https://doi.org/10.26599/IJCS.2022.9100020 International Journal of Crowd Science

Data-Driven Artificial Intelligence Recommendation Mechanism in Online Learning Resources

Lina Yang[1] ✉, Yawen Yu[2] , and Yonghong Wei[3]

ABSTRACT

This study attempts to reveal the intelligent recommendation mechanism of online learning resources. The "multimodal data fusion" aspect is adopted, illustrating online learning resource modeling, learning preference modeling, learning preference evolution, and referral engine smart design. Multimodal learning resources are key constituents of multidimensional intelligent recommendation services. The learner model that integrates multimodal preference data is the key to implementing smart recommendations. Learning preference evolution is a key factor in sustaining learner model robustness. The intelligent recommendation engine is the technical guarantee for developing an intelligent recommendation. Providing learning resources is an important part of online learning services, which mediate online learning processes. Intelligent recommendation, as an effective personalized servicing strategy, recommends differentiated, personalized, and precise learning resources to learners, thereby promoting the effectiveness of online learning performance. This study constructs a framework that reveals an intelligent recommendation mechanism for online learning resources.

KEYWORDS

data-driven; online learning resource; intelligent recommendation

The rapid development of mobile Internet technology and the prevalence of smart terminals have gradually brought online learning into the mainstream. At present, the technical and resource environment that online learning relies on has been available. However, inconsistency is observed between the rapid growth of massive learning resources and the ability to accurately match individual needs. As an effective mechanism for resolving information overload and providing customized services, artificial intelligence recommendation (AIRec) has been used extensively in customized learning services.

Scholars in China and abroad have conducted research and practice on AIRec for online learning resources with adaptive capability and obtained promising results. For example, Zhao et al.[1] provided learner knowledge and knowledge resource on the basis of knowledge recommendation technologies, such as ontological technology. Under pedagogical guidance, research on the personalized recommendation of knowledge-based learning resources has been conducted. Yin et al.[2] established an optimal solution-based learning model to maximize the learning efficiency of students by considering the relevance of learning objectives and environmental factors in the physical world. Petkovič et al.[3] and Tarus et al.[4] adapted ontological technology to denote knowledge structures and optimized personalized recommendations standing on the construction of ontology-based knowledge with advanced performance in terms of coverage, diversity, personalization, and cold start performance. Li et al.[5] proposed a personalized recommendation method on the basis of information gap and information loss gap by simulating user interest distribution. The similarity algorithm based on comprehensive information level distance and the similarity algorithm grounded information loss distance were used for such a distribution.

Although these studies have revealed resource modeling, algorithm optimization, and recommendation efficacy for AIRec, the following issues must be addressed: the acquisition strategy for learner preference data from multiple sources, learner preference adaptive mechanism, learner model construction by blending preference data from multiple sources, and AIRec model construction by integrating data from multiple sources. A successful solution to these problems is the foundation and key to improving the intelligence level of e-learning resource services.

This study aims to adopt a data-driven perspective and focuses on essential issues, such as learning resource modeling, learner modeling, learning preference evolution, and AIRec service engine design for online learning resources. The design aims to accommodate a reference for research on the AIRec of online learning resources.

1 Multimodal Online Learning Resource Modeling

With the continual advancement of the development and application of online learning resources, new trends have emerged in the scope, organization, design, and application and service mode of online learning resources[6]. These trends are mainly reflected in the extension of online learning resource scope, diversification of organizational forms, generation of design and application forms, and smart features for delivery service modes. In this study, we define all aforementioned online learning resources as multimodal learning resources. We also define online learning resources as learning contents (e.g., micro-lessons, videos,

1 School of Communication, Tianjin Foreign Studies University, Tianjin 300204, China
2 School of Education, The University of Hong Kong, Hong Kong 999077, China
3 School of Artificial Intelligence, Tianjin University of Science and Technology, Tianjin 300457, China
Address correspondence to Lina Yang, yanglina@tjsfu.edu.cn

handouts, materials, exercises, and assignments) that exist in the online learning environment, those that are constantly updated and generated during classroom interactions (e.g., asking questions, answering questions, responding to questions, resolving doubts, and collaborating with review resources), and social cognitive network resources based on online learning interactions (e.g., learning companions, learning circles, knowledge groups, and interactive communities). They are all considered online learning resources. On the basis of the definitions of online learning resources, this study constructs a multimodal online learning resource model for resource types, organizational forms, application behaviors, and resource evolution, as demonstrated in Fig. 1.

This learning resource model incorporates the entire process of designing and applying, organizing, producing, and evolving e-learning resources. This study categorizes online learning resources into three: fundamental, generative, and community resources.

Foundational resources refer to ones that are uploaded to the platform, such as teaching videos, course handouts, post-lesson exercises, post-lesson assignments, and course materials. These resources are structured ones that allow learners to systematically learn and interact and communicate with their peers during online learning sessions.

Generative resources are created based on foundational resources, which rely on online learning platform, question and answer sessions, interactive discussions, sustainable inquiries on knowledge, and other process-oriented resources emerging as students collaboratively editing on learning resources. The generative resources are dynamically updating and iterative, which characterize the generative and expansive nature of a learning process and provide important service for intelligent recommendation of online learning resources.

Community-based learning resources are online learning partners that learners meet during learning interactions, reciprocal learning groups (learning communities) based on a particular problem-solving exercise, and inquiry groups based on a particular discussion topic. Resources in this category are created and developed with learners' social learning process and are core service content from the AIRec online learning resources.

Given the differences in designs, organizational forms, and data formats of online learning resources, the organizational forms of online learning resources are mainly audio and video resources, multimedia resources, and learning resource databases aggregated in data centers of online learning platforms, common learning problem databases, and learners' personal knowledge banks. These different organized resource formats provide various forms of resources for different learning tasks, problems, subjects, needs, and preferences. They are also key resources for developing AIRec services in online learning resources.

A significant type of big data is how learners apply resources. The application behaviors of learners' online learning resources mainly include navigation, bookmarking, tracking, downloading, sharing, appreciation, and evaluation. Although these learning resource application behaviors are choices that learners make intentionally or unintentionally during the learning process, they can record and identify learner preferences and interests in learning resources from various aspects. Therefore, learners' different application behaviors with learning resources are critical data sources for building learner preference models and important data support for developing AIRec services based on learner behavioral characteristics.

The evolution of online learning resources mainly refers to the process of updating, iterating, and constantly generating learning resources. The online learning resources discussed in this study include not only structured and static learning resources researchers commonly note (e.g., learning videos and course handouts) but also learning resources continuously being updated, generated, and iterated during the learning process, such as different versions of resources generated by online learners in the collaborative editing process of certain resources, learning resources updated by instructors, and learning resources on course knowledge points or knowledge subjects that are constantly improved, updated, and aggregated through online learning platforms. The process of updating, generating, and modifying resources is a critical type of resource. Specifically, these resources are important types of tacit knowledge resources. By analyzing them, discovering learners' potential preferences for learning resources and interests is possible. In this study, these resources are considered important types of intelligent recommendation resources and crucial data sources for withdrawing learners' multisource preferences. These dynamic resources are useful for refining and improving the tacit knowledge of learners and promoting the internalization of their knowledge.

2 Learner Modeling Incorporating Multiple Preference Data Sources

Learner modeling is a comprehensive process for identifying, extracting, characterizing, and processing information about

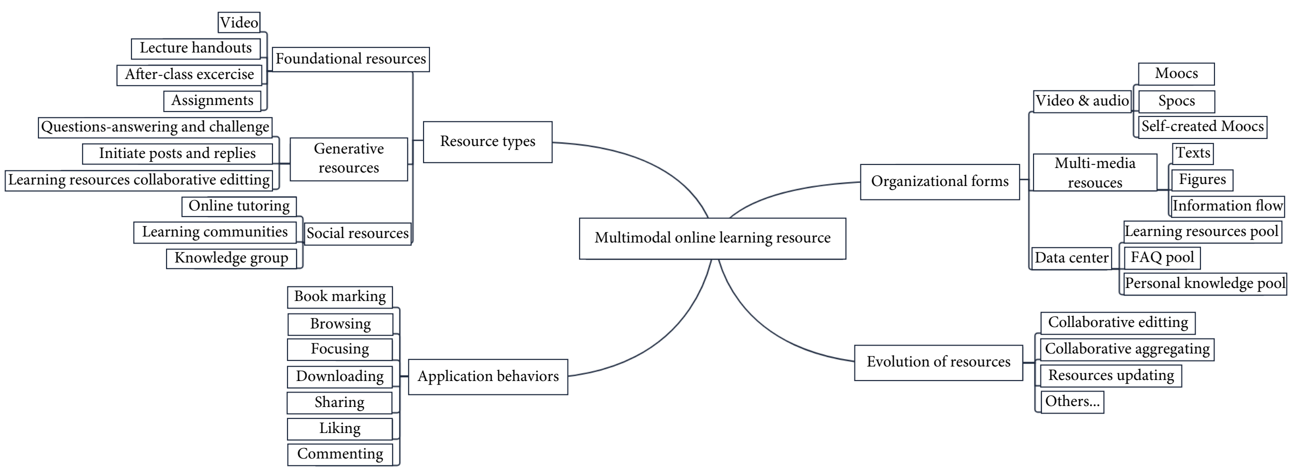

Fig. 1 Multimodal online learning resource model.

learner needs, interests, and preferences. In terms of mobility, production, and personalization of online learning, learner resource needs and preferences are influenced and adjusted by factors such as learning time, location, task, operation, and setting. To improve the accuracy of building a learner model, integrating preference data from multiple sources is necessary. Two key issues must be addressed to construct the learner model incorporating multiple sources of preference data: (1) preference data extraction from multiple sources; (2) learning preference model construction.

2.1 Preference data extraction from multiple sources

In traditional AIRec research, learner preference modeling is often constructed on the basis of a single behavioral trait. Such a modeling strategy relies too much on the type and number of learner behaviors and is effective for behavior-driven preference modeling. However, for data-driven resource recommendations, learner behavioral patterns can only represent their preferences for resources from one aspect but cannot fully express learner preferences for individualization and generative changes[7]. Meanwhile, given that learner interests constantly change across learning sessions, contexts, problems, and tasks, aggregating existing learner preference data and integrating the ever-changing preference data generated by learners are of great significance. Doing so also improves learning resource recommendations. Accordingly, to provide data support for building a learner model, this study concentrates on learner preference data from three dimensions: learner attributes, context perceptions, and socialization processes in learning based on the influencing factors of multiple source preferences.

2.1.1 Preference data based on learner characteristics

Learner characteristics are often described by specific attributes they possess. Variabilities of different learner characteristics can influence their preferences for learning resources. According to the marketing theories proposed by Kotler et al.[8], consumer purchasing preferences and behaviors are influenced by a combination of geographic, human, psychological, and behavioral factors related to user characteristics. Drawing on Kotler et al.'s[8] view of the effects of user characteristics on their preference behaviors, we proposed that online learner resource preferences also share similarities with user purchasing preferences in the commercial domain. Therefore, the preference data based on learner characteristics should include a wide range of dimensions and sources. In existing studies on intelligent recommendations of online learning resources, learner preferences are mostly modeled according to a single dimension of exogenous behavior. Few studies have examined a combination of learner characteristic factors, such as basic demographic information and learner psychological traits. Due to the multiple dimensions of learner characteristics, this article characterizes preference data on the basis of learner characteristics in terms of behavioral characteristics, basic demographic characteristics, and learning patterns.

2.1.2 Preference data based on learning contexts

Considering the online learning mobile nature, learning content generation, and social learning process, learner resource preferences are highly context-sensitive. Many factors influence the online learning context. Therefore, this study draws on Schmidt and Winterhalter's[9] idea of integrating key contextual information into digital learning service systems to quantify online learning context representation. It also argues that key contexts influencing online learner preference formation can be adapted to analyze contextualized learner preference needs. Moreover, learning resource attributes, learner categories, learning tasks, and learning processes are examined as key contextual factors for online learning. By aggregating, exploring, and analyzing these factors, learner resource preferences or preference tendencies can be explicitly or implicitly explored from the learning context perspective to provide a basis for AIRec standing on the ground of learning context perception.

2.1.3 Preference data based on learning community

Online learning is not only an interactive process between environments and resources but also among humans. Teacher-student and student-student interactions on online learning platforms accumulate a large amount of learning interaction data. These data not only reflect the social cognitive networks established between teachers and students but also imply learner and interaction preference patterns. By delving into and analyzing online learning social data, we not only can formally characterize the social cognitive networks established between teachers and students but also can predict learner preference patterns through the big data mining and analysis process. The essence of social cognitive network-based learner preference patterns is the exploration and analysis of potential learner preference patterns. Potential learner preferences are generally ambiguous, uncertain, and variable but often contain real learner needs on resources. Therefore, this research considers data generated during the socialization process in an online learning community as an important type of preference data, providing data support for learning preference model construction.

2.2 Learner model construction

2.2.1 Preference data based on learning contexts

Based on different organizational forms and service orientations of online learning resources, customization, tagging, and data-mining strategies are combined to build a learner model in this study. Preference modeling based on a personalization strategy enables learners to proactively and explicitly provide their preferences of interest. To provide learners with basic resource services and relevant recommendations, data on their personalized preferences are typically obtained from learners as they register and update their basic information. Labeling-based modeling is a strategy to identify and gather learner preferences by analyzing information on labels that learners put on the resources they use. By mining and analyzing tag data from learners, potential user resource preference patterns can be discerned. Learner preference modeling based on the data-mining strategy is used for analyzing and discovering preference patterns implicit in learners' characterization data, learning behavior data, and social learning data. This strategy builds the learner model by aggregating, analyzing, and uncovering potential or vague hobbies and interests implicit in learner characteristics, learning behaviors, and social cognitive networks[7]. This study combines customization, labeling, and discovery strategies to aggregate data on learner preferences and formalizes learner preferences by enhancing the traditional 2D approach. To solve the cold start and data-sparse problems of 2D arrays, building on the preference data from multiple sources described above, a brand new 2D scoring matrix is constructed by analyzing and uncovering potential preference patterns in online learner resource application behaviors and quantifying learner preference data from multiple sources. The problems can be solved by mining and formalizing learner preference data from multiple sources. The accuracy of learning resource recommendations can be improved at the same time. This article uses Eqs. (1) and (2) to construct scoring data elements in a 2D table that characterizes resource preferences.

$$r_{i,j}=\sum_{k=1}^{m}\frac{1}{1+\mathrm{e}^{-x/n+A}} \tag{1}$$

$$x=\sum_{h=1}^{n}\alpha\times G\_R_{(i,j,h)} \tag{2}$$

where $r_{i,j}$ represents learner i's rating on resource j, which is obtained by quantifying learner i's multiple resource application behaviors (e.g., browsing, printing, downloading, sharing, following, and rating) and covering various types of explicit and implicit behaviors that can characterize learner i's preference on applying learning resources. m indicates the types of application behaviors when learner i experiences resource j. n indicates the total number of application behaviors that have occurred while learner i uses resource j. $\sum_{k=1}^{m}\frac{1}{1+\mathrm{e}^{-x/n+A}}$ indicates the preference degree of learner i for resource j after m types of behaviors and n times of applications, in which x represents learner i's preference adjustment factor during n times of application behaviors in source j. The factor is determined by a recent (nearly one month) comprehensive evaluation $G\_R_{(i,j,h)}$ of all learners using the resource in the online learning environment and the weight α of this rating. A indicates the average preference threshold for an online learning resource. When an overall score for a specific resource in an e-learning environment exceeds this threshold, the learner preference level for that resource increases rapidly. The online learning resource preference scoring array, constructed from Eqs. (1) and (2), is as follows:

$$\begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,i} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,i} & \cdots & r_{2,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ r_{u,1} & r_{u,2} & \cdots & r_{u,i} & \cdots & r_{u,n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ r_{p,1} & r_{p,2} & \cdots & r_{p,i} & \cdots & r_{p,n} \end{pmatrix}$$

2.2.2 Learner model generation

Learner preference data and modeling strategies from multiple sources are defined to build an accurate learner model, and the learner modeling process is completed according to the above three types of preference data and modeling strategies from multiple sources, as represented in Fig. 2. Learner modeling comprises four key stages: data preparation, preference data analysis and convergence from multiple sources, learning resource preference generation, and learner modeling.

In the data preparation phase, three types of data (learner attributes, learning contexts, and social learning data) are processed to remove noise (irrelevant data) and are collected. Learner attribute data comprise data covering three main aspects: basic information (e.g., gender, age, education, occupation, and income), behavioral characteristic (e.g., autonomy, activity, and participation), and learning style (e.g., field-dependent or field-independent). Learning context data primarily include learning resource attribute data (e.g., resource format, category, access, and method sharing), learner types (e.g., new or old learner, active learner level), learning tasks (e.g., learning themes, ease of access, task type), and learning progress (e.g., before learning, during learning, after learning). Social learning data mainly comprise data generated during the cognitive network process (e.g., peers or study groups based on a particular knowledge point or learning task), task inquiry (e.g., collaborative inquiry processes driven by a learning task), and collaborative learning (e.g., peer mutual aid learning based on the learning theme or problem-solving). Although online learning platforms gather a great deal of learning data, given the unstructured and generative nature of the online learning process, this big dataset also contains useless, invalid, disorderly or meaningless data, which we refer to as "noisy data" or "noise". To screen online learner preference data from multiple sources and improve learner modeling accuracy, three major data types must be carefully handled to remove any noise. By removing noise and aggregating diverse online learning data from multiple sources, big data can support multisource preference data analytics and convergence.

The analysis and convergence phase of preference data from multiple sources includes four major tasks, including learning content, learning behavior, and learning interaction data analyses. Learning content data analysis mainly includes resource content analysis, resource type, content objective, and learning input data analysis. In addition, learning content data analysis mainly includes resource content analysis, resource type, content objective, and learning starting point data analysis to support content preference data generation. Learning behavior analysis is primarily about learner completion degree, learning engagement,

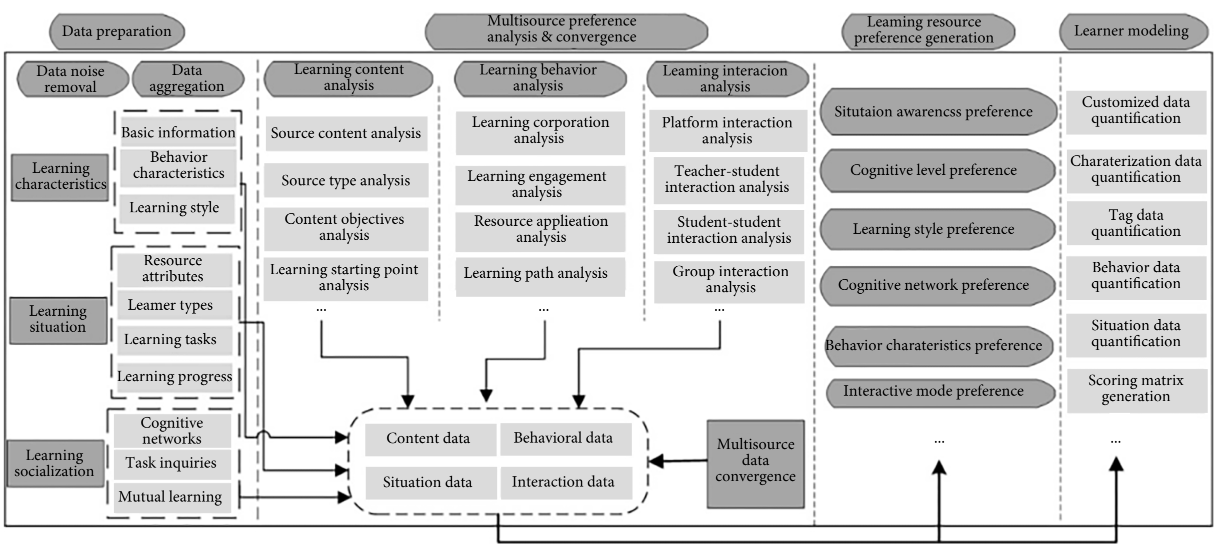

Fig. 2 Learner modeling process that incorporates preference data from multiple sources.

resource application, and learning path data, which are all analyzed to support behavioral preference data generation. Learning interaction analysis mainly involves the analysis of data such as interactions in platforms, interactions between students and teachers, student–student interactions, and group interactions to support the production of data on interaction preferences. Furthermore, by consolidating learning context data at the data preparation stage and adopting big data convergence technology, these multisource big data (including content, behavioral, context, and interaction data) are further extracted and converged to provide support for learner preference generation with different observable dimensions.

The learning resource preference generation phase focuses on resource preference aggregation for different service purposes to meet the intelligent and personalized needs of AIRec services for online learning resources. Hence, the learning resource preference generation process should be equipped with a multidimensional preference model generation mechanism. It concerns mainly six dimensions of learning resource preference generation: preference models based on learning context awareness, cognitive ability, learning style, cognitive network, interactive pattern, and behavioral pattern. The generation of learning resource preference models based on different observable dimensions is designed to meet the different learning resource needs of learners across different learning situations, thereby achieving the goals of recommending appropriate learning resources in a timely and on-demand manner and promoting effective learning for learners.

The last component is learner model generation. Multisource preference data and learner modeling strategies (by quantifying customized data, learner characterization data, learning resource tag data, learning behavior data, and learning context data) guide the construction of a learner's quantified scoring matrix for learning resources, providing data preparation for the selection and optimization of AIRec algorithms[10]. It also provides prototypic data support for evolving learning resource preferences.

3 Learning Resource Preference Evolution

A robotic learner model should be learning and evolving, capable of identifying, exploiting, and rapidly updating changes in learner preferences. It is a safeguard mechanism for realizing the self-adaptive service logic of AIRec. The subjective, mobile, contextual, and on-demand characteristics of online learning determine that a learner's resource preference is not constant but constantly updated by changes in learning situations, objectives, tasks, activities, and themes. This study refers to the constant process of learner resource preferences changing according to learning situations and practices as the dynamic evolution of learner resource preferences. Learner resource preference evolution is a logical abstraction of the generation, dynamics, and growth of online learner needs. To obtain precise, non-adversarial, and adaptive resource preferences for learners, this research draws on traditional analytical methods in the field of evolutionary computing. It focuses on investigating the evolving mechanisms of learner preferences in terms of learner characteristics, learning behavior evolution, and social cognitive network characteristics. It also uses formal characterization methods to represent learning resource preference evolution. The outline is expressed in Eqs. (3)–(6).

$$R_{i,t,j} = R_{i,t-1,j} + \frac{1}{\theta} \times \Phi\left(R_{i,t-1,j}\right) \times R_{i,t,j}^{\text{others}} \times \frac{\left(R_{\text{all},t,j}^{\text{others}} - R_{i,t-1,j}\right)}{D} \tag{3}$$

$$\Phi\left(R_{i,t-1,j}\right) = 1 - \frac{1}{1 + \mathrm{e}^{-\left(R_{i,t-1,j} - D\right)} / \sigma} \tag{4}$$

$$R_{i,t,j}^{\text{others}} = \sum_{k=1}^{m} \frac{1}{1 + \mathrm{e}^{-x/n+A}} \tag{5}$$

$$x = \sum_{h=1}^{n} \alpha \times G\_R_{(i,j,h)} \tag{6}$$

where $R_{i,t,j}$ represents learner i's preference for resource j at time t. $R_{i,t-1,j}$ represents learners preference for resource j at time $t-1$. $\frac{1}{\theta}$ is an evolutionary factor of preference, which determines how quickly a learner's preference for a particular resource evolves after multiple uses of it.

D is the upper threshold of a learning resource preference in an online learning environment. It is the average of the highest ratings by the vast majority of learners in an online learning environment for a specific resource or resource category, reflecting the degree of precision and personalization learners expect from learning resource recommendations. It is achieved through the extraction and analysis of measures of behaviors in the use of e-learning resources.

$\Phi(R_{i,t-1,j})$ is the preference tuning function. The parameter σ is the acceleration factor of the tuning function, which is used to adjust the preference changes of resources with high preference values and reduce their growth rates. The lower the value, the steeper the curve in the adjustment function and the greater the function. The tuning functions with different values of σ are different, and but their effects vary according to the relationship between learners' preference(s) for particular online learning resources and their preference's upper threshold. $\sum_{k=1}^{m} \frac{1}{1+\mathrm{e}^{-x/n+A}}$, m, n, and A have the same meanings noted above. These do not need to be repeated here.

$R_{\text{all},t,j}^{\text{others}}$ indicates the overall preference for resource j at time t for all learners except learner i. $\frac{\left(R_{\text{all},t,j}^{\text{others,}} - R_{i,t-1,j}\right)}{D}$ represents the amount of deviation from the overall preference for resource j at time t for all learners except learner i and for learner i's preference for resource j at time t–1. The effect of this preference deviation is to truly reflect how learner preferences change after online learning resource experiences. If the resource preference deviation distribution for two consecutive moments has a bias value of less than zero over a certain period and the peak value is greater than 0, then the AIRec engine does not extract new learner preferences or potential resource preference patterns well and must adjust the AIRec strategy and optimize its recommendation algorithm accordingly. The research and application exploration of this evolutionary mechanism is an important feedback mechanism for improving online learning resources for AIRec services and optimizing its recommendation algorithms.

4 Online Learning Resource AIRec Engine Design

The AIRec engine is a comprehensive representation of the service's core components for learning resource recommendation and its artificial intelligent (AI) capabilities. Its core mission is to establish a self-adaptive and dynamic matching mechanism between learner needs and learning resources and to recommend learning resources that are personalized and contextualized for individual learners. The online learning resource model and the learner preference model established by the research mentioned above are the foundation and key to the delivery of AIRec for online learning resources. The learning resource model provides a resource matching source for AIRec. The learner model serves as the basis for choosing and optimizing AIRec algorithms. The AIRec engine is the operational logic and technical assurance to implement the AIRec of online learning resources. Based on the online learning process and the key steps for AIRec implementation, this study identifies that the AIRec engine comprises the underlying data layer, model generation layer, recommendation algorithm layer, and recommendation service layer. The online learning resource AIRec engine is designed, as illustrated in Fig. 3.

4.1 Underlying data layer

Data are the cornerstone of AIRec. High volumes of accurate data are needed to model learning resources and learners. The underlying data layer is responsible for the noise removal, screening, collation, and data transformation of online learning big data, supporting the accurate construction of the learning resource model and learner model with big data. Big data uncovered at the underlying data layer primarily comprise sensory data captured from sensing devices in the real world and teaching and learning data from the virtual world[11]. Sensory data from detection devices are unstructured in which smart sensors, radio frequency identification (RFID), GPS, and other devices fully discern learning situations, which include learning time, location, surroundings, and network information. Education and learning data in the virtual world mainly include basic learner information, learning resources, learning behaviors, and learning data that are continually generated throughout the learning process.

4.2 Model generation layer

The model generation layer gathers sensory, teaching, and learning data from the underlying data layer by adapting data aggregation, mining, quantification, and visualization techniques to build and generate learning resource and learner models. The process of building both types of models has already been described, so repeating it here is no longer necessary. The learning resource model is a key component of AIRec engine services. Given the generative and evolutionary nature of online learning resources, the learning resource model contains a dynamic update mechanism for updating learning resources, learning interactions, and procedural resources that are constantly generated, changed, and updated during the online learning process. It is done in real-time to match learner needs and preferences for dynamically shifting resources. The learner model is a critical basis for AIRec engine services. The precision on which the learner model is built directly determines and influences the precision with which the AIRec engine works. Without a doubt, the learner model directly determines the selection and optimization of the AIRec algorithm. Given the dynamic evolution of online learner resource preferences, the learner model has a self-adaptive and updating mechanism that dynamically updates and evolves on the basis of the preference evolution mechanism designed above.

4.3 Recommendation algorithm layer

The recommendation algorithm layer consists of a

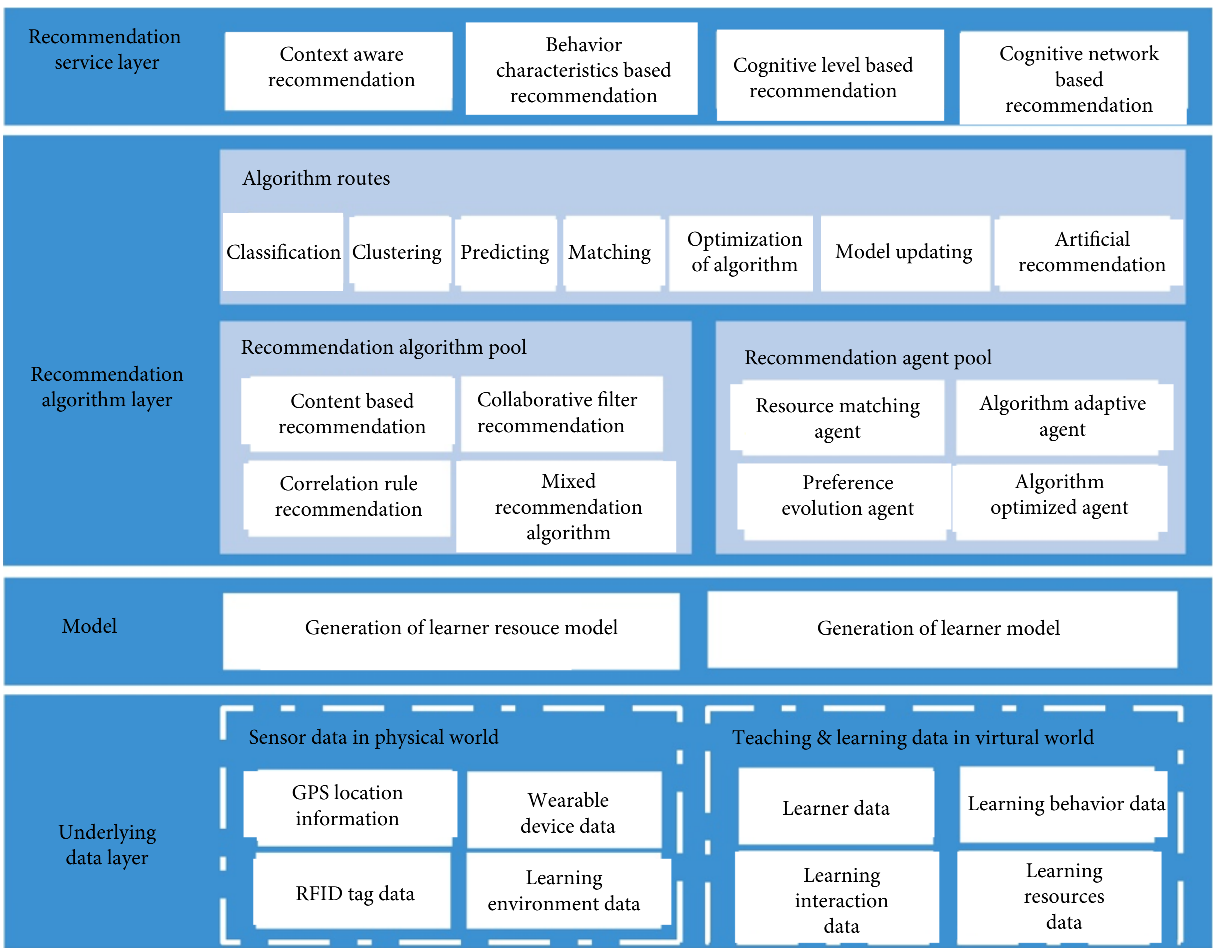

Fig. 3 Online learning resource AIRec engine.

recommendation algorithm, which groups together the construction of the recommendation agent library and the AIRec algorithm implementation route. The recommendation algorithm library is made up of classic recommendation algorithms, such as content-based recommendations[12], collaborative filter recommendations, correlation rule recommendations, and hybrid recommendation algorithms[13]. The referral agent library is primarily stocked with agent designs to encapsulate the key technical logic of AIRec learning resources. The agent is a software entity that can identify and solve problems and communicate with the outside world. It can continue to function autonomously and has extensive learning capabilities to track learning trajectory analysis results and automatically suggests relevant information resources to learner clients. The key implementation logic implemented by AIRec is encapsulated in resource matching, preference evolutionary, algorithm-adaptive, and algorithm-optimized agents, all of which work to encapsulate key technical logic for AIRec implementation, matching learning resources to learner model, learner preferences, adapting and optimizing recommendation algorithms. The AIRec algorithm routing is a key implementation logic characterization of AIRec algorithms, consisting essentially of the classification and clustering of big data, prediction and analysis of learner preferences, optimization of AIRec algorithms, updating of resources and learner models, and implementation of the AIRec on this basis.

4.4 Recommendation service layer

The recommendation service layer is a service adaptation layer for online learners. It provides recommendation services utilizing a multi-agent coordinated intelligent recommendation engine to provide multimodal, accurate, and novel online learning resource services for online learners, including resource recommendations based on learning context perceptions, behavior characteristics, cognitive levels, and cognitive networks[14]. The recommended learning resources include not only structured online learning micro classes, course handouts, and learning resources but also procedural resources that are constantly generated during the learning process, such as interactive themes, high-praise posts, follow-ups, learning companions, learning activities, and learning strategies to help online learners improve their learning effectiveness, enhance their cognitive abilities and learning efficiencies. Given that the AIRec engine contains a mechanism for the learning and dynamic updating of learner resource needs and preferences, the recommendation service layer presents a different service interface and recommendation resources to various learners. It is an effective mechanism for personalizing online learning resources.

5 Conclusion

With the rapid development of the Internet and big data technology, the scale of information systems becomes increasingly large, the structure and content of information become increasingly complex, and the amount of information increases exponentially, which may lead to the problem of “information overload”. E-learning has progressively become a new norm for learning. As an important online learning medium and service, providing appropriate learning resources is an important factor affecting online learning effectiveness. Carrying out the intelligent recommendations of online learning resources is a useful exploration to improve online learning effectiveness and enrich the learning experience. It is also an effective way to solve information overload caused by the massive growth of learning resources. High-quality data are the cornerstone to ensure the effects of intelligent recommendations of online learning resources. The accurate identification and acquisition of learner preferences are the basis for obtaining accurate recommendation services.

Although existing research has investigated learner preferences from multiple perspectives to construct user preference models, only a few studies have integrated information from an authentic environment. Specifically, in an open and personalized online learning environment, learner needs and preferences are dynamically changing, with changes in learning tasks, problem-solving skills, and learning situations. To investigate the intelligent recommendation mechanism of online learning resources, we must analyze learning resources, learner preferences and their evolution, and how intelligent recommendation algorithms and intelligent recommendation services adapt to the dynamic changes. This study analyzes the implementation mechanism of the intelligent recommendations of online learning resources from perspectives of data-driven and multisource data fusion. The findings indicate that multisource big data are the cornerstone of intelligent recommendations. The learner model integrating multisource preference data is the key to the development of intelligent recommendations, and the intelligent recommendation engine with an adaptive learning mechanism is the technical guarantee of intelligent recommendations. With the continued advancement of online learning research and practice, the personalized and smart needs of online learning resource services are emerging. Further exploring and adopting relevant information technologies are necessary to investigate and apply the service levels of online learning resources for promoting the effectiveness of online learning for learners.

Acknowledgment

This work was supported by the National Social Science Foundation (No. BCA180095).

Dates

Received: 16 March 2022; Revised: 11 May 2022; Accepted: 11 May 2022

References

[1] W. Zhao, Q. Jiang, P. Wang, and L. Wang, Ontology-driven personalized recommendation of knowledge resource in e-Learning, (in Chinese), *China Educ. Technol.*, vol. 5, pp. 84–89, 2015.

[2] P. Y. Yin, K. H. Chuang, and G. J. Hwang, Developing a context-aware ubiquitous learning system based on a hyper-heuristic approach by taking real-world constraints into account, *Univers. Access Inf. Soc.*, vol. 15, no. 3, pp. 315–328, 2016.

[3] D. Petkovič, N. Denić, and G. Perenić, An ontology-based model for contextual recommendations in e-learning, *Int. J. Technol. Educ. Sci.*, vol. 1, no. 1, pp. 18–23, 2017.

[4] J. K. Tarus, Z. Niu, and G. Mustafa, Knowledge-based recommendation: A review of ontology-based recommender systems for e-learning, *Artif. Intell. Rev.*, vol. 50, no. 1, pp. 21–48, 2018.

[5] X. W. Li, S. Ying, and W. Hong, Research on personalized recommendation method based on ontology and information fusion, (in Chinese), *Inf. Sci.*, vol. 37, no. 9, pp. 90–95, 2019.

[6] M. del Carmen Rodríguez-Hernández and S. Ilarri, Ai-based mobile context-aware recommender systems from an information management perspective: Progress and directions, *Knowl.-Based Syst.*, vol. 215, p. 106740, 2021.

[7] L. Yang, N. Xiao, P. Yin, and H. Ma, Modeling strategies for user

preferences from multi-source data convergence in ubiquitous learning personalized recommendation, (in Chinese), *J. Tianjin R TV Univ.*, vol. 20, no. 2, pp. 10–16, 2016.

[8] P. Kotler, G. Armstrong, S. H. Ang, S. M. Leong, C. T. Tan, and D. K. Tse, *Principles of Marketing: An Asian Perspective*. Singapore: Pearson Education Asia Limited, 2011.

[9] A. P. Schmidt and C. Winterhalter, User context aware delivery of e-learning material: Approach and architecture, *J. Univers. Comput. Sci.*, vol. 10, no. 1, pp. 38–46, 2004.

[10] A. Y. Alsobhi and K. H. Alyoubi, Adaptation algorithms for selecting personalised learning experience based on learning style and dyslexia type, *Data Technol. Appl.*, vol. 53, no. 2, pp. 189–200, 2019.

[11] S. Ahmed, S. Javaid, M. F. Niazi, A. Alam, A. Ahmad, M. A. Baig, H. K. Khan, and T. Ahmed, A qualitative analysis of context-aware ubiquitous learning environments using Bluetooth beacons, *Technol., Pedag. Educ.*, vol. 28, no. 1, pp. 53–71, 2019.

[12] J. Shu, X. Shen, H. Liu, B. Yi, and Z. Zhang, A content-based recommendation algorithm for learning resources, *Multimedia Syst.*, vol. 24, no. 2, pp. 163–173, 2018.

[13] J. Xu, T. Xing, and M. van der Schaar, Personalized course sequence recommendations, *IEEE Trans. Signal Process.*, vol. 64, no. 20, pp. 5340–5352, 2016.

[14] J. Muangprathub, V. Boonjing, and K. Chamnongthai, Learning recommendation with formal concept analysis for intelligent tutoring system, *Heliyon*, vol. 6, no. 6, p. e05227, 2020.