Relevant tables

This supplementary material contains several tables cited in the main text. These tables summarize the literature on cognitive diagnosis (Table S1), learning style analysis (Table S2), student sentiment analysis (Table S3), student behavior analysis (Table S4), student performance prediction from a non-cognitive perspective (Table S5), personalized learning path recommendation (Table S6), personalized course recommendation (Table S7), and personalized exercise recommendation (Table S8). It also includes Table S9, which summarizes mainstream intelligent educational software and their characteristics.

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Table S1 Summary of cognitive diagnosis literature

References	Categories	Technique	Motivation 1)	Dataset	Indicator	Code 1)
[1]	Pedagogical theory-driven	Fuzzy Theories, Assumptions	Partial data utilization, narrow scope of analysis	FrcSub, Math1, Math2	RMSE, MAE	No
[2]	Pedagogical theory-driven	NS, MF, CF	Incomplete information modeling	FrcSub, Math2015, ASSISTments	RMSE, ACC, Precision, Recall, F1	No
[3]	Pedagogical theory-driven	Context-aware Modeling, Hierarchical Attentive Network	Introducing educational contexts	PISA 2015	RMSE, AUC, ACC	No
[4]	Pedagogical theory-driven	Rough Concept Analysis, IRT	Multidimensional	FrcSub, Math1, Math2	MAE, RMSE	No
[5]	Pedagogical theory-driven	Psychometric-based Ability Estimation Paradigm	Uncertainty	FrcSub, Math, Eedi	Customizable	Yes
[6]	Data-driven (Deep-learning)	Relation Map Driven, Hierarchical Attention Network	Exploring deeper concept relationships	Junyi, ASSISTments	RMSE, ACC, AUC	Yes
[7]	Data-driven (Deep-learning)	Knowledge Embedding Matrix	Exploring deeper concept relationships	Junyi, Math	RMSE, ACC, AUC	Yes
[8]	Data-driven (Deep-learning)	Neural Network, Graph-Based Representation	Exploring deeper concept relationships	ASSISTments, Math	RMSE, ACC, AUC	No
[9]	Data-driven (Deep-learning)	Self-Supervised Learning, Graph-Based	Data sparsity	ASSISTments, Junyi	RMSE, ACC	Yes
[10]	Data-driven (Deep-learning)	Deep Neural Network, MIRT	Cross-modality, Partial data utilization	Self-built data, Junyi	RMSE, ACC, AUC, Precision, Sensitivity, F1	No
[11]	Data-driven (Deep-learning)	GCN	Zero-shot	Core Math, Advanced Math, Junyi, ASSISTments	RMSE, ACC, AUC	Yes
[12]	Data-driven (Deep-learning)	Neural Network	Limited feature representation	FrcSub, Math1, Math2, ASSISTments	RMSE, MAE, ACC, AUC	Yes
[13]	Data-driven (Deep-learning)	Neural Network	Exploring deeper concept relationships	ASSISTments, Math, Algebra, Bridge	RMSE, ACC, AUC	No
[14]	Data-driven (Deep-learning)	Information-weighted Sampling Strategies	Data sparsity, Long-tail	Junyi, ASSISTments	RMSE, ACC, AUC	Yes
[15]	Data-driven (Deep-learning)	Heterogeneous Graph, Attention Mechanism	Incomplete information modeling	ASSISTments	RMSE, ACC, AUC	No
[16]	Data-driven (Deep-learning)	Self-Attention Gating, Meta-Learning	Zero-shot	ASSSITments, FrcSub, Math1, Math2	RMSE, Precision, F1, AUC	No
[17]	Data-driven (Deep-learning)	Homogeneous Group Mining, Multi-Grained Modeling	Group cognitive diagnosis	ASSISTments	RMSE, MAE	No
[18]	Data-driven (Deep-learning)	NN, Multi-Task Learning	Multidimensional	PISA 2015, Math, Junyi, ASSISTments	RMSE, ACC, AUC	No

Table S1 (continue)

References	Categories	Technique	Motivation1)	Dataset	Indicator	Code1)
[19]	Data-driven (Deep-learning)	Transfer Learning, Dual Regularization	Zero-shot	iFLYTEK Learning Machine1	RMSE, ACC, AUC	Yes
[20]	Data-driven (Deep-learning)	Clustering, Sampling Strategies, Self-Attention	Data sparsity	ASSISTments, Math	RMSE, ACC, AUC	Yes
[21]	Data-driven (Deep-learning)	Neural Network	Interpretability	ASSISTments, Algebra, Math1, Math2	RMSE, ACC, F1, DOA, Customizable	Yes
[22]	Data-driven (Deep-learning)	GNN, Transformer, Hierarchical Graph Construction	Group cognitive diagnosis	ASSISTments, NIPS-Edu, SLP	RMSE, MAE	No
[23]	Data-driven (Deep-learning)	GCN, Induction	Zero-shot, Interpretability	FrcSub, EdNet-1, ASSISTments, NeurIPS20	RMSE, ACC, AUC, DOA	Yes
[24]	Data-driven (Deep-learning)	GNN	Group cognitive diagnosis	ASSISTments, NIPS_Edu, SLPbio, SLPmath	RMSE, MAE	Yes
[25]	Data-driven (Deep-learning)	Response-aware GCN	Oversmoothing	ASSISTments, EdNet-1, Junyi, XES3G5M	ACC, AUC, DOA, Custom Oversmoothing Metric	Yes
[26]	Data-driven (Non-deep-learning)	ACO Algorithm	Limited applicability and slow convergence of heuristics	self-built	A/B testing	No
[27]	Data-driven (Non-deep-learning)	Feature Extraction, Traditional Optimization	Incomplete information modeling	Math1, Math2	RMSE, MAE	No
[28]	Data-driven (Non-deep-learning)	Causal Model	Data sparsity, Interpretability	Junyi, Math1, Math2	DOA, AH Metric	No
[29]	Data-driven (Non-deep-learning)	Bayesian Network, Meta-Learning, Variational Reasoning	Interpretability	ECPE, ASSISTments, EXAM	ACC, AUC, ECE	No
[30]	Data-driven (Non-deep-learning)	Bayesian Network	Exploring deeper concept relationships	Junyi, Math	RMSE, ACC, AUC, F1, ODA	Yes
[31]	Data-driven (Non-deep-learning)	Item Response Ranking, Pairwise Learning	Incomplete information modeling	ASSISTments, Math	AUC, Precision, Recall, F1, DOA	No
[32]	Data-driven (Non-deep-learning)	Causal Reasoning, Statistical Learning	Fairness issues	PISA 2015	ACC, AUC, DOA, Customized metrics	Yes
[33]	Integration methods	DNN, LSTM, IRT	Improvements in traditional methods	self-built	RMSE, MAE, ACC, AUC	No
[34]	Integration methods	Context-aware Attention Network, Neural Network	Group cognitive diagnosis	ASSISTMents, Math	RMSE, MAE	No
[35]	Integration methods	Monotonicity Assumption, Neural Network	Limited feature representation	ASSISTments, Math	RMSE, ACC, AUC, DOA	Yes
[36]	Integration methods	Monotonicity Assumption, Neural Network	Limited feature representation, Exploring deeper concept relationship	ASSISTments, Math	RMSE, ACC, AUC	Yes

Table S1 (continue)

References	Categories	Technique	Motivation[1]	Dataset	Indicator	Code[1]
[37]	Integration methods	Bayesian Network, NN, Causal Inference, Feature Engineering	Interpretability	ASSISTments, Junyi, Math1, Math2	RMSE, ACC, AUC, DOA	No
[38]	Integration methods	Adversarial Learning, Theoretical Analysis	Fairness issues	PISA-OECD, PISA-deen	RMSE, MAE, ACC, AUC, —F_{CD}—	No
[39]	Integration methods	Affective State Modeling, NN	Introducing the affective element	ASSISTments, Junyi	RMSE, ACC, AUC	No

[1]"Motivation" refers to the primary research objective of the article, highlighting the key problem it addresses. "Code" indicates whether the article has publicly released its code, with 'yes' denoting availability and 'no' indicating non-disclosure.

[2]NS: Neutral Set Theory, CF: Collaborative Filtering, MF: Matrix Factorization, GNN: Graph Neural Network, GCN: Graph Convolutional Network, DNN: Deep Neural Networks, LSTM: Long Short-Term Memory, NN: Neural Networks

Table S2 Summary of studies on learning style analysis

References	Style	Technique	Study Type	Dataset		Indicator	Research Outcomes
				Name	Link		
[40]	FSLSM	ACS, ANN, Confidence-based Segmentation	System development	Self-built data	NA	SIM, ACC, LACC, %Match	Proposing a common architecture that can be integrated into education systems
[41]	FSLSM	Multilayer Perceptron, DT	System development	Self-built data	NA	Correctly classified instances, Kappa statistics, Root mean squared error	Developed a tool that can consider multiple learning modalities
[42]	FSLSM	K-means, NB	Algorithm validation	E-learning platform log files	http://www.supmanagement.ma/fc/login/index.php	Confusion matrix	Propose a method for automatic detection of learning styles
[43]	FSLSM	Multi-target Classification, ANN	Algorithm validation	Self-built data	NA	Sensitivity, Specificity, Prevalence, PPV, NPV, ACC, Precision, Recall, F1, ACC	Proposing a deep multi-objective prediction algorithm
[44]	FSLSM	Improved K-means	Practical experiments on moodle	Moodle learning management system	NA	NA	Practical experiments on the Moodle LMS
[45]	FSLSM	DT, RF, KNN, NN, Cluster Analysis	Algorithm validation	Stanford edX "Statistical Learning" (Winter 2015 & 2016), provided by CAROL	NA	Confusion matrix, ACC, Precision, Recall, F1, Macro-precision	Existing classification methodology test
[46]	FSLSM	NN	Algorithm validation	Self-built data	NA	Verification in practical experiments	Recognizing learning styles with neural networks
[47]	FSLSM	Fuzzy Mean, BPNN, GSA	Algorithm validation	Website collection	http://www.mitelearning.com	Precision, Recall, F1, ACC	Proposing a method for automatic detection of learning styles
[48]	FSLSM	K-means, RF, SVM, DT, LR	Algorithm validation, System development	Stanford edX "Statistical Learning" (Winter 2015 & 2016), provided by CAROL	NA	Verification in practical experiments	A personalized adaptive e-learning system, "Adaptivo," is proposed

Table S2 (continue)

References	Style	Technique	Study Type	Dataset		Indicator	Research Outcomes
				Name	Link		
[49]	FSLSM	RF, Voting Ensemble	Algorithm validation	Self-built data	NA	T-test, VIF	The impact of learning styles on academic achievement is explored, emphasizing that while changes in learning styles can improve short-term engagement and comprehension, effective study habits play a more critical role in ensuring long-term academic success
[50]	FSLSM	K-means, Dynamic Bipartite Graph, LSTM	Algorithm validation	KDDCup 2015	NA	ACC, Precision, Recall, F1	Proposing a learning style detection method based on bipartite graph
[51]	FSLSM	NB, NN, DT, RF	Algorithm validation,system development	XuetangX	https://www.xuetangx.com/	ACC, Precision, Recall, Macro-averaged precision, Micro-averaged precision	A prediction system is proposed
[52]	FSLSM	self-training, SVM	Algorithm validation	Self-built data	NA	Precision, Recall, AUC	The introduction of self-training machine learning methods
[53]	VARK	K-means, SVM, DT	Algorithm validation	Self-built data	NA	Verification in practical experiments	A study of the performance of classification algorithms
[54]	VARK	K-means, XGBoost, SVM, LR	System development	Self-built data	NA	ACC	A Moodle-compatible plugin was implemented within the learning management system (LMS)
[55]	MI Theory	DT, SVM, K-nearest neighbors, NB, LDA, RF, LR	Algorithm validation	Self-built data	NA	ACC, AUC, Precision, Recall, F1	Existing classification methodology test
[56]	Kolb	Clustering, SMOTE, Semi-supervised, RF, GDBT, SVM, MLP, LR	Algorithm validation	Self-built data	NA	ACC, Recall, Precision, F1	Proposing multiple classification model fusion methods
[57]	Kolb	Matching	Application	Self-built data	NA	Relevance	Application of learning styles

[0]ACS: Ant Colony System, ANN: Artificial Neural Networks, NN: Neural Networks, BPNN: Back Propagation Neural Network, GSA: Gravity Search Algorithm, RF: Random Forest, SVM: Support Vector Machine, DT: Decision Tree, LR: Logistic Regression, LDA: Linear Discriminant Analysis, NB: Naïve Bayes, KNN:k-Nearest Neighbors

[0]SIM: Similarity, ACC: Accuracy, LACC: Lowest Accuracy, %Match: Customized metrics

Table S3 Summary of studies on student sentiment analysis

References	Classification	Technique	Study Type	Dataset		Indicator	Research Outcomes
				Name	Link		
[58]	Machine learning, MOOCs/Online learning	SVM, NB, LR, GB, RF, NN	Algorithmic model	Self-built data	NA	ACC, Precision, Recall, F1, Kappa	Sentiment analysis of comments on MOOC forums and existing classification methodology test
[59]	Machine learning, MOOCs/Online learning	KNN, GDBT, SVM, LR, NB	Algorithmic model	Self-built data	NA	ACC, Precision, Recall, F1, Kappa	Using machine learning algorithms to analyze student satisfaction with MOOCs
[60]	Machine learning	NB, Multinomial NB, SVM, ME	Algorithmic model	Self-built data from Twitter, Facebook and Moodle	NA	ACC, Precision, Recall, F1	Analyzing student sentiment using machine learning algorithms
[61]	Machine learning	Multi-swarm Particle Swarm Optimization	Algorithmic model	Massive open online course	http://open.163.com/	Precision, Recall, F1, AUC	Dimensionality and redundancy reduction in feature space
[62]	Machine learning	Crowdsourcing, SVM, RF	Algorithmic model	Self-built data	NA	Recall, Precision, F1, Negative class recall	Improving sentiment analysis through student crowdsourcing labels and analyzing the differences between crowdsourcing and expert annotations
[63]	Machine learning, Educational environments	NB, SVM, DT, RF	Algorithmic model	Self-built data	NA	Precision, Recall, F1, AUC	Existing classification methodology test
[64]	Deep learning, MOOCs/Online learning	Weakly Supervised, CNN	Algorithmic model	Self-built data (Coursera)	NA	Precision, Recall, F1	Recognizing student emotions using weakly supervised signals
[65]	Deep learning, Educational environments	LSTM	Algorithmic model	Self-built data	NA	ACC, Precision, Recall, F1	Sentiment analysis of student feedback for instructional performance evaluation
[66]	Deep learning, MOOCs/Online learning	BERT, CNN, Self-Attention	Algorithmic model	Self-built data (MOOC course reviews)	NA	ACC, F1	Reducing the parameters of BERT by half achieves almost the same performance
[67]	Deep learning, Educational environments	SVM, CNN	Algorithmic model	Self-built data	NA	ACC, Precision, Recall, F1	Using sentiment analysis for academic prediction
[68]	Deep learning	Bi-LSTM, Attention, Average Pooling	Algorithmic model	Self-built data	NA	Precision, Recall, F1	Research has shown that models that use subject dictionaries as inputs perform best in combination with attentional mechanisms
[69]	Deep learning	TextBlob, Bi-LSTM	Application systems	Self-built data	NA	Precision, Recall, F1	Analyzing and categorizing students' qualitative feedback using Biggs models
[70]	Hybrid and advanced techniques	Albert, Attention Mechanisms, BiGRU, Capsule Networks	Algorithmic model	Self-built data (MOOC course reviews)	NA	ACC, Precision, Recall, F1	Addresses the limitation of traditional sentiment analysis in distinguishing word meanings across contexts
[71]	Hybrid and advanced techniques	BNN, CNN, LSTM	Algorithmic model	Coursera	https://www.kaggle.com/septa97/100k-courseras-course-reviews-dataset	ACC, Precision, Recall, F1	Quantifying uncertainty in sentiment analysis tasks

Table S3 (continue)

References	Classification	Technique	Study Type	Dataset		Indicator	Research Outcomes
				Name	Link		
[72]	Hybrid and advanced techniques, MOOCs/Online learning	EvoMSA, NB, KNN, DT, SVC, RF, LSTM, CNN, BERT, EvoMSA	Algorithmic model	Self-built data (Udemy, Platzi, YouTube)	NA	ACC	Existing classification methodology test
[73]	Hybrid and advanced techniques, MOOCs/Online learning	BERT, LSTM, CNN	Algorithmic model	Self-built data (Coursera)	NA	ACC, Precision, Recall, F1	Multiple model fusion modeling
[74]	Hybrid and advanced techniques	Multi-Task Cascaded Convolutional Networks	Algorithmic model	Self-built data	NA	Verification in practical experiments	Algorithmic bias analysis, integration of sentiment and classroom data, Improved accuracy and fairness of sentiment identification in education
[75]	Hybrid and advanced techniques	LLM	Algorithmic model	Self-built data	NA	Confusion matrix, ACC, Precision, Recall, F1, Kappa, Mathew Correlation Coefficient	Explored the potential of LLM in sentiment analysis
[76]	Educational environments	Relevance Mining	Algorithmic model	Self-built data	NA	ACC, Precision, Recall, F1	Researching student attitudes toward classroom instruction and identifying strategies for instructional improvement
[77]	Educational environments	NA	System development	Coursera, Self-built data	NA	Verification in practical experiments	Presentation of the SA system
[78]	Educational environments	LLM	Algorithmic mode	Self-built data (Twitter)	NA	ACC, Precision, Recall, F1	Proposing a sentiment analysis model for tweets related to ChatGPT in education
[79]	MOOCs/Online learning	Learning Analysis	Algorithmic model	Self-built data	https://media.readthedocs.org/pdf/devdata/latest/devdata.pdf	Verification in practical experiments	Observed a decrease in positive sentiment over time and before the deadline for open-ended assignments
[80]	MOOCs/Online learning	Recursive CNN	Algorithmic model	Class Central	https://www.classcentral.com/help/highest-rated-online-courses	Precision, Recall, F1	Using sentiment analysis and deep learning to identify key factors influencing learner satisfaction
[81]	MOOCs/Online learning	Crowdsourcing	Algorithmic model	Self-built data (Coursera)	NA	Data analysis	Identifying key factors like course design and material quality that drive MOOC success

Table S4 Summary of student behavior analysis literature

References	Algorithm Category	Technique	Behavioral factor	Dataset	Indicator	Research Outcomes
[82]	Cluster algorithm, Association rule	K-Mediods, Eclat	Frequency of Consumption, Books borrowed amounts, Frequency of Library visits, Total Study Time	Self-built data	Correlation analysis	A hybrid student behavior analysis algorithm incorporating clustering and association rules is proposed
[83]	Cluster algorithm	Self-Organizing Map Clustering	Questionnaires, Academic performance, Number of forum visits, Participation in online courses	Self-built data	Verification in practical experiments	Behavioral analysis using Self-organizing map artificial neural network
[84]	Cluster algorithm	DBSCAN, K-Means	Average consumption level , Library access, Average daily online hours	Self-built data	Verification in practical experiments	Analyzed the relationship between different behavioral patterns and students' GPA
[85]	Cluster algorithm, Machine learning	K-Means, PCA	Average consumption level , Library access, Online activity duration, Workout log	Self-built data	Cluster analysis	Simple behavioral analysis
[86]	Cluster algorithm	LDA	Student self-evaluation text	Self-built data	Correlation analysis	The LDA model can efficiently extract keywords and fuzzy recognize different levels of student groups
[87]	Association rule	Data Correlation Mining	Academic performance, Average consumption level, Breakfast frequency, Average daily online hours, Canteen meal frequency, Books borrowed amounts	Self-built data	Chi-square test	Designing a four-tier architecture for data correlation mining, encompassing data collection, storage, computation, and analysis
[88]	Machine learning	NB, DT, RF	Basic student information, Video viewing hours, Chapter quiz scores, Programming exam scores	Self-built data	Verification in practical experiments	Proposing quantitative metrics to assess learners' motivation and the stability of blended learning behaviors.
[89]	Machine learning	NB, DT, NN	Average consumption level, Books borrowed amounts, Average daily online hours, Academic performance, Number of physical activities	Self-built data (Spark Platform)	Verification in practical experiments	Simple behavioral analysis
[90]	Machine learning	NB, DT, KNN, NN, RF	Information literacy learning Data	Self-built data	PCC, ACC, Precision, Recall, F1, KIA	A significant correlation was found between information thinking traits and learning outcomes
[91]	Machine learning	IPW, SA	Interactive information on curriculum resources	Self-built data	Customized metrics	Assessed the causal impact of the Learning Analytics Dashboard on student behavior and achievement, highlighting the interplay between motivation, self-regulation, and prior achievement
[92]	Machine learning	Supervised Machine Learning	Online learner behavior	Self-built systematic collection	Confusion matrix, ACC, Precision, Recall, Sensitivity, F1	A supervised machine learning-based intelligent model is proposed for e-learning systems
[93]	Integrated Study	Apriori, Hadoop MapReduce	Number of visits to the LMS, tools used by students and their related incidents	Self-built data	Case Studies	Conducting case studies on student behavior

Table S4 (continue)

References	Algorithm Category	Technique	Behavioral factor	Dataset	Indicator	Research Outcomes
[94]	Integrated Study	Sequence Analysis	Cloud classroom learning behavior: Video watching, Submitting assignments, Viewing announcements	Self-built data	Verification in practical experiments	Analyzing the main reasons behind the different behavioral patterns of students in the cloud classroom
[95]	Integrated Study	SVD, GB, NN	Errors made while learning an introductory C programming course	Self-built data	MAE, PCC	Exploring the use of historical student data to predict future compiler errors
[96]	Integrated Study	LLM	Classroom behavior video	Self-built data	Verification in practical experiments	Analyzing classroom student behavior using temporal action detection and advanced large-scale language models

[0]LDA: Latent Dirichlet Allocation, PCC: Pearson Correlation Coefficient, SVD: Singular Value Decomposition, GB: Gradient Boosting, IPW: Inverse Probability Weighting, SA: Structured Analysis

Table S5 Summary of studies on student performance prediction (non-cognitive)

References	Algorithm Category	Technique	Dataset		Indicator	Research Outcomes
			Name	Link		
[97]	Machine learning	K-means	Self-built data	NA	ACC	Improvement of the traditional K-means algorithm by using objective quantitative analysis to determine the number of clusters
[98]	Machine learning	NB, RF, SVM, KNN, NN, LR	Self-built data	Publicly available in the form of an annex	ACC, Precision, Recall, F1	A simple comparison of existing algorithms
[99]	Machine learning	LR, LDA, KNN, DT, NB, SVM	Self-built data	NA	ACC, Precision	A simple comparison of existing algorithms
[100]	Machine learning	NB, DT, MLP, SVM	Self-built data	NA	ACC, Precision, Recall, F1	A simple comparison of existing algorithms
[101]	Machine learning	RF, DT, NB, NN, KNN	Self-built data	NA	confusion matrix, ACC, Precision, Recall, F1	A simple comparison of existing algorithms
[102]	Machine learning	PCA, RF	Self-built data	NA	ACC, Precision, Recall, F1	An analysis of learning behavior data identified course duration, document study time, average test scores, and video completion rates as key factors in student performance prediction
[103]	Machine learning	DT, NN, SVM	Self-built data	NA	Spearman's nonparametric correlation analysis	Examining the correlation between Internet use (surfing) and student academic achievement
[104]	Machine learning	KNN, SVM, RF	Self-built data	NA	ACC, Precision, Recall, F1	Integration of existing machine learning algorithms
[105]	Ensemble learning	RF, AdaBoost, XGBoost	ASSISTments, Andes, Synthetic	https://sites.google.com/site/assistmentsdata/home/2009-2010-assistment-data/skill-builder-data-2009-2010., [106], NA	Confusion matrix	Student performance prediction based on different ensemble models
[107]	Ensemble learning	K-Means, RF, DT, CatBoost, XGBoost, AdaBoost, LGBM	Kaggle	https://www.kaggle.com/aljarah/xAPI-Edu-Data	ACC, Precision, Recall, F1	A simple comparison of existing algorithms
[108]	Ensemble learning	LSTM, RF, GB	Self-built data, OULAD	NA, https://analyse.kmi.open.ac.uk/open_dataset#description	ACC, Precision, Recall, F1	A system combining a four-layer stacked LSTM network, RF and GB is designed
[109]	Ensemble learning	Ensemble Learning, Domain-Specific Knowledge	Self-built data	NA	ACC	Built a two-tier architecture based on integrated learning
[110]	Ensemble learning	CatBoost, Residual Error	UCI Machine learning repository, Kaggle	https://archive.ics.uci.edu/ml/datasets/student+performance	RMSE, MAE, MAC, SD	A residual error model was designed to complement the performance of CatBoost

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Table S5 (continue)

References	Algorithm Category	Technique	Dataset		Indicator	Research Outcomes
			Name	Link		
[111]	Ensemble learning	RF, CatBoost	UCI Machine learning repository	https://archive.ics.uci.edu/ml/datasets/student+performance	RMSE, MAE, MAC, SD	Multilayer CatBoost
[112]	Deep learning	DNN	Self-built data	NA	Confusion matrix	Prediction of team performance and analysis of the impact of positive and negative traits
[113]	Deep learning	Transformer	OULAD	https://analyse.kmi.open.ac.uk/open_dataset#description	ACC, F1	Proposed a transform-based approach to grade prediction
[114]	Deep learning	Hypergraph Neural Networks, Attention Mechanisms	OULA, UCI Machine learning repository	https://analyse.kmi.open.ac.uk/open_dataset#description, https://archive.ics.uci.edu/ml/datasets/student+performance	ACC	Propose framework based dual hypergraph neural networks
[115]	Other	LLM, MF	ASSISTments, i-ScreamEdu	https://sites.google.com/site/assistmentsdata/home/2009-2010-assistment-data/skill-builder-data-2009-2010., NA	ACC, Precision, Recall, F1	The integration of multimodal auxiliary information through a large language model showcases a novel approach to applying language modeling and multimodal learning in deep learning
[116]	Other	Signed Graph Neural Networks, LLM, Contrastive Learning	PeerWise platform's fve real data	NA	Binary-F1, Micro-F1, Macro-F1, AUC	The problem of noise and sparsity in educational data is addressed by integrating symbolic graph neural networks and large language model embeddings

[0] NB: Naïve Bayes, RF: Random Forest, SVM: Support Vector Machine, KNN: k-Nearest Neighbors, NN: Neural Networks, LR: Logistic Regression, LDA: Linear Discriminant Analysis, DT: Decision Tree, PCA: Principal components analysis, GB: Gradient Boosting, DNN: Deep Neural Networks, MF: Matrix Factorization

Table S6 Summary of studies on personalized learning path recommendation

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[117]	Self-build	NA	Average score increase	Case-Based Reasoning	Proposes a case-based reasoning model for personalized learning path recommendation
[118]	Self-build	NA	Hit Ratio	Knowledge Graph, Transfer Probability	Proposes a method to generate personalized learning paths using knowledge graphs and transition probabilities
[119]	Moocs	http://moocdata.cn/data/MOOCCube	Precision	LSTM Neural Networks, Clustering	Proposes a full-path learning recommendation model using LSTM neural networks
[120]	Canvas	https://www.canvas.net/	Average Grade	Network Embedding, Learning Effects	Proposes a learning path generation algorithm based on network embedding and learning effects
[121]	Self-build	NA	AUC, F1, Precision, Recall	Deep Learning Algorithm	Proposes a personalized learning model using deep learning
[122]	Enki, Mooshak	NA,NA	MAE	Depth-First Search, Time and Score Estimation	Recommends successful learning paths under time constraints
[123]	Self-build	NA	Student Score	Ant Colony Optimization, Genetic Algorithm	Combines ant colony optimization and genetic algorithms to construct personalized learning paths
[124]	Self-build	NA	User interactions	Peer-Inspired Learning Path Planning	Proposes PeerLens, an interactive system for learning path planning based on peer exercise history
[125]	Moocs	http://moocdata.cn/data/MOOCCube	Precision	Clustering, Learning Networks	Proposes a learning path combination recommendation method based on learning networks
[126]	Self-build	NA	Average grades	Deep Learning	Proposes a personalized learning model using deep learning
[127]	Self-build	NA	Average grades	Multidimensional Knowledge Graph	Proposes a learning path recommendation model based on a multidimensional knowledge graph
[128]	Self-build	NA	Reward	Reinforcement Learning, Hierarchical Skill Model	Proposes an optimal learning policy using reinforcement learning and a hierarchical skill model
[129]	Self-build	NA	NA	Knowledge Graph, Graph Convolutional Network (GCN)	Proposes a personalized English learning recommendation method using knowledge graphs and GCN
[130]	ASSIST09, ASSIST12	https://sites.google.com/site/assistmentsdata	Hit Ratio	Temporal Convolutional Network, Graph Attention Network, Reinforcement Learning	Combines TCN and GAT into the knowledge tracing model and uses it as the environment of the reinforcement learning model
[131]	Self-build	NA	Questionnaire	Learning Style Questionnaire, Moodle Behavior Analysis	Designs a Moodle plugin that generates personalized learning paths according to students' learning styles
[132]	Self-build	NA	Precision	Graph-based Genetic Algorithm (GBGA)	Uses GBGA to optimize the alignment of features between learners and learning objects (LOs)

Table S6 (continue)

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[133]	Junyi, ASSITments2015	https://www.kaggle.com/datasets/junyiacademy/,https://sites.google.com/site/assistmentsdata/datasets	Reward	Hierarchical Reinforcement Learning, Graph-based Candidate Selector, DKT Model	Presents a Graph Enhanced Hierarchical Reinforcement Learning framework for goal-oriented learning path recommendation
[134]	Movielens-1M, LastFM, Self-build	NA,NA,NA	AUC,F1	Multidimensional Knowledge Graph, Graph Convolutional Network	Proposes a learning path recommendation model based on a multidimensional knowledge graph framework
[135]	COCO, Xuetang	NA,https://www.xuetangx.com/	NCDG, Recall, Hit Ratio, Precision	Reinforcement Learning, Knowledge Graphs	Proposes an explainable recommendation system for MOOCs using graph reasoning
[136]	Self-build	NA	Recall, Precision, F1	Knowledge Graphs, Large Language Models (LLMs)	Utilizes knowledge graphs as factual context for LLM prompts to reduce model hallucinations
[137]	Self-build	NA	NA	Artificial Intelligence, Adaptive Systems	Discusses the impact of AI on education, focusing on AI-driven personalized learning paths
[138]	Moocs	Hit Ratio, NDCG	http://moocdata.cn/data/MOOCCube	LLMs	Proposes LPR model leveraging LLMs to extract coherent learning pathways from students' course enrollment histories
[139]	Self-build	NA	RMSE, R2	Real-time Learning Analytics, Knowledge Building, Learning Performance Analysis	Proposes an adaptive learning path recommendation model considering static and dynamic learner parameters

Table S7 Summary of studies on personalized course recommendation

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[140]	MOOCCube	http://moocdata.cn/data/MOOCCube	Regret Comparison	Hierarchical Bandits, Reinforcement Learning	Proposes a methodology for personalized course recommendation using hierarchical bandits to optimize decision-making at multiple levels
[141]	MERLOT	https://merlot.org/merlot/	RMSE	Multi-modal Matrix Factorization, Collaborative Filtering	Proposes xSVD++, a model combining multi-dimensional matrix factorization and collaborative filtering to improve recommendation accuracy
[142]	Xuetangx 2013–2014	https://github.com/THU-KEG/MOOCCubeX	MRR	HITS Algorithm, Social Learning Network	Proposes a dynamic online course recommendation method using social learning networks and the HITS algorithm
[143]	T10I4D100K, T25I10D10K	http://fimi.ua.ac.be/data/,http://www.philippe-fournier-viger.com/spmf/index.php?link=datasets.php	execution time	Distributed Computing, Association Rule Mining	Introduces MCRS, a course recommendation system for MOOCs based on distributed computing and an improved Apriori algorithm
[144]	MOOCCube	http://moocdata.cn/data/MOOCCube	HR,NDCG	Hierarchical Reinforcement Learning	Proposes a hierarchical reinforcement learning algorithm to revise user profiles and tune the recommendation model
[145]	MOOCCube	http://moocdata.cn/data/MOOCCube	precision, recall, and F1-score	AMSLSTM Network, Autoencoder	Proposes an AMSLSTM network and autoencoder to construct course relevance and improve recommendation accuracy
[146]	Self-built	NA	RMSE, MAE, Precision, Recall, F1	Graph Neural Network, Tensor Factorization	Proposes a hybrid recommendation model combining graph neural networks and tensor factorization
[147]	MOOCCube	http://moocdata.cn/data/MOOCCube	Regret Comparison	Knowledge Graph, LDA, Contextual Multi-Armed Bandit	Proposes a semantic and relationship-aware online course recommendation scheme using LDA, knowledge graph embedding, and a contextual multi-armed bandit algorithm
[148]	CSM, Eco	https://www.xuetangx.com/,NA	Precision, Recall, F1-measure	Neural Attention Network, Prerequisite Relation Embeddings	Proposes a method to recommend courses using neural attention networks and prerequisite relation embeddings
[149]	MOOCCube	http://moocdata.cn/data/MOOCCube	Precision,Hit Ratio	Cognitive Diagnosis, MIRT, Collaborative Filtering	Integrates MIRT into recommendation models to dynamically update learners' capacities and improve recommendation effectiveness
[150]	Xuetangx	https://github.com/THU-KEG/MOOCCubeX	Precision, Recall	Knowledge Graph, Collaborative Filtering	Combines knowledge graph representation learning with collaborative filtering to enhance recommendation performance
[151]	POJ, Liulishuo	NA,NA	NDCG,HR	Knowledge-enhanced Multi-task Learning	Proposes a knowledge-enhanced multi-task learning model for course recommendation integrating an improved knowledge tracing task
[152]	Xuetangx	https://github.com/THU-KEG/MOOCCubeX	Hit Ratio, NDCG, MRR	GCN-based Attentive Decay Network	Introduces a GCN-based Attentive Decay Network for course recommendation

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Table S7 (continue)

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[153]	XuetangX, MOOCCube	https://github.com/THU-KEG/MOOCCubeX,http://moocdata.cn/data/MOOCCube	Hit Ratio, NDCG, MRR, AUC	Meta-Relationship	Proposes Meta-Relationship Course Recommendation to enrich relational information using graph embedding and optimized matrix factorization
[154]	ESOF,XuetangX	https://www.ebssw.kr/,https://www.xuetangx.com/	user satisfaction	Knowledge Graph Enhanced	Proposes KPCR, a knowledge graph-enhanced personalized course recommendation framework
[155]	MOOCCube	http://moocdata.cn/data/MOOCCube	Hit Ratio, NDCG	Context-aware Reinforcement Learning	Introduces Hierarchical and Recurrent Reinforcement Learning for course recommendation
[156]	XuetangX	https://www.xuetangx.com/	Hit Ratio, NDCG	Hierarchical Reinforcement Learning with Dynamic Recurrent Mechanism	Proposes HELAR to address the exploration-exploitation trade-off in user profile construction
[157]	MOOCCube	http://moocdata.cn/data/MOOCCube	Recall, NDCG, AUC	Knowledge Grouping Aggregation Network (KGAN)	Proposes a knowledge graph-enhanced course recommendation model using intra-group and inter-group attention operators
[158]	Self-build	NA	Recall, Precision, F1	Deep Learning, BERT, LSTM, Multi-Head Attention	Proposes a personalized course resource recommendation method using BERT, LSTM, and multi-head attention
[159]	Self-build	NA	RMSE, AUC, NDCG, Recall	Factor Memory Network and Graph Neural Network (MG-CR)	Constructs a heterogeneous information network and uses factor memory network and graph neural network for high recommendation accuracy
[160]	MOOCCube	http://moocdata.cn/data/MOOCCube	Precision, Hit Ratio, Recall, NDCG	Deep Reinforcement Learning (DRL)	Integrates DRL and multi-agent approach for personalized course recommendation
[161]	XuetangX, KDDCUP	https://www.xuetangx.com, NA	MAE, RMSE, Hit Ratio, Recall, Precision	Quantified Engagement and Engagement Neural Network	Proposes a method to quantify learner engagement and apply it to personalized course recommendations
[162]	XuetangX, Canvas	https://www.xuetangx.com/, https://www.canvas.net/	NDCG	Survival Analysis	Enhances collaborative filtering-based course recommendations using survival analysis

Table S8 Summary of studies on personalized exercise recommendation

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[163]	Self-build	NA	Precision	Collaborative Filtering, Knowledge Diagnosis	A novel exercise recommendation algorithm integrating learning objectives and assignment feedback, enhancing precision and recall through real-world dataset experiments
[164]	Self-build	NA	Precision	Knowledge Graph	Pioneering approach leveraging student learning status and prerequisite dependencies for personalized exercise recommendation, improving precision and diversity
[165]	Self-build	NA	Precision, Recall, F1	Knowledge Tree, Tree Exploration	An automatic exercise recommendation approach based on learning objectives, utilizing knowledge tree models to enhance personalization
[166]	MATH, PROGRRAM	https://zhixue.com,https://poj.org	NDCG, MAP, F1	Reinforcement Learning	A Deep Reinforcement Learning framework for multi-objective exercise recommendations, optimizing review, difficulty, and engagement through novel reward functions
[167]	ASSISTments 2009–2010, Algebra 2005–2006, OLIES 2011	https://sites.google.com/site/assistmentsdata/,https://github.com/hcnoh/knowledge-tracing-collection-pytorch,https://edudata.readthedocs.io/en/latest/build/blitz/OLI_Fall2011/OLI_2011F_transaction.html	Acc, Novelty, Diversity	RNN, DKT	A hybrid method using RNNs and DKT for personalized exercise recommendation, optimizing difficulty, diversity, and novelty
[168]	Self-build	NA	ACC, Recall, F1, Diversity	Knowledge Graph, RWMD	A personalized exercise recommendation method for computer network courses using knowledge graphs for efficient recommendations
[169]	Self-build	NA	Hit Ratio	Cognitive Diagnosis Method, LSTM	An exercise recommendation method improving student performance through enhanced cognitive diagnosis and LSTM
[170]	Self-build	NA	Recall, Precision	DINA Model, Clustering, Collaborative Filtering	A personalized exercise recommendation method for English learning, achieving higher precision, recall, and efficiency
[171]	MOOCERS	NA	NDCG	Reinforcement Learning	An exercise recommender system for MOOCs using reinforcement learning, integrating review, difficulty, and learning objectives

Table S8 (continue)

References	Dataset		Indicator	Technique	Research Outcomes
	Name	Link			
[172]	ASSISTments, Algebra, OLI Statics	https://sites.google.com/site/assistmentsdata/,https://github.com/hcnoh/knowledge-tracing-collection-pytorch,NA,https://edudata.readthedocs.io	ACC, Novelty, Diversity	Knowledge Graph, Knowledge Tracing	ER-KTCP, a method capturing student knowledge state changes for exercise recommendation, introducing a new metric for performance evaluation
[173]	Self-build	NA	ACC	Collaborative Filtering, KNN	A personalized exercise recommendation method for teaching objectives, achieving a high prediction success rate
[174]	Assistments 2009, Algebra 2005, Statics 2012	https://sites.google.com/site/assistmentsdata/,https://github.com/hcnoh/knowledge-tracing-collection-pytorch,https://edudata.readthedocs.io	ACC, Novelty	Knowledge Graph, LSTM	KG4Ex, a knowledge graph-based exercise recommendation method with superior performance and strong explainability
[175]	Assistment, Eedi	https://edudata.readthedocs.io/	AUC,ACC	Knowledge Graph, Cognitive Diagnosis Model	A framework enhancing knowledge graphs for exercise recommendation, improving student performance through neural attentive cognitive diagnosis
[176]	Assistments 2009, Algebra 2005, Statics 2011	https://sites.google.com/site/assistmentsdata/,https://github.com/hcnoh/knowledge-tracing-collection-pytorch,https://edudata.readthedocs.io	ACC, Novelty, Diversity	Self-Attention Networks, Knowledge Tracing Model	MulOER-SAN, a 2-layer multi-objective framework for exercise recommendation, outperforming state-of-the-art methods
[177]	Assistments 2009, Assist12-13, Ednet, BePKT	https://edudata.readthedocs.io	Hit Ratio, NDCG	Contrastive Learning, Reinforcement Learning	RCL4ER, a framework combining contrastive learning and reinforcement learning for effective exercise recommendation, promoting student learning ability

Table S9 The existing adaptive learning systems

System	Web-site	Type	Developers	Year	Charges	Cloud	Mobile	Local	Cognitive modeling	Non-cognitive modeling	Personalized recommendations
Knewton	knewton.com	ALS	Jose Ferreira	2008	Pay	+	+	-	✓		✓
Smart Sparrow	smartsparrow.com	ALS	University of New South Wales	2010	Trial/Pay	+	+	-	✓		✓
Codecademy	codecademy.com	ALS	Zach Sims	2011	Free/Pay	+	+	-			✓
DreamBox	dreambox.com	ALS	Lou Gray, Ben Slivka	2006	Trial/Pay	+	+	-	✓		✓
ALEKS	aleks.com	ALS	Jean-Claude Falmagne	1996	Pay	+	+	-	✓		✓
Tandem	tandem.net	VEA	Arnd Aschentrup, Tobias Dickmeis, Matthias Kleimann	2015	Free/Pay	+	+	-			✓
Duolingo	duolingo.com	VEA	Luis von Ahn, Severin Hacker	2011	Free/Pay	+	+	+	✓	✓	✓
Jill Watson	-	VEA	Ashok Goel	2016	-	+	-	-			
Woebot	www.woebot.io	VEA	Alison Darcy	2017	Pay	+	+	-		✓	✓
IBM Watson Assistant for Education	ibm.com/watson/education/pearson	VEA	-	2016	Pay	+	+	-	✓		✓
AskAway	askaway.org	VEA	-	-	Free	+	+	-			
Coursera	coursera.org	OLP	Andrew Ng, Daphne Koller	2012	Free/Pay	+	+	+			✓
EdX	edx.org	OLP	Harvard University, MIT	2012	Free/Pay	+	+	+			✓
Udemy	udemy.com	OLP	Eren Bali, Gagan Biyani, Oktay Caglar	2010	Pay	+	+	+			✓
Udacity	udacity.com	OLP	Sebastian Thrun, David Stavens, Mike Sokolsky	2011	Pay	+	+	-			✓
Khan Academy	khanacademy.org	OLP	Salman Khan	2008	Free	+	+	+	✓		✓
Carnegie Learning	carnegielearning.com	OLP	Carnegie Mellon University	1998	Pay	+	+	-	✓		✓
FutureLearn	futurelearn.com	OLP	The Open University	2012	Free/Pay	+	+	-			✓
CodeCademy	code.org	OLP	Hadi, Ali Partovi	2013	Free	+	+	-			✓
Rosetta Stone	rosettastone.com	OLP	Allen Stoltzfus	1992	Pay	+	+	+	✓	✓	✓
Learning Locker	www.learninglocker.net	LAT	HT2 Labs	2014	Pay	+	-	-			
Blackboard Analytics	blackboard.com	LAT	Michael Chasen, Matthew Pittingsky	1997	Pay	+	+	-			
Cognos Analytics for Education	-	LAT	-	-	Pay	+	+	-			
Brightspace Insights	community.d2l.com/brightspace	LAT	John Baker	-	Pay	+	+	-			
IBM Watson Education	-	LAT	-	-	Pay	+	+	-	✓		✓
Moodle	moodle.org	LMS	Martin Dougiamas	2002	Free/Pay	+	+	+			
Blackboard Learn	blackboard.com	LMS	Michael Chasen, Matthew Pittingsky	1997	Pay	+	+	+			
Canvas	instructure.com/canvas	LMS	Brian Whitmer, Devlin Daley	2008	Pay	+	+	+			
Schoology	schoology.com	LMS	Jeremy Friedman, Ryan Hwang, Tim Trinidad, Bill Kindler	2009	Free/Pay	+	+	-			
Minecraft: Education Edition	education.minecraft.net	EG	Markus Persson, Mojang	2011	Free	+	+	+		✓	✓
BrainPOP	brainpop.com	EG	Avraham Kadar	1999	Pay	+	+	-			
Scratch	scratch.mit.edu	EG	Mitchel Resnick	2007	Free	+	+	+			
Prodigy	prodigygame.com	EG	Alex Peters, Rohan Mahimker	2011	Free/Pay	+	+	-	✓		✓
Tinkercad	tinkercad.com	EG	Kai Backman, Mikko Mononen	2011	Free	+	-	-			
Autodesk Education	autodesk.com/education	EG	John Walker	1982	Free	+	+	+			