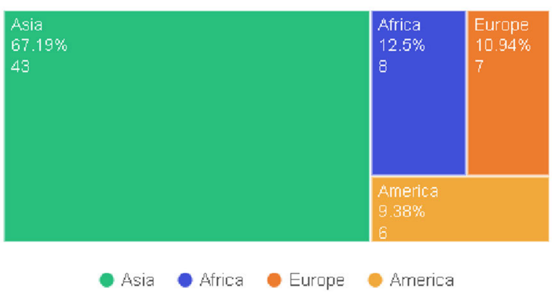

FIGURE 9. **Statistics of published studies by region.**

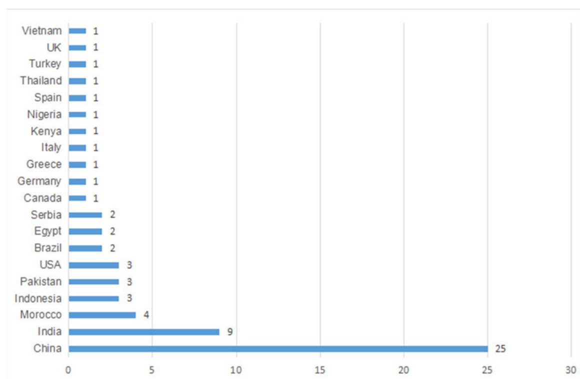

FIGURE 10. **Number of studies published by different nations.**

multi-layer network architectures. The methods also require extensive sample data for model training and significant computational resources to build PLRS.

The session-based learning recommendation method still needs further research on internal structure processing and relationship modeling between sessions.

C. ANALYSIS OF THE CURRENT STATUS OF PLRS RESEARCH

As seen in Fig. 9, researchers in Asia, Europe, Africa, and the Americas are studying PLRS globally. 43 out of 64 articles are from Asian researchers. In Fig. 10, China has a significant number of studies in Asia, with 25 articles, followed by India. From the regional distribution of the literature study, researchers in Asia, especially in East and South Asia, have a higher degree of enthusiasm for PLRS research. Researchers in other regions have a slight difference in the research intensity of this field, and the statistics on the number of research articles from different countries can be seen in Fig. 10.

Table 12 demonstrates the technology adopted by the recommendation systems in this study. Table 12 shows that studies adopting hybrid learning recommendations are the most. It also reflects the methodology and idea of the researchers' concern in the research in the field of learning recommendation from one point of view.

Fig. 11 shows the keyword data of the research hotspots in personalized e-learning. Fig. 12 shows recommendation

TABLE 12. Types of learning recommendations found in studies.

Recommendation Technology	Studies
Recommendation based on Learner modeling	LR1,LR2,LR3,LR4,LR5,LR6,LR7, LR8,LR10,LR11,LR12,LR13,LR14,LR15,LR16,LR17
Recommendation based on Learning object modeling	LR6,LR7,LR25,LR26,LR27,LR28,LR29,LR30,LR31,LR32,LR33,LR34,LR35,LR36
Content-based learning recommendations	LR4,LR5,LR6,LR26,LR34,LR37,LR38,LR39,LR40,LR41
Collaborative filtering-based learning recommendation	LR4,LR5,LR7,LR9,LR22,LR27,LR28,LR31,LR34,LR42,LR43,LR44,LR45,LR46
Hybrid learning recommendation	LR4,LR5,LR7,LR8,LR9,LR19,LR33,LR34,LR42, LR45,LR47,LR48,LR49,LR50,LR51,LR52,LR53, LR54,LR55
Session-based learning recommendation	LR14,LR40,LR56,LR57,LR58,LR59,LR60,LR61, LR62,LR63,LR64
Recommendation based on Learner modeling	LR1,LR2,LR3,LR4,LR5,LR6,LR7, LR8,LR10,LR11,LR12,LR13,LR14,LR15,LR16,LR17

FIGURE 11. Key words in studies.

methods used in the studies. Among them, recommendation algorithms based on artificial intelligence include ML, deep neural networks, and RL, which are very popular in researching recommendation systems. In addition, CF, CB, and ontology-based recommendation techniques are widely researched and applied.

Table 13 is the recommendation system used for the articles covered in this study. Fig. 13 shows that researchers have been paying more and more attention to AI-based recommendation algorithms in recent years. Furthermore, researchers have paid more attention to deep neural network-based algorithms in the last five years, according to the statistics of Fig. 14.

The current research on learner-based modeling technology mainly uses knowledge-based and user-feature-based methods. Among the knowledge-based methods, ontology technology is the main method to achieve learner modeling. Among the user-feature-based methods, the learning style model is the most studied. Among the four commonly used LSMs, the Fslsm model is the most widely used learning style model. There are three main types of modeling methods based on learning objects: dynamic and static modeling techniques and knowledge-based modeling techniques. Knowledge-based modeling technology is the most widely used method in learning object modeling methods. Building learning object models based on ontology is the most widely used among knowledge-based modeling technologies.

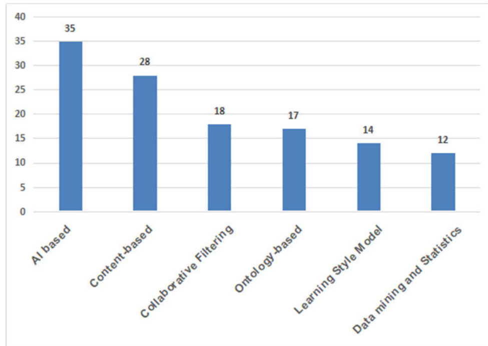

FIGURE 12. Different types of recommendation algorithms used in studies.

TABLE 13. Recommendation algorithms used in studies.

Technology and Algorithms	Studies
AI based	LR8,LR9,LR10,LR14,LR18,LR20,LR21,LR23,LR25,LR26,LR27,LR28,LR30,LR38,LR40,LR41,LR44,LR45,LR46,LR47,LR50,LR51,LR52,LR53,LR54,LR55,LR56,LR57,LR58, LR59,LR60,LR61,LR62,LR63,LR64
Content-based	LR1,LR4,LR7,LR9,LR13,LR16,LR17,LR20, LR21,LR22,LR26,LR27,LR30,LR34,LR36,LR37,LR38,LR39,LR40,LR41,LR42,LR47,LR48,LR50,LR52,LR55,LR62,LR64
Collaborative Filtering	LR4,LR5,LR7,LR9,LR19,LR21,LR22,LR28, LR31,LR34,LR42,LR43,LR44,LR45,LR46,LR47,LR54,LR27
Ontology-based	LR1,LR2,LR3,LR4,LR5,LR6,LR7,LR11,LR29,LR30,LR31,LR32,LR33,LR34,LR35,LR36,LR38
Learning Style Model	LR3,LR7,LR8,LR11,LR12,LR18,LR19,LR20,LR21,LR22,LR23,LR24,LR35,LR39
Data mining and Statistics	LR5,LR9,LR10,LR11,LR33,LR34,LR37,LR41,LR49,LR51,LR53,LR64

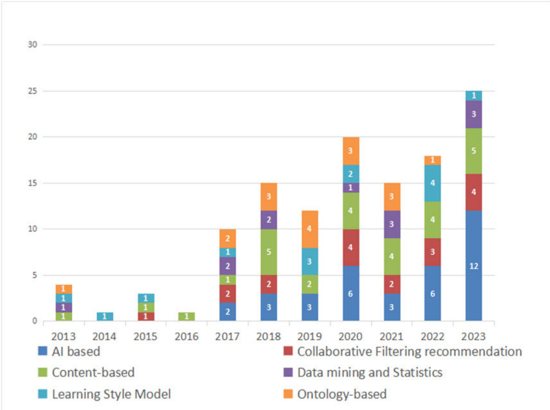

FIGURE 13. Recommendation algorithms used in studies from 2013 to 2023.

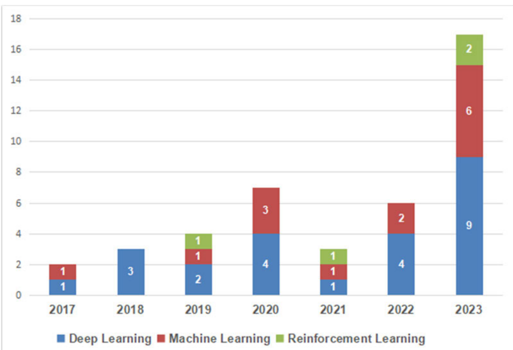

FIGURE 14. Different types of AI algorithms used in studies.

In addition to simply using ontology models, many studies combine other algorithms with ontology models, including CB, CF, and neural networks.

There are four main learning recommendation algorithms used in PLRS. In addition to the classic CB and CF algorithms, session-based learning recommendation algorithms have attracted more and more attention from researchers in the past five years. In session-based learning recommendation algorithms, deep neural network models are mainly used. Among these neural network models, in addition to the classic CNN and RL models, sequence processing models and graph neural network models represented by self-attention mechanisms have attracted more and more attention from researchers in recent years.

The datasets used for experimental verification of recommendation algorithms and technologies in PLRS are mainly open data sets and real datasets obtained from MOOC platforms. Only a small number of studies use simulated data. Open datasets are represented by MovieLens and DBpedia. MOOC datasets are mainly datasets collected from actual teaching use on XuetangX and Coursera platforms, as well as datasets generated in actual use on LMS platforms of colleges and universities.

The highlights and limitations of the recommendation algorithms related to PLRS are analyzed and explained in Table 6 to Table 10. This study analyzed 64 related research papers and found that these learning recommendation models and recommendation algorithms have achieved the requirements of personalized learning content recommendation for Du Yu learners to a certain extent, and a considerable number of personalized learning recommendation algorithms have achieved good recommendation accuracy. However, these algorithms still need to be improved to adapt to different types of courses in different learning fields. In addition, the problem of system cold start needs to be further improved.

IV. CONCLUSION AND FUTURE WORK

This section answers the research question RQ5.

A. CONCLUSION

PLRS greatly enhances learners' interest and motivation in learning by recommend the courses and learning contents which learners are interested in and promotes the development of e-learning. In recent years, many research articles related to PLRS have been published in this field, and it has become a key research direction in e-learning. It has attracted the attention of many researchers.

This study discusses the research contents and characteristics of PLRS related to learners, learning object modeling, and personalized learning recommendation algorithms. Current research in this field is classified and summarized. This study will help researchers understand the research content, research difficulties, and research lineage of PLRS. It will stimulate researchers to think about future research on PLRS, inspire researchers to propose new methods, and promote the innovative application of PLRS.

B. PROBLEMS

There are still three issues that need to be solved in PLRS research.

Based on this research work, it is deemed that there are three issues in PLRS that are still shallow and require in-depth solutions to mitigate the problem.

1) THE ADAPTABILITY OF RECOMMENDATION METHODS

Recommendation frameworks are usually developed for a specific problem, and different methods apply to different objects. In addition, there are differences in the requirements of recommendation algorithms in different educational fields, such as primary education, higher education, vocational education, and adult continuing education. Suitable recommendation algorithms should be chosen when recommending learning resources, and corresponding parameters for different learners and teaching levels should be set.

2) PRIVACY PROTECTION

Nowadays, learners pay more and more attention to protecting personal privacy, especially protecting personal data to prevent the leakage of personal information. Since the recommendation algorithms of e-learning resources need to collect learners' personal information, social information, learning

TABLE 14. Primary studies in 10 years.

ID	Title	type	Ref	Database	Quality Assessment Scoring					
					QA1	QA2	QA3	QA4	QA 5	Score
LR1	Ontology-Based Personalized Learning Path Recommendation for Course Learning	conference	[10]	IEEE	3	4	1	3	4	3
LR2	BROAD-RSI–educational recommender system using social networks interactions and linked data	journal	[11]	Springer	3	4	5	3	4	3.8
LR3	An ontology-based approach for user modelling and personalization in e-learning systems	conference	[12]	Worldwide Science	3	4	1	3	4	3
LR4	An ontology-based hybrid e-learning content recommender system for alleviating the cold-start	journal	[13]	Springer	3	3	4	3	4	3.4
LR5	An improved hybrid ontology-based approach for online learning resource recommendations	journal	[14]	Springer	3	4	4	3	4	3.6
LR6	ERSDO: E-learning recommender system based on dynamic ontology	journal	[15]	Springer	3	3	4	4	4	3.6
LR7	An Ontology-based Model for Contextual Recommendations in e-learning.	journal	[16]	Worldwide Science	3	3	1	4	4	3
LR8	A learning style-based Ontology Matching to enhance learning resources recommendation	conference	[17]	IEEE	4	3	1	3	4	3
LR9	The new e-learning adaptation technique based on learner's learning style and motivation.	journal	[18]	Worldwide Science	3	4	3	3	4	3.4
LR10	Social context-aware recommendation for personalized online learning	journal	[21]	Springer	3	4	1	3	4	3
LR11	Concept Based Approach for Adaptive Personalized Course Learning System	journal	[22]	Worldwide Science	2	3	4	3	4	3.2
LR12	Learning object recommendations based on quality and item response theory	conference	[23]	IEEE	2	3	4	3	3	3
LR13	Adaptive learning path generation using colored Petri nets based on behavioral aspects	conference	[24]	Worldwide Science	3	4	1	3	4	3
LR14	Exploiting cognitive structure for adaptive learning.	conference	[25]	ACM	3	3	4	2	3	3
LR15	Discover learning path for group users: A profile-based approach	journal	[26]	ScienceDirect	4	3	3	3	4	3.4
LR16	A multi-constraint learning path recommendation algorithm based on knowledge map	journal	[27]	ScienceDirect	4	4	4	4	4	4

TABLE 14. ***(Continued.)*** **Primary studies in 10 years.**

ID	Title	type	Ref	Database	Quality Assessment Scoring					
					QA1	QA2	QA3	QA4	QA5	Score
LR17	Adaptive learning path recommender approach using auxiliary learning objects	journal	[28]	ScienceDirect	3	4	5	3	4	3.8
LR18	Utilizing Clustering Algorithms to Provide Vark Learning Style Recommendations	conference	[29]	IEEE	3	3	3	3	3	3
LR19	Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs.	journal	[30]	Worldwide Science	3	3	4	3	3	3.2
LR20	Improving online education through automatic learning style identification using a multi-step architecture with ant colony system and artificial neural networks	journal	[31]	ScienceDirect	4	4	3	3	4	3.6
LR21	LSBCTR: A learning style-based recommendation algorithm	conference	[32]	IEEE	3	3	4	3	3	3.2
LR22	AI-based learning style prediction in online learning for primary education	journal	[33]	IEEE	3	4	3	3	4	3.4
LR23	Learning Style Integrated Deep Reinforcement Learning Framework for Programming Problem Recommendation in Online Judge System	journal	[34]	Springer	4	4	4	3	4	3.8
LR24	Personalized E-learning recommendation model based on psychological type and learning style models	conference	[35]	IEEE	3	3	4	3	3	3.2
LR25	MOOCRC: A Highly Accurate Resource Recommendation Model for Use in MOOC Environments	journal	[37]	Springer	3	3	4	3	4	3.4
LR26	A content-based recommendation algorithm for learning resources	journal	[38]	Springer	3	3	5	3	3	3.4
LR27	Improving Deep Item-Based Collaborative Filtering with Bayesian Personalized Ranking for MOOC Course Recommendation	conference	[39]	Springer	2	3	5	3	3	3.2
LR28	A Novel Deep Learning-Based Collaborative Filtering Model for Recommendation System	journal	[40]	IEEE	4	3	5	3	4	3.8
LR29	Ontology and Rule-Based Recommender System for E-learning Applications	journal	[41]	Worldwide Science	3	4	1	3	4	3
LR30	Ontology based E-learning framework: A personalized, adaptive and context aware model	journal	[42]	Springer	3	3	5	3	3	3.4
LR31	Development of an Ontology-Based Personalised E- Learning Recommender System	journal	[43]	Worldwide Science	3	3	3	3	3	3
LR32	A fog based recommendation system for promoting the performance of E-Learning environments	journal	[44]	ScienceDirect	4	4	5	3	4	4

TABLE 14. ***(Continued.)*** **Primary studies in 10 years.**

ID	Title	type	Ref	Database	Quality Assessment Scoring					
					QA1	QA2	QA3	QA4	QA5	Score
LR33	A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining	journal	[45]	ScienceDirect	3	3	5	3	3	3.4
LR34	Ontology-Based Personalized Course Recommendation Framework	journal	[46]	IEEE	4	4	5	3	4	4
LR35	An ontology model for content recommendation in personalized learning environment	conference	[47]	ACM	3	3	4	3	3	3.2
LR36	A Semantic Web-Based Recommendation Framework of Educational Resources in E-Learning	journal	[48]	Springer	3	4	1	3	4	3
LR37	Online Learning Video Recommendation System Based on Course and Sylabus Using Content-Based Filtering	journal	[49]	Worldwide Science	3	3	5	3	3	3.4
LR38	Ontology-based E-learning Content Recommender System for Addressing the Pure Cold-start Problem	journal	[50]	ACM	4	4	4	3	4	3.8
LR39	A Rule-Based Approach for Adaptive Content Recommendation in a Personalized Learning Environment: An Experimental Analysis	conference	[51]	IEEE	3	2	3	4	3	3
LR40	Research on Teaching Resource Recommendation Algorithm Based on Deep Learning and Cognitive Diagnosis	journal	[52]	Worldwide Science	3	4	3	3	4	3.4
LR41	SeqSense: Video Recommendation Using Topic Sequence Mining	conference	[53]	Springer	3	3	4	3	3	3.2
LR42	Innovative methods for the E-learning recommendation	conference	[54]	IEEE	3	2	4	3	4	3.2
LR43	Application of Personalized Recommendation Technology in MOOC System	conference	[55]	IEEE	3	2	3	3	4	3
LR44	DBNCF: Personalized Courses Recommendation System Based on DBN in MOOC Environment	journal	[56]	IEEE	3	2	5	3	3	3.2
LR45	Personalized Hybrid Recommendation Algorithm for MOOCs Based on Learners' Dynamic Preferences and Multidimensional Capabilities	journal	[57]	Worldwide Science	3	4	5	3	4	3.8
LR46	E-Learning Course Recommender System Using Collaborative Filtering Models	journal	[58]	Worldwide Science	4	3	3	3	4	3.4
LR47	Collaborative Filtering Recommendation of Music MOOC Resources Based on Spark Architecture	journal	[59]	Worldwide Science	3	4	4	3	3	3.4
LR48	A learner oriented learning recommendation approach based on mixed concept mapping and immune algorithm	journal	[60]	ScienceDirect	3	4	1	3	4	3

TABLE 14. *(Continued.)* **Primary studies in 10 years.**

ID	Title	type	Ref	Database	Quality Assessment Scoring					
					QA1	QA2	QA3	QA4	QA5	Score
LR49	Design and Analysis of a Cluster-Based Intelligent Hybrid Recommendation System for E-Learning Applications	journal	[61]	Worldwide Science	3	4	3	3	4	3.4
LR50	Online course resource recommendation based on deep learning	journal	[62]	ScienceDirect	3	3	4	3	4	3.4
LR51	Attentional Graph Convolutional Networks for Knowledge Concept Recommendation in MOOCs in a Heterogeneous View	conference	[63]	ACM	3	4	5	3	4	3.8
LR52	ConceptGCN: Knowledge concept recommendation in MOOCs based on knowledge graph convolutional networks and SBERT	journal	[64]	ScienceDirect	4	4	5	4	4	4.2
LR53	Reinforced MOOCs Concept Recommendation in Heterogeneous Information Networks	journal	[65]	ACM	4	4	5	3	4	4
LR54	Developing a Personalized E-Learning and MOOC Recommender System in IoT-Enabled Smart Education	journal	[66]	IEEE	4	4	5	3	4	4
LR55	Semantics aware intelligent framework for content-based e-learning recommendation	journal	[67]	ScienceDirect	3	4	5	3	4	3.8
LR56	A Session-Based Recommender System for Learning Resources	conference	[69]	Springer	3	2	5	3	3	3.2
LR57	Session-based Course Recommendation Frameworks using Deep Learning	journal	[70]	Worldwide Science	3	2	4	3	3	3
LR58	STR-SA: Session-based Thread Recommendation for Online Course Forum with Self-Attention	conference	[71]	IEEE	3	3	5	3	4	3.6
LR59	HGNN: Hyperedge-based graph neural network for MOOC Course Recommendation	journal	[72]	ScienceDirect	3	4	4	2	4	3.4
LR60	Adaptive course recommendation in MOOCs	journal	[73]	ScienceDirect	3	4	4	3	4	3.6
LR61	Attention-Based CNN for Personalized Course Recommendations for MOOC Learners	journal	[74]	IEEE	2	4	5	3	4	3.6
LR62	Top-N personalized recommendation with graph neural networks in MOOCs	journal	[75]	Springer	3	4	5	3	3	3.6
LR63	Smart E-Learning Framework for Personalized Adaptive Learning and Sequential Path Recommendations Using Reinforcement Learning	journal	[76]	IEEE	4	4	3	3	4	3.6
LR64	Top-N Knowledge Concept Recommendations in MOOCs Using a Neural Co-Attention Model	journal	[77]	IEEE	4	4	5	3	4	4

level, and other data while analyzing learners' preferences, the current recommendation algorithms have given less consideration to the privacy protection of personal information.

3) COLD-START PROBLEM

Since the number of course resources and learners on the e-learning system increases gradually after the LMS is implemented, the cold-start problem exists for new e-learning systems and newly registered learners. Although researchers have tried many methods to alleviate the cold-start problem in recommendation algorithms, the solutions adopted in other fields do not necessarily apply to e-learning.

C. FUTURE RESEARCH AND PROSPECTS

With the wide application of e-learning and artificial intelligence technology, personalized learning recommendation technology is also developing continuously. Many researchers have achieved many research results in this process. However, due to many problems in the current PLRS, there is a need to continue exploring key technologies such as the recommendation system framework, learning object, and learner modeling. Future research can be carried out in the following five aspects.

1) IMPROVE THE MODELING OF LEARNERS AND LEARNING OBJECTS

Due to the static characteristics of courses and learning materials, it is relatively easy to model learning objects. However, the dynamic characteristics are more representative of learners' course preferences. PLRS tends to recommend more popular courses and ignore the long-tailed courses when recommending courses. However, learners are often interested in those long-tailed courses, so the ability to recommend courses accurately is challenged. While it is easy to obtain explicit information about learners, implicit feedback data from learners can be used to build a rich user profile of learners. Information such as the learner's behavior in the LMS and other log records will help improve the recommendation system's accuracy.

2) ADAPTIVE AND FEEDBACK MECHANISM OF PLRS

Learning is a dynamic process. For a long learning process, cognitive level, emotional state, learning style, and other characteristics will change with the learning activities. Capturing the changes in these characteristics in time, representing them effectively, and dynamically adjusting the content of the recommendations given by PLRS to follow the changes in learners' characteristics and states will be essential in the research of learner modeling.

3) STRONGLY INTERPRETABLE RECOMMENDATIONS

The purpose of PLRS is to recommend course content that suits the learner's ability level or interest. Most existing PLRS methods only provide the prediction accuracy of recommended courses or learning resources, especially deep learning-based methods, which use complex multi-layer artificial neural networks to achieve the recommendation. The principle of recommendation is a "black box" for researchers and lacks theoretical proof, which is not conducive to learners' understanding and trust in the recommendation results. Therefore, improving the interpretability of this kind of recommendation system is one of the significant issues that need to be solved in the current e-learning recommendation method.

4) RECOMMENDER SYSTEMS AND INTERDISCIPLINARY

PLRS itself is characterized as a teaching aid aiming to improve learners' learning efficiency. In the related recommendation system research, the following methods can be considered. Applying the theories and methods of pedagogy, psychology, and other teaching-related fields to design the recommendation system. Designing a more comprehensive and applicable learner-oriented recommendation effect evaluation system. Promoting the technological innovation of e-learning systems.

5) PRIVACY PROTECTING

PLRS needs to obtain the learner's personality trait information and interaction log data on the e-learning system. Then PLRS provide learners with the corresponding recommended learning content to achieve the goal of personality-based learning. As the learner's data obtained in the recommendation system is in plaintext and not desensitized, it is easy to cause the learner's privacy to be analyzed and snooped on. This results in more and more learners worrying about the leakage of their personal information. Therefore, acquiring learners' data in recommendation systems while protecting their privacy is necessary. So the privacy protection problem of PLRS will become a new hot direction for future research.

APPENDIX
PRIMARY STUDIES IN 10 YEARS

See Table 14.

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