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Chatgpt and Ai-Enabled Technologies for Personalized Learning: A Scientometric Analysis using Citespace

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Abstract:
With the rapid development of ChatGPT and artificial intelligence (AI) technologies, education has gradually begun to apply ChatGPT and AI techniques to enhance teaching effectiveness and personalized learning experiences in recent years. Personalized learning has attracted considerable interest because of its ability to improve educational results by customizing teaching to meet the specific needs of each learner. There has been a surge in research exploring the application of AI technologies in personalized learning. This paper presents a scientometric analysis of research on AI-enabled technologies for personalized learning Using CiteSpace for visualization and analysis. The study provides an overview of the research landscape, identifying key themes, influential authors, and highly cited publications. The analysis reveals the interdisciplinary nature of the research, with contributions from fields such as educational technology, cognitive science, and machine learning. Additionally, it highlights the emergence of novel AI techniques, including adaptive learning systems, intelligent tutoring systems, and recommender systems. The findings contribute to understanding the current state of the art, identifying research trends, and guiding future studies in developing and implementing AI-enabled technologies for personalized learning.

Keywords: personalized learning, AI, CiteSpace

INTRODUCTION

Emerging technologies, such as ChatGPT and artificial intelligence (AI), have been widely applied in the field of education, leading to profound transformations in learning concepts and approaches in recent years. Particularly, towards the end of 2019, the outbreak of the novel corona virus COVID-19 on a global scale propelled the rapid development of online education systems represented by platforms such as Coursera, Udacity, Khan Academy, Tencent Classroom, NetEase Cloud Classroom, and China University MOOC [1]. These platforms have provided learners with more convenient and efficient learning platforms, partially addressing the challenges students face in their learning processes. However, traditional online education systems predominantly adhere to a one-to-many resource allocation model, overlooking the variances in learners' knowledge backgrounds, disparities in learning abilities, and diversity in learning objectives. As a result, they have not effectively addressed the difficulties learners encounter in acquiring new knowledge. Consequently, in current research, solving the personalized needs of learners has become a paramount concern in achieving personalized teaching tasks [2]. Within this context, the use of AI technology to automatically and efficiently recognize learners' characteristics, effectively organize and distribute learning resources, and design personalized pathways for each individual has become an urgent problem to be tackled in the research of precise education resource-matching mechanisms focused on individuals.

Personalized learning, which aims to tailor education to the individual needs and preferences of learners, has gained considerable attention in recent years [3]. The rapid advancements in AI and related technologies have provided new opportunities to enhance personalized learning experiences [4]. In this paper, we present a scientometric analysis using CiteSpace to summarize and analyze the contribution of various AI-enabled technologies, such as machine learning, graph neural networks, collaborative filtering, data mining, and knowledge graphs, in the field of personalized learning. These technologies have facilitated the analysis of educational data, prediction of learners' preferences, and recommendation of tailored learning resources. Thanks to AI-driven technologies, individualized education could transform conventional teaching methods and offer learners more engaging and effective educational experiences [5].

Literature Review

An emerging educational strategy, personalized learning customizes instruction to address the distinct needs, preferences, and skills of each student. Researchers and educators have sought to leverage AI-enabled technologies to enhance personalized learning experiences [6]. AI technologies have shown great potential in analyzing large amounts of data collected from learners to provide tailored instruction, adaptive content, and personalized feedback [7].

Machine learning has emerged as a potent tool in the realm of personalized learning, providing novel approaches to adapt instruction and tailor educational experiences to the specific needs of individual learners. Researchers have explored various machine learning algorithms for tasks such as learner modeling, adaptive content delivery, and intelligent feedback provision. One prominent area of study involves the use of recommendation systems to personalize learning materials [8]. These systems utilize machine learning algorithms to analyze learner preferences, behavior, and performance data, enabling the delivery of relevant and targeted recommendations. Machine learning techniques have also been applied in learner modeling, wherein individual learner characteristics are captured and represented to inform instructional decision-making. Models that are based on machine learning algorithms extract patterns from learner data, aiding in the identification of learner strengths, weaknesses, and preferences [9]. These models have been utilized to tailor learning pathways, adapt instructional materials, and offer personalized feedback that is tailored to the unique needs of each learner. Additionally, researchers have explored the application of machine learning in intelligent tutoring systems (ITSs), which provide individualized support and guidance to learners. ITSs utilize machine learning algorithms to model learner knowledge, track progress, and make real-time adaptations to instruction [10]. By personalizing the learning experience, ITSs powered by machine learning have demonstrated improved learning outcomes and increased learner satisfaction [11].

Reinforcement learning offers valuable opportunities for personalizing learning experiences by optimizing instructional strategies, adaptive content delivery, and learner support systems [12]. By leveraging reinforcement learning techniques, personalized learning environments can dynamically adapt to individual learners' needs, promoting engagement, knowledge acquisition, and skill development [13].

Data mining techniques enable the extraction of valuable knowledge and patterns from large-scale datasets, facilitating evidence-based decision-making and personalized adaptations in instruction, learner support, and content delivery systems. Researchers have utilized data mining techniques to analyze learner data and extract meaningful patterns regarding learners' behaviors, preferences, and performance [14]. These models provide insights into individual learner characteristics and inform the design of personalized interventions and instructional strategies. Data mining techniques have also been applied to predict learner outcomes and identify at-risk students. By analyzing historical data, researchers can build predictive models that forecast student performance and dropout risks [15]. Furthermore, data mining has been used to develop recommendation systems that personalize content delivery. These systems leverage data mining algorithms to analyze learner profiles and preferences, suggesting relevant learning resources and activities [16].

Graph Neural Networks are capable of capturing and representing intricate relational structures present in educational data, such as learner interactions, social networks, and knowledge graphs. These models leverage graph-based representations to extract meaningful features from interconnected data, enabling personalized adaptations in instruction, content recommendation, and learner support systems. Researchers have employed GNNs to capture the dependencies and dynamics of learner interactions, facilitating accurate prediction of future collaborative behavior [17]. Personalized interventions can be designed to foster effective collaboration and peer learning by incorporating information about social connections and interaction patterns. GNNs have also been applied to recommend personalized content. By modeling the relationships between learners, learning resources, and their attributes, GNNs can generate personalized recommendations that align with individual preferences and needs [18]. The utilization of GNNs provides the opportunity for more precise and contextually aware content suggestions, leading to improved engagement and satisfaction for learners. Moreover, GNNs have been employed for the purpose of modeling knowledge graphs and facilitating personalized representation and reasoning of knowledge. By harnessing graph-based representations of domain knowledge, GNNs enable personalized tracing of knowledge and adaptive sequencing of content [19].

Collaborative filtering focuses on predicting the preferences of learners based on the preferences and behaviors of similar users. This technique can be applied to various aspects of personalized learning, including content recommendation, group formation, and peer assessment. Researchers have explored collaborative filtering algorithms to identify similar learners and recommend learning resources that align with their interests and needs [20]. By analyzing learner profiles and preferences, collaborative filtering algorithms can identify compatible group members, enhancing collaboration and knowledge sharing within groups [21]. Furthermore, collaborative filtering techniques have been employed in peer assessment systems [22]. These systems leverage the ratings and feedback provided by learners to assess and provide constructive feedback on the work of their peers.

Knowledge graphs organize information in a graph-like structure, representing entities, relationships, and attributes of knowledge concepts. These graphs enable the storage, retrieval, and reasoning over interconnected knowledge elements, supporting personalized adaptations in instruction, content recommendation, and learner support systems. Researchers have utilized knowledge graphs to model the dependencies between learning concepts, enabling personalized sequencing of learning materials

[23]. By analyzing the knowledge of states and mapping learners to the knowledge graph, adaptive content delivery systems can provide tailored learning paths that address individual knowledge gaps and promote efficient learning. Knowledge graphs also facilitate personalized recommendations by capturing the relationships between learners, learning resources, and their attributes. By leveraging the rich semantic information encoded in knowledge graphs, recommender systems can generate personalized suggestions that align with the specific needs and preferences of learners [24]. The use of knowledge graphs enhances the accuracy and relevance of content recommendations, leading to improved learner engagement and satisfaction. Furthermore, knowledge graphs have been employed in learner modeling to capture and reason about learners' knowledge states, skills, and competency levels. These models enable personalized feedback, assessment, and intervention strategies based on learners' unique profiles within the knowledge graph [25]. By utilizing the structure of the knowledge graph, personalized interventions can be designed to address individual misconceptions and promote deeper understanding.

OpenAI's Generative Pre-trained Transformer (GPT) model, known as ChatGPT, facilitates engaging and conversational exchanges between students and the AI platform. It offers personalized assistance, feedback, and content delivery that adapts to individual learner needs and preferences. Researchers have explored ChatGPT for answering learner questions, explaining concepts, and providing tailored explanations [26]. By leveraging the power of language generation, ChatGPT can engage learners in interactive conversations, providing personalized guidance and clarifications in real time. ChatGPT also facilitates adaptive content delivery by generating personalized recommendations based on learner preferences and interests. By analyzing learner interactions and feedback, ChatGPT can suggest relevant learning resources, activities, or next steps, enhancing learner engagement and satisfaction [27]. The conversational nature of ChatGPT allows for dynamic and interactive personalized content delivery. Furthermore, ChatGPT has been applied in personalized assessment and feedback systems. By analyzing learner responses and providing instant feedback, ChatGPT supports formative assessment and adaptive feedback [28]. Its ability to simulate human-like conversations enables learners to receive personalized feedback and guidance, promoting self-reflection and improvement.

AI-enabled technologies like ChatGPT have immense potential for personalized learning. Educators can use these technologies to develop personalized learning experiences that address diverse needs, increase engagement, and improve learning outcomes. Ongoing research, development, and responsible integration of ChatGPT and AI in personalized learning will contribute to a future of education that is accessible and effective for all learners.

Objectives and Contribution

The main goal of this study is to carry out a comprehensive and methodical exploration of knowledge mapping related to AI-enhanced personalized learning research. This investigation employs CiteSpace analytical and visualization methods to successfully recognize and understand various research areas, new trends in personalized learning, and the evolving pathways within this domain. The detailed aims of this study are outlined as follows:

1. The aim of this research is to employ co-citation analysis for uncovering the intellectual framework related to intelligent technologies in the context of literature focused on personalized learning. This methodology, co-citation analysis, is well-established and facilitates the identification of key research themes and prominent publications in a specific field.

2. The aim of this research is to perform a thorough citation burst analysis to explore contemporary research areas that are in high demand and to observe the continual advancements in these fields. This method is particularly useful for recognizing emerging research themes that attract significant interest within the scientific community.

3. This study aims to examine the increase in scientific publications, the citation structure, and the prominent countries within the knowledge field.

4. The main aim of this study is to uncover various research dynamics in the field, which encompass CHATGPT technologies, key research hotpots, and significant focal points. The results of this study will lay the groundwork for determining future research avenues in this area.

The document is organized into four distinct sections. The first section outlines the problem that has been identified and offers relevant background details. In Section 2, which focuses on methodology, the employed approach and search strategy are thoroughly described. Section 3 features an analysis and results segment that addresses aspects like the analysis of publication patterns, prominent countries, co-citation analysis by domain, and references with significant bursts. Lastly, Section 4 summarizes the findings of the analysis and wraps up the study.

METHODOLOGY

We use CiteSpace software to conduct a comprehensive analysis of publishing patterns, citations, collaborations, academic exchanges, and future trends in the paper. This program allowed for a visual investigation into the development and progression of a particular field of study. Through the use of this resource, we systematically examined extensive datasets of scientific publications, which helped minimize the effects of personal biases. Moreover, it provided us the capability to detect new research domains and patterns without the sway of individual viewpoints or inclinations.

CiteSpace serves as a popular tool for scientometric analysis, facilitating the visualization and examination of citation networks. Its widespread use among scholars demonstrates the software's effectiveness in identifying clusters of related research areas and illustrating the co-citation relationships that exist among them [29]. Researchers have recognized that CiteSpace provides a detailed view of the intellectual landscape, particularly excelling at pinpointing turning points and shifts in research areas [30]. A key feature of CiteSpace is its capacity to offer a range of customizable visualization options, which enables researchers to investigate their data from various perspectives. In this paper, the CiteSpace tool was employed to conduct analyses including literature co-citation, country contribution, and burst reference reviews to explore scientific knowledge, as shown in Figure 1.

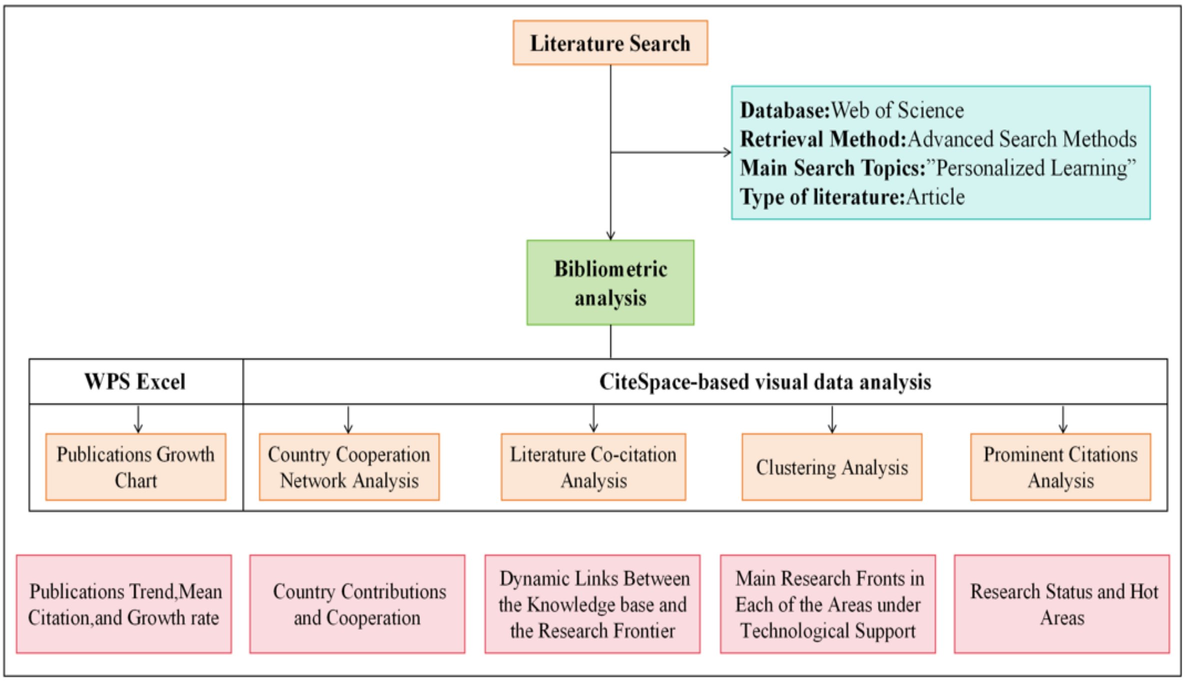

Figure 1. Research design.

The study utilized the Web of Science database to gather an extensive datasets for examination. Web of Science, developed by Clarivate Analytic, is a comprehensive and renowned online research database widely used by the scientific community. It provides access to an extensive collection of scholarly literature across various disciplines, including natural sciences, social sciences, engineering, and humanities. It offers a vast repository of peer-reviewed journals, conference proceedings, patents, and book chapters, making it an indispensable tool for conducting literature reviews and staying up-to-date with the latest advancements in a particular field. It is an essential resource for researchers looking to explore, analyze, and track scholarly publications, citations, and research trends across diverse scientific disciplines.

The researchers made use of the sophisticated query feature within the database to gather all pertinent records for the paper. The main search terms implemented included "AI" and "personalized learning." In order to develop a datasets classified by technology sectors, the researchers systematically integrated relevant keywords from each chosen sector, applying the "AND" operator in conjunction with the primary key phrases. To enhance the specificity of the datasets, the researchers utilized the "AND NOT" operator to minimize overlaps among the seven research sectors. Furthermore, the datasets was refined according to subject area, document type, and language to yield more applicable records. The process is illustrated in Figure 1. After applying the inclusion/exclusion criteria and eliminating duplicates, this study yielded a total of 2879 records. Additionally, the datasets was categorized by domain, leading to a total of 3912 records, as displayed in Table 1.

Table 1. Scientific literature in different fields of AI

Serial No.	Categories	Documents
1	Machine learning	1015
2	Reinforcement learning	180
3	Data mining	501
4	Graph Neural Networks & Knowledge graphs	362
5	Collaborative filtering	357
6	ChatGPT & Natural Language	485

RESULTS AND DISCUSSION

Publications and Citation Structure Analysis

The examination of growth in publications includes assessing the trends and patterns of research output in a particular field or subject area over a specified time frame. This analytical approach offers important insights into the evolution and advancement of the research domain, aiding in recognizing areas with either rising or falling research activity.

Table 1 illustrates the allocation of research publications among various technological fields related to AI-enabled technologies for personalized learning. A detailed analysis of each category reveals that machine learning leads with the most publications (1015), succeeded by data mining (501) and collaborative filtering (357). Conversely, reinforcement learning (180) records the fewest publications, trailed by chat bots and natural language processing (485), as well as graph neural networks and knowledge graphs (362).

Figure 2 illustrates the overall publication pattern of the quantity, growth rate, and average citation count in the past six years. The years from 2018 to 2023 are depicted along the X-axis. Meanwhile, the primary Y-axis indicates the volume of publications, and the secondary Y-axis shows the average number of citations for these works. The results of the analysis demonstrate that the majority of publications emerged during the period from 2020 to 2022. Due to the outbreak of the pandemic in 2020, online education began to play a unique role in this special context. With the support of artificial intelligence and big data technology, data-driven personalized learning has increasingly become a focal point in education, gradually evolving into a new paradigm of AI-based educational technology.

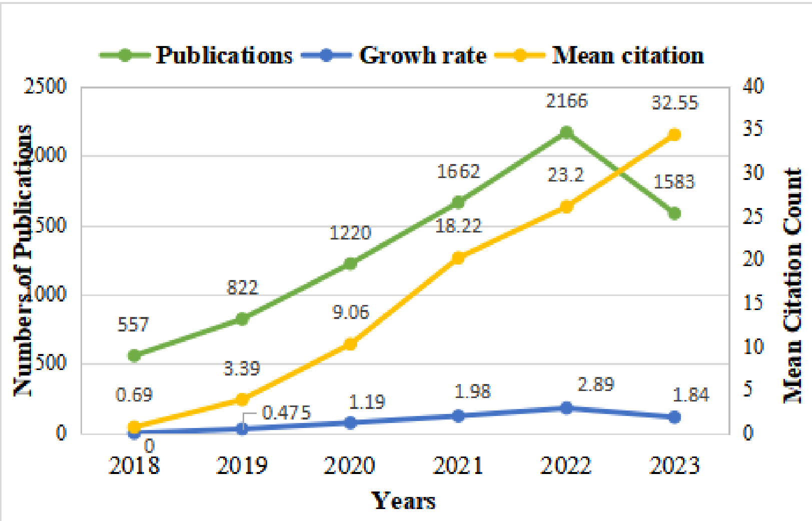

Figure 2. Publication growth pattern from 2018 to 2023

Therefore, during this period, there were relatively more publications on applying AI-empowered technologies in personalized learning research. However, with the development of the large-scale model ChatGPT, researchers have started to develop and utilize innovative ChatGPT technology to address personalized learning problems.

Nevertheless, it has also been noted that although there was a reduction in the number of publications in 2023 (583) in comparison to 2022 (2166), the average citation counts increased from 23.2 to 32.55. This indicates that researchers might be channeling their efforts into carrying out studies that are more impact, therefore, yield a greater number of citations. Additionally, it's important to highlight that journals known for their high impact and citation metrics are capable of disseminating the most groundbreaking and perceptive research. As research in AI-enabled technologies for personalized learning continues to evolve, it is anticipated that additional opportunities will arise to build upon previous studies and create influential research. This progression can ultimately result in an elevation of the average citation counts, reflecting the increasing importance and influence of the research being performed in this area.

The aim of this study is to pinpoint the leading nations in a specific area of research. This examination offers important perspectives on the worldwide research environment and assists in assessing which nations contribute the most substantial advancements to a given discipline.

Table 2 presents a list of the top 10 nations actively engaged in personalized learning research, making significant contributions to this field. The table presents data including the count of published papers (n), total citation figures (TC), share of total publications (n%), average citations per publication (MC), and the relative citation score (RCS) for every country.

Table 2. Top-10 Leading Countries.

No.	Country	Centrality	n	TC	n(%)	TC(%)	MC	RCS
1	USA	0.12	3015	60983	30.47%	48.70%	22.65	1.60
2	PEOPLES R CHINA	0.15	2809	24337	28.39%	19.44%	9.84	0.68
3	ENGLAND	0.22	900	22290	9.10%	17.80%	25.87	1.96
4	GERMANY	0.06	632	17398	6.39%	13.89%	29.15	2.17
5	AUSTRALIA	0.1	528	15220	5.34%	12.16%	29.94	2.28
6	ITALY	0.04	517	12224	5.22%	9.77%	24.45	1.87
7	CANADA	0.01	510	13464	5.15%	10.75%	27.01	2.09
8	SPAIN	0.06	500	12469	5.05%	9.96%	25.9	1.97
9	SOUTH KOREA	0.11	444	5291	4.49%	4.23%	12.17	0.94
10	TAIWAN	0.09	402	14269	4.06%	11.40%	36.69	2.81

According to the analysis, the United States leads with the highest publication share (3015, 30.47%), followed by the People's Republic of China (2809, 28.39%) and England (900, 9.10%). These countries have respective total citation counts of 60983, 24337, and 22290. Additionally, China-Taiwan (36.69), Australia (29.94), and Germany (29.15) exhibit high mean citation values, indicating the production of high-quality research papers in this domain. Germany also boasts the highest centrality value (0.22), which signifies its position as the most collaborative and influential country within the collaboration network. People's Republic of China follows closely behind with a centrality value of 0.15. Similarly, the relative citation score (RCS) evaluates the worldwide visibility and impact of a country's research in the field of ChatGPT and AI-enabled technologies for personalized learning.

$$RCS = \frac{Citiation\ Rate\ of\ the\ country\ (TC\%)}{Pubication\ Rate\ of\ the\ \ country(n\%)} \qquad (1)$$

When RCS= 1, it indicates that the citation rate of the country (TC%) is comparable to the global citation rate(n%). When RCS > 1, it indicates (TC%) is higher than the(n%); when RCS < 1, it indicates (TC%) is lower than the (n%).

Table 2 demonstrates that South Korea and the People's Republic of China are among the top-ranking countries, but their RCS is lower than the (n%). Conversely, the other countries have RCS values higher than the (n%) in the list, indicating their high citation rates.

Literature Co-citation Analysis

Co-citation represents a fundamental technique in the realm of bibliometrics and scientometrics, entailing the concurrent citation of two or more documents within subsequent scholarly publications. Employed as a tool to uncover interwoven relationships and connections among academic papers or sources, co-citation analysis hinges on the examination of shared citations [31]. This method is instrumental in pinpointing seminal works and prominent contributors, thus facilitating the investigation of noteworthy research trajectories and emerging trends.

Document co-citation analysis (DCA) represents a sophisticated bibliometric methodology that probes into the intricate web of relationships and inter connectivity among scholarly papers. This is achieved by evaluating the instances in which these documents are concurrently cited by other works in the field. The crux of this approach lies in the detection of co-citation patterns, which serve to illuminate the intellectual linkages and thematic consonance across a body of literature. CiteSpace stands out as a premier software instrument for executing DCA, primarily by providing a visual breakdown of the co-citation networks through compelling graphical interfaces such as network diagrams and chronological visualizations. These insightful depictions empower researchers to pinpoint clusters of interrelated documents, identify key papers that act as nodes linking disparate clusters, and recognize the seminal contributions within the scholarly network.

DCA of machine learning

Machine learning, a cornerstone of AI-driven technology, has experienced a remarkable uptick in both research and innovation. DCA analysis sheds light on the dynamic evolution of machine learning research by spotlighting foundational papers, pivotal authors, and the progression of critical concepts and methodologies. Such analysis is invaluable for discerning the most influential research trajectories and for steering subsequent inquiries within the domain.

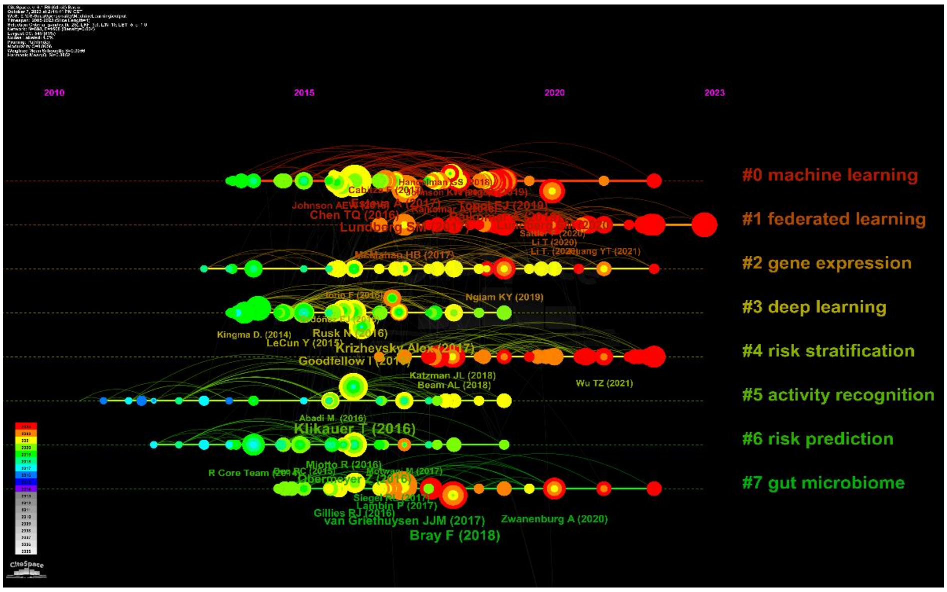

Figure 3. DCA timeline view of machine learning.

Figure 3 illustrates the temporal DCA network of machine learning, consisting of a complex network of 898 cited references and 1608 co-citation links, spanning thirteen years from 2010 to 2023. CiteSpace applies a logarithmic likelihood ratio (LLR) weighting algorithm to accurately label clusters, capturing the fundamental concepts inherent to each group. The integrity of these clusters is quantified by silhouette scores that evaluate their internal homogeneity and coherence. Moreover, CiteSpace deploys a suite of clustering algorithms, such as k-means, hierarchical clustering, and cluster analysis based on density to analyze the co-citation network characteristics, notably including the calculation of silhouette scores for the individual clusters [32]. The silhouette coefficient is essential for measuring the indeterminacy involved in defining cluster attributes. It assigns a scalar value ranging from -1 to 1, which reflects the degree of certainty necessary for analyzing clusters. A coefficient of 1 indicates an absolute disjunction from adjacent clusters, signifying a stark distinction. Furthermore, silhouette coefficients ranging from 0.7 to 0.9 or above are generally associated with enhanced efficacy in discerning cluster delineation and facilitating associated integrative tasks, consequently simplifying the analytical process [33]. In the current study, the six predominant clusters register scores in excess of 0.8, reflecting their robustness and their nearness to the maximal score of 1.00. In the present analysis, Cluster #0, associated with machine learning, emerges as the most extensive, comprising 83 member citations, and is notably larger than its counterparts. In contrast, Cluster #6, due to its reduced magnitude, stands as the least consequential within the network. Table 3 presents comprehensive details regarding the clusters, including identifier (ID), silhouette scores, cluster labels, and principal research themes within this sphere of knowledge. Machine learning, federated learning, gene expression, deep learning, risk stratification, activity recognition, and risk prediction are the primary research fronts in the area. The research specifically concentrates on the most substantial and relevant clusters as identified by the domain of inquiry and analysis using CiteSpace to ascertain the most prolific citing entities and clusters.

Cluster #0, titled “Machine Learning”, involves research on detecting this precision medicine and individualized medicine. The active period of the cluster is from 2013 to 2022. This indicates that significant research activity has occurred within this domain, as illustrated in Figure 4 by a solid line representing cluster #0. The most frequently cited works within the cluster and their corresponding references. These works demonstrate a dynamic interrelationship between the intellectual core of the cluster and potential research directions. Significantly, the paper is most frequently cited in this cluster [34]. It provides a comprehensive overview of the development of machine-learning-based tumor classifiers that can be applied to various types of cancer. Artificial intelligence has various applications in medicine, including precision medicine, individualized medicine, faster diagnosis, personalized treatments, and better control measures.

Cluster #1, titled "Federated Learning," encompasses research on personalized federated learning, collaborative work, and edge computing. This cluster spans from 2017 to 2023. The most cited paper [35] demonstrates that federated learning among 10 institutions yields models that achieve 99% of the model quality attained with centralized data, while also assessing the generalization of data from external institutions beyond the federation in this cluster. The study concludes that the clinical adoption of federated learning is anticipated to enable training models on datasets of unprecedented size, thereby exerting a catalytic impact on precision/personalized medicine. Similarly, the most cited article [36] proposes the FedHealth framework as a solution to address the challenges of building personalized models in wearable healthcare. Through the combination of federated learning and transfer learning, FedHealth provides a means to aggregate data and leverage the knowledge gained from multiple users, ultimately enhancing the accuracy and effectiveness of personalized models in the field of healthcare.

Table 3. Cluster information of machine learning.

No.	Size	Silhouette	Lable	Research topics
0	83	0.822	machine learning	precision medicine; individualized medicine; artificial intelligence
1	55	0.926	federated learning	personalized federated learning; collaborative work; edge computing
2	50	0.85	gene expression	interpretable deep learning; in silico; in-hospital mortality; covid-19
3	49	0.923	deep learning	computational intelligence; mild cognitive impairment; recurrent neural networks
4	46	0.884	risk stratification	prognosis; immune micro-environment; risk model; information fusion
5	43	0.96	activity recognition	psychiatry; cancer cell lines; activity recognition; SVM; deep learning
6	40	0.91	risk prediction	trial of labor; big data; prediction; outcomes; eye fatigue

Cluster #2, titled "Gene Expression", focuses on the representation of features and privacy concerns related to the use of interpretative deep learning. This cluster includes research conducted between 2013 and 2021. Indicating that significant research in this domain took place only within this time-frame, with limited activity before and after. The most cited article in the cluster [37] illustrates how deep learning can assist in diagnosing diseases by analyzing various medical images, including radiology scans, pathology slides, and retinal images. Errors or biases in the training data can impact the performance and validity of deep learning models. To mitigate these issues, it is crucial to ensure data quality and address potential biases.

DCA of graph neural networks

The graph neural network (GNN) is a deep learning model that leverages graph structures. It is widely used in personalized learning research. By constructing a graph structure between learners and learning resources, GNNs can extract learners' characteristics and the correlations between learning resources.

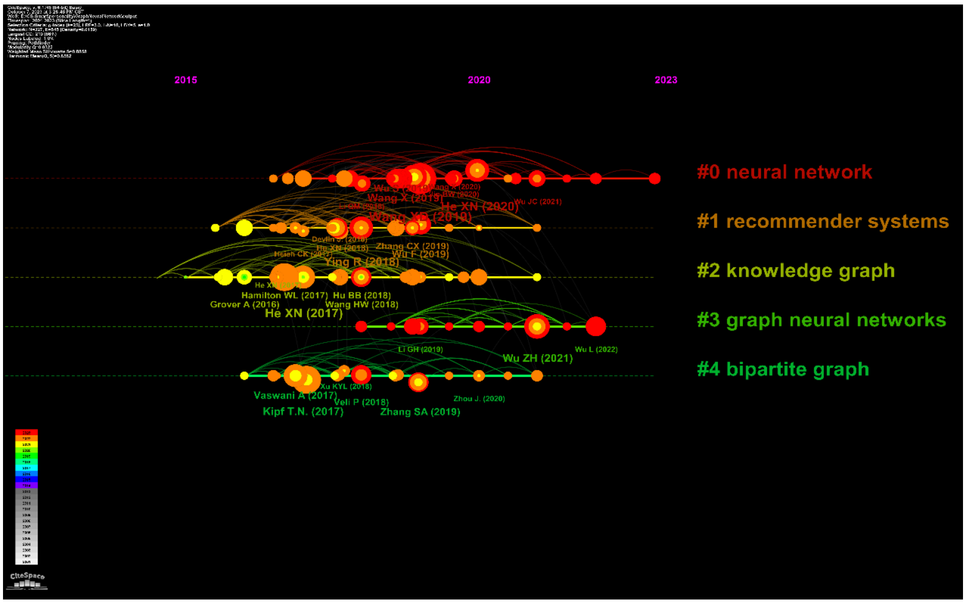

Figure 4. DCA timeline view of graph neural networks.

Figure 4 illustrates the temporal DCA network of GNN, consisting of a complex network of 327 cited references and 845 co-citation links, spanning seven years from 2014 to 2023. Notably, the three largest clusters have scores above 0.8, indicating their dependability and proximity to the highest score of 1.00. Cluster #0, which pertains to the strategic driver, is the most sizable, encompassing 45 member references, comparatively more significant than other network clusters. Conversely, cluster #4, owing to its smaller size, is the least significant in the network. Table 4 shows detailed information on clusters in terms of identifier (ID), silhouette score, cluster label, and major research topics. neural networks, recommend systems, knowledge graphs, and graph neural networks are the major research fronts of the cluster.

This facilitates personalized learning. Neural networks are computational models that simulate the human brain's neural network. They are also widely employed in personalized learning research. Through training, neural network models can discern complex relationships between numerous learners and learning resources from data. Consequently, they can provide personalized learning suggestions and recommendations for each learner. The knowledge graph is a graph structure used to represent knowledge. It is also extensively used in personalized learning research. By constructing a knowledge graph between learners and learning resources, the relationships between learners' individual characteristics and learning resources can be delineated as entities and relationships within the graph structure. Utilizing the knowledge graph, it is possible to analyze and infer learners' personalized learning needs, thereby offering them personalized learning support.

Cluster #0, titled "neural network", includes research on topics such as deep learning and federated transfer learning. This cluster includes research conducted between 2017 and 2023.The most cited article mentions that the application of graph-structured data deep neural networks to larger scale web recommendation tasks remains elusive, so the authors develop data-efficient Graph Convolution Network (GCN) algorithms, which improve the robustness of the converged model by relying more on difficult examples than the traditional GCN algorithm's training method. Experimental data and test results show that the method generates higher quality learned recommendations [38]. The more cited article mentions federated learning, a distributed machine learning framework with privacy-preserving, secure encryption techniques. Due to the differences between users, it improves the prediction of global aggregation obtained from local specific demands. This results in a personification problem, which the authors propose transfer algorithms with mechanisms to solve. The results show that convolution neural networks applying mechanisms can significantly improve the accuracy [39].

Cluster #1, titled "Recommend systems", involves studies on efficient recommendation and behavioral sciences. This cluster includes research conducted between 2016 and 2021.The related article points out that personalized recommend systems need to both provide high-quality content that is appropriate for the user and adapt quickly to changing environments. The authors propose incremental solutions that balance efficiency and quality, reducing time while ensuring accuracy [40]. The more cited article points out that due to the strong subjectivity and modification of news language, there is a problem of recommending content as a simple extension in news recommendation, so the researcher proposes to merge the graph representation into the recommendation of the deep knowledge-aware network (DKN) to predict the content framework. It also additionally designs the attention module to consider the user's interest and history comprehensively. Based on a large amount of real test data it is concluded that the model outperforms the traditional model [41].

Table 4. Cluster information of graph neural networks.

No.	Size	Silhouette	Lable	Research topics
0	45	0.856	neural network	deep learning; collaborative filtering; item commonality; federated transfer learning
1	36	0.842	recommend systems	behavioral sciences; sequential recommendation; efficient recommendation
2	34	0.838	knowledge graph	news recommendation; multi-context modeling; information filters; acoustics
3	32	0.940	graph neural networks	survival prediction; deep reinforcement learning (DRL); gradual pruning
4	29	0.863	bipartite graph	systems biology; point-of-interest recommendation; graph deep learning

DCA of knowledge graph

Knowledge Graph is a structured data model that builds a vast network of information by linking entities, attributes and relationships. With learners' behavioral data and points of interest, AI can recommend customized content such as courses, resources or answers based on the knowledge graph. This approach can more accurately meet the differentiated needs of each student, promote deep and exploratory learning, and enhance teaching effectiveness.

Figure 5 illustrates the temporal DCA network of knowledge graph, consisting of a complex network of 353 cited references and 894 co-citation links, spanning eight years from 2015 to 2023.From Table 5 it is clear that the three largest clusters have scores higher than 0.8, indicating that the samples are well assigned to the clusters in which they are located.Cluster#0, named Knowledge graph, contains 57 member references, which is the largest and the most important of these six clusters. On the contrary, cluster#6 is smaller and contains only 14 members and is the least important in the network. Table 5 shows detailed information on clusters in terms of identifier (ID), size, silhouette score, cluster label, and major research topics. Knowledge graph, Knowledge point, recommended system, Knowledge graphs, Markov processes and extraterrestrial measurements are the main research interests of the cluster.

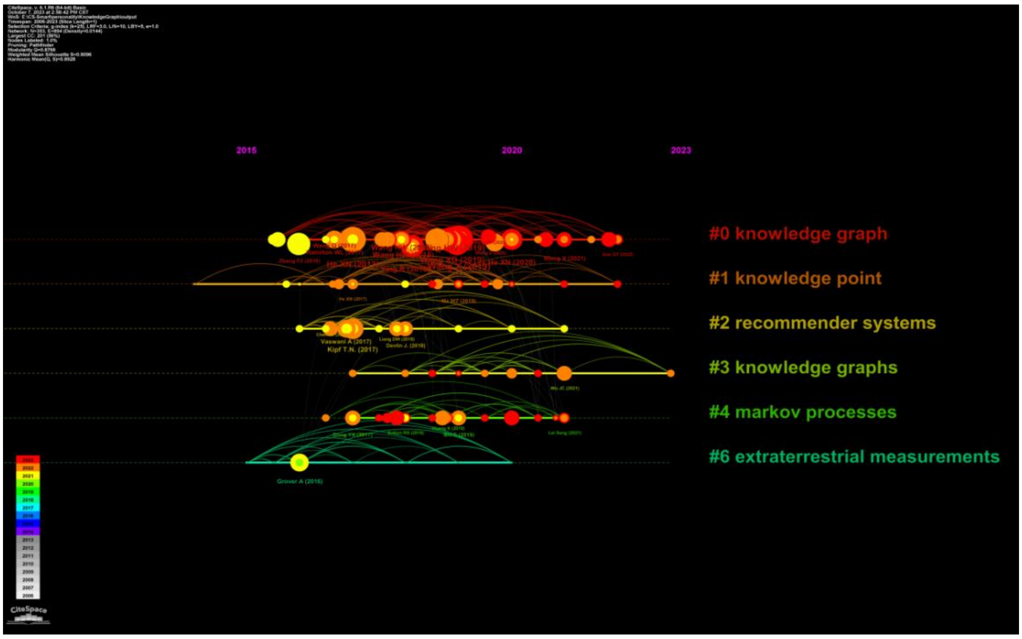

Figure 5. DCA timeline view of knowledge graph.

Cluster #0, titled "knowledge graph", includes research on topics such as graph convolution network and intelligent path-switching. This cluster includes research conducted between 2016 and 2022.The most citing article highlights the importance of using knowledge graphs to accurately model user preferences in personalized recommend systems, and that integrating knowledge graphs can effectively improve the performance and interoperability of recommendations. The authors designed CUIKG, a convolution-based approach that combines KG learning on both the user side and the project side. Experimental results show that CUIKG outperforms other methods [42]. The more citing article proposes a Deep Knowledge Graph Reinforcement Learning (DKRL) framework that enables intelligent switching of path guidance [43].

Table 5. Cluster information of knowledge graph.

No.	Size	Silhouette	Lable	Research topics
0	57	0.859	knowledge graph	intelligent path-switching; graph convolution network; social networking
1	32	0.855	knowledge point	Personalized recommendation; intelligent tutoring system; contrastive learning
2	25	0.912	recommend system	generative adversarial network; deep learning; network embedding;
3	24	0.972	knowledge graphs	data ecosystems; healthcare systems; tour recommendation;
4	22	0.934	Markov processes	user-interest Markov trees; learning path recommendation; cognitive graph; cognitive map;
6	14	1	extraterrestrial measurements	edge computing; searching service; task analysis;

Cluster #1, titled “knowledge point”, includes research on topics such as personalized recommendation and contrastive learning. This cluster includes research conducted between 2017 and 2022.The most cited article points out that existing studies have mainly ignored the basic relationships between knowledge points, which are essential for constructing effective learning sequences. Therefore the authors propose a weighted graph-based approach (WKG-R). The method is innovative in quantifying various test behaviors and improves the validity of recommendations through dependency analysis [44]. The most cited article introduces Comparative Trajectory Learning (CTLTR) to a Personal Travel Recommendation (PTR) system, which addresses the problems of traditional methods due to sparse data and uneven popularity of attractions [45].

DCA of big data

Big data refers to extremely large, diverse and rapidly generated data sets that are often beyond the capabilities of traditional data processing systems and involve structured, semi-structured and unstructured data sources. Supported by AI-enabled technologies, personalized learning leverages big data for in-depth analysis and mining, with the goal of accurately understanding and responding to learners' individual needs. Big data technologies can reveal learners' behavioral patterns, preferences and learning paths, providing key decision support and insights for personalized learning platforms.

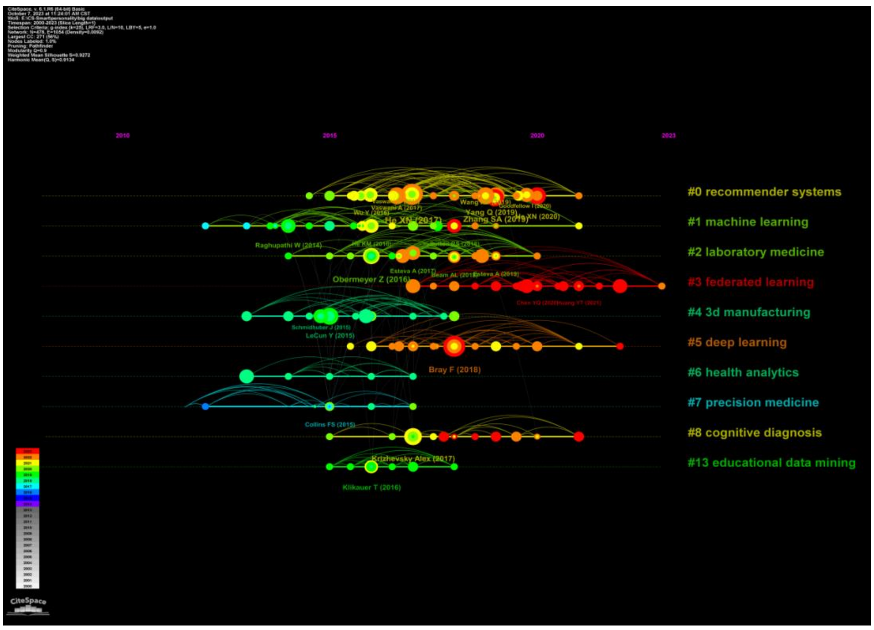

Figure 6. DCA timeline view of big data.

Figure 6 illustrates the temporal DCA network of big data, consisting of a complex network of 478 cited references and 1054 co-citation links, spanning eleven years from 2012 to 2023.All ten clusters have scores above 0.7. Cluster#0 labeled recommend systems is the largest, containing 46 member references, and is the most important of these ten clusters. On the contrary, cluster#13 labeled educational data mining is the smallest and relatively unimportant. Table 6 shows the ID, Size, Silhouette, Lable of the ten clusters and the research theme of the cluster. Recommend systems, machine learning, l aboratory learning, federated learning,3d Recommend systems, machine learning, laboratory learning, federated learning, 3d manufacturing, deep learning, health analytic, precision medicine, cognitive diagnosis and educational data mining are the main research areas of the cluster.

Cluster #0, titled “recommend systems”, includes research on topics such as neural networks and intelligent path-switching. This cluster includes research conducted between 2015 and 2021.The most cited article discusses the impact of digitization on transforming reality into big data, focusing on the role of web search engines and recommend systems as key interfaces for user experience [46]. The more cited articles explore the current role of educational recommend systems (RS) as an important tool to support human interaction patterns in learning environments. It is the age of big data, but the quality of recommendations from educational recommend systems and other services is declining. The authors propose a method for recommending resources based on an individual's learning progress and needs. It integrates an evaluation module in the recommendation process that uses analytic, artificial intelligence techniques and fuzzy logic to simulate reasoning and deal with uncertainty in educational environments [47].

Cluster #3, titled “federated learning”, includes research on topics such as edge computing and contrastive learning. This cluster includes research conducted between 2017 and 2023.The most cited article highlights how edge computing can improve content delivery and quality of service by leveraging the network edge to increase cloud capacity. To integrate intelligent systems, the authors propose a deep reinforcement learning federation framework that promotes collaborative node intelligence while minimizing unnecessary system load. The results show that the performance of the low-overhead learning and adaptive cognitive system is close to optimal [48]. The most citing article proposes the Feature Comparison Joint (FcgFed) method, which aims to analyse the information and employs comparative methods to mitigate disagreement in the learning process [49].

Table 6. Cluster information of big data.

No.	Size	Silhouette	Lable	Research topics
0	46	0.96	recommend systems	neural networks; sequential recommendation systems; knowledge engineering
1	42	0.78	machine learning	psychological profiles; computational social science; moral foundations;
2	41	0.922	laboratory learning	live clinical workflow; outpatient psychotherapy; prognosis optimization;
3	41	0.991	federated learning	knowledge distillation; edge computing; contrastive learning
4	23	0.876	3d manufacturing	3d printing; computer-aided manufacturing; additive manufacturing
5	22	0.971	deep learning	Convolution neural network; colonic neoplasms; neural network;
6	20	0.961	health analytic	Caber-physical systems; social networks analysis; social networks analysis
7	14	0.978	precision medicine	p4 medicine; artificial intelligence; biomedical informatics
8	13	0.966	cognitive diagnosis	intelligent tutoring systems; user modeling; neural network design
13	9	1	educational data mining	distance learning; learning analytic; learning analytic

CONCLUSION

This paper visualizes techniques related to personalized learning in the context of AI support through a scientific bibliometric analysis of 3,912 papers from the web of science database.

This study evaluates the effectiveness of AI technology applied to personalized learning and finds that AI not only enhances the degree of personification of learning, but also dramatically improves the efficiency, experience and effectiveness of learning, opening up more possibilities for future education models. The research frontier shows that deep learning, collaborative filtering and large language models are the latest trends in AI research. These technologies have been widely used in personalized learning, improving the monotony and dullness of traditional learning. Intelligent tutoring systems, data analysis of learning behaviors, and emotion recognition and regulation are current research hot-spots in this field. In addition, the fairness and inclusiveness of personalized learning, real-time learning feedback and interaction, and the collaboration mechanism between teachers and AI are receiving extensive attention from the scientific community.

The study highlights the importance of collaboration, innovation and technological advancements in driving AI-enabled personalized learning. While AI technologies, data analytic, smart recommendations, and other technologies have great potential to significantly enhance the personalized learning experience, successful implementation requires the collaboration of experts from all relevant fields. However, the study also points out the limitations and challenges of applying relevant technologies, such as cross-cultural adaptation, model updating, resource allocation issues, and ethical issues. Therefore, the study highlights the need for collaboration and communication between researchers in various fields and industry stakeholders. It is crucial to adopt a systematic and scientific approach to maximize the benefits of personalized learning from AI technologies while reducing the risks of their application.

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