Educational Recommender Systems: A Systematic Literature Review

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Abstract
Recommendation systems were implemented as a solution to reducing the time and effort required by a user to search for information. In the development of the recommendation systems that offer the best performance, artificial intelligence algorithms are used, in combination with various recommendation approaches. However, in the educational context these systems have a different connotation since their objective It focuses on improving educational quality and not only on offering the user the option that best suits them. Educational recommendation systems (ERS) are those information systems that have been developed with the purpose of being used in an educational institution or organization with the purpose of recommending the different actors of the educational system: students, teachers, researchers or others, educational articles such as: programs, subjects or subjects, exercises, educational resources, etc. that contribute to raising educational quality. This scientific work seeks to determine what type of educational recommendation systems contribute to the educational quality of different education centers worldwide. To answer this question, the Cochrane methodology for the systematic review of ERS has been used. As a result, the recommendation systems implemented within the educational context raise the results of several educational quality indicators, including the student graduation rate and the academic performance of the students.

Keywords: Educational Quality, Teachers, Students, Educational Recommender Systems

Introduction

Recommender systems (RS) are software tools that assist users in the decision-making process by applying information filtering, data mining, and prediction algorithms (Urdaneta-Ponte et al., 2021). These systems provide personalized suggestions about products, services, information, or content. There is a wide variety of RS in e-commerce services, video and music (Vara et al., 2022), streaming, search engines, social networks, among others. The first RS were developed for companies such as Amazon and Netflix, however, the transversality of the technology has achieved its use in the fields of health, transportation, agriculture, media, smart cities, education, and others.

The international body that defines criteria and indicators of educational quality is UNESCO, under this body every nation in the world within its governance has one or more bodies that maintain an accreditation system that ensures educational quality. In Spain the higher education accreditation body is the National Agency for Quality Assessment and Accreditation (ANECA), in Chile there is the National Accreditation Commission (CNA) (Aucancela, 2019) and in Ecuador the Council for Quality Assurance in Higher Education (CACES). For (UNESCO, 2023), the dimensions of educational quality are: learner characteristics, material and human inputs, teaching and learning, outcomes, and context. Some indicators of educational quality are retention rate and graduation rate (Modelo de Evaluación Externa de Universidades y Escuelas Politécnicas 2019, 2019). Retention rate refers to the number of students who remain in the same institution from the beginning to the end of a programme (Laura Horn, 2000). The graduation rate refers to the percentage of students who complete their education on time or in one more academic year in relation to their entry cohort (University of Castilla-La Mancha, 2021).

On the above-mentioned aspects, through this work, the following question will be answered: what type of educational recommendation systems (ERS) contribute to the educational quality of different education centers worldwide? Now answering this question means address research domains related to SR, machine learning and education.

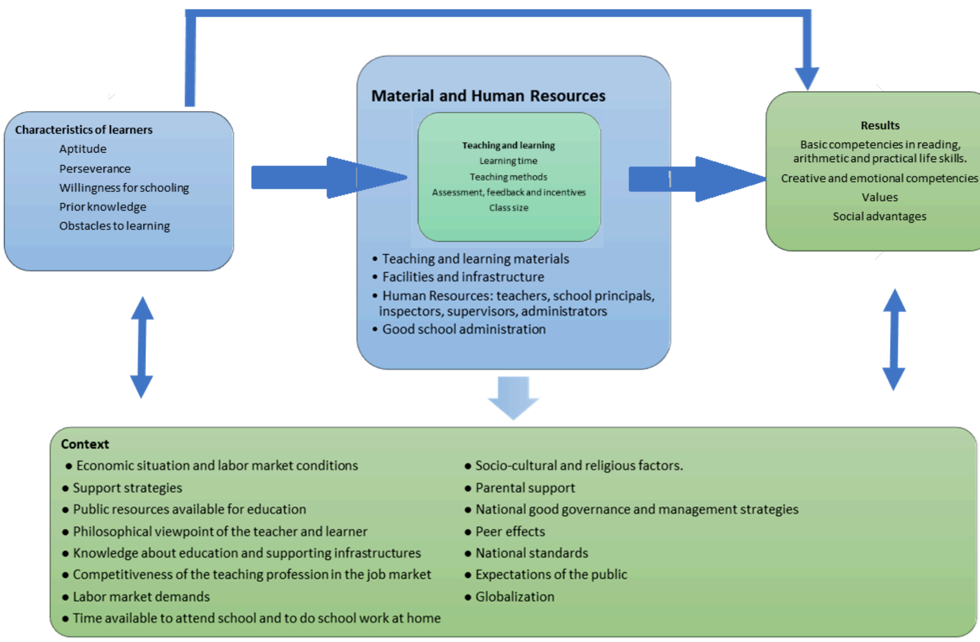

Figure 1: Education quality scheme (UNESCO, 2005)

The rest of the article is structured so that in section 2 the works related to this research are presented, in section 3 the methodology used for the development of this scientific work is presented, in section 4 the results are presented and in the Section 5 presents the conclusions.

Related Works

The integration of technology into teaching and learning processes has generated multiple benefits such as: improvements in the learning experience, personalization of teaching and promotes collaborative learning (Dao et al., 2022). The technology that was integrated into teaching and learning processes are educational recommender systems (ERS), which are tools that use algorithms to provide course recommendations, curricula and personalized learning resources to students: such as textbooks, activities and educational games (da Silva et al., 2022). In the work of (Urdaneta-Ponte et al., 2021) a systematic review on ERS is performed, however, it is necessary to determine which educational processes use ERS to improve educational quality, in the work of (Kulkarni et al., 2020) a study of e-learning challenges and methodologies is presented, however, it is necessary to know the elements involved in the development of an ERS and to determine what is the role that recommendation approaches and artificial intelligence algorithms have in the development of an ERS. In the work of (Roy & Dutta, 2022) a systematic review of the literature on ERSs is performed, however, it is necessary to identify the educational contexts and the objectives of ERS development.

Methodology

To develop this research work, the Cochrane methodology for the development of systematic reviews was used as a reference; this methodology proposes following the steps shown in Figure 2 (Pardal-Refoyo et al., 2020):

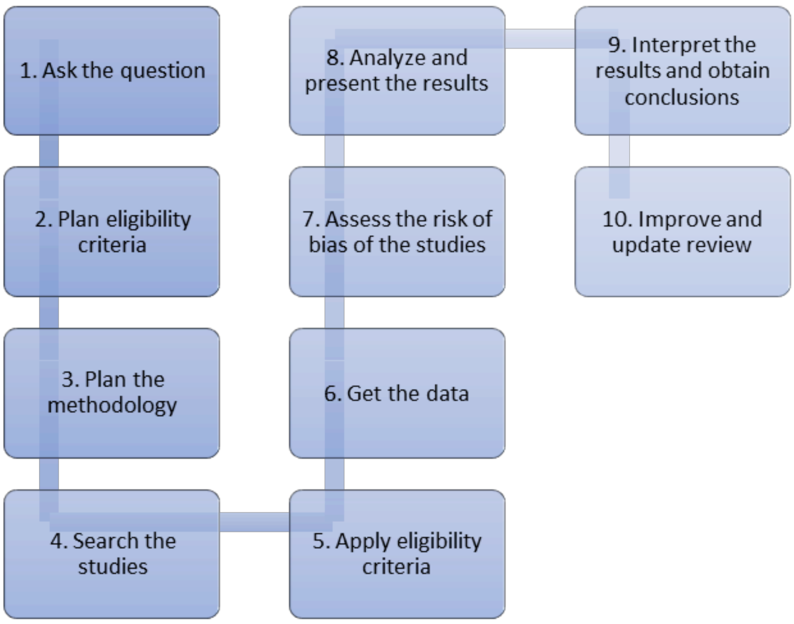

Figure 2: Main steps of the Cochrane methodology (Pardal-Refoyo et al., 2020)

First, a general review of ERS was conducted to understand the research problem and its context, and then the following questions were posed:

Q1. What are educational recommender systems (ERS)?
Q2. What elements are involved in an ERS?
Q3. What are recommender approaches?
Q4. What artificial intelligence (AI) algorithms have been used in ERSs?
Q5. What kind of recommender systems contribute to the educational quality of different educational institutions worldwide?

The planned eligibility criteria respond to the following details:

a. Articles published from 2018 through 2023.
b. Articles from Web of Science (WOS) and Scopus scientific databases.
c. Articles published in the English language.
d. Articles related to recommender systems, machine learning and education.

Once the eligibility criteria were defined, the methodology was planned, and the following activities were carried out:

a. Obtaining scientific articles: a search string was formed with the following terms: "recommendation systems", "machine learning" and "education". Applying the eligibility criteria, 141 articles were obtained, 60 articles from the WOS database and 81 from the SCOPUS database.
b. Elimination of articles: using Excel pivot tables, a cross-checking of the obtained articles was performed, 12 duplicate articles were found, then 47 articles that did not respond to the research topic were eliminated.
c. Review of scientific articles using the Askyourpdf platform to speed up the exploration.

Results

The review of more than 80 scientific articles detected a relevant gap due to the fact that the majority of them present general topics on ERS or the development of a specific ERS, which motivated to: determine the educational processes that are automated by ERS, identify the elements involved in ERS, determine the importance of recommendation approaches, perform a rough categorization of AI algorithms as a way to organize the knowledge on this topic and define the objectives of ERS development.

Q1. What are ERS?

By using AI in education two disciplines were developed: educational data mining (EDM) and learning analytics (LA), EDM focuses on the analysis of educational data to improve teaching and learning, while LA focuses on the analysis of student data to improve educational decision making, both contribute to improve educational quality through data analysis and the application of machine learning techniques (Charitopoulos et al., 2020).

ERS appear as an emerging discipline resulting from the use of AI in education, initially ERS were focused on improving learning (T. N. De Oliveira et al., 2021), however, comparing the (External Evaluation Model of Universities and Polytechnic Schools 2019, 2019) with the ERS found, it is evident that ERS are used in multiple educational processes other than the teaching-learning process, which motivated to think of an integral approach. See Figure 3. An integral vision of the educational context allows extending the development objectives of the ERS to improvements in educational quality.

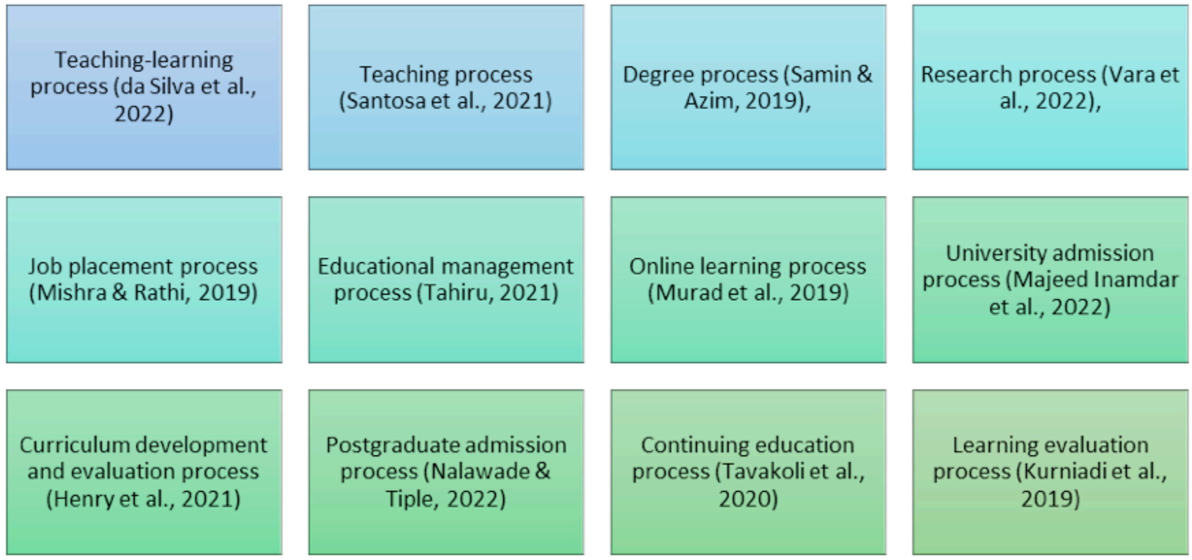

Figure 3: Educational processes automated by an SRS

The relationship between educational processes indicates that, if an educational process is automated, improved or strengthened by an ERS, it influences another process; an example of this is the positive influence of the teaching-learning process on the teaching process. An ERS of the teaching-learning process suggests courses, reading materials, videos, exercises and other learning resources according to the preferences and needs of each student (da Silva et al., 2022), improving the results evidenced in quality indicators such as academic performance (Jalota & Agrawal, 2019) and the graduation rate of students (Fernández-García et al., 2020). The teaching process affected by the teaching-learning process allows professors to make decisions on how to design and deliver courses and curricula, which improves the effectiveness and efficiency of teaching and learning (Charitopoulos et al., 2020).

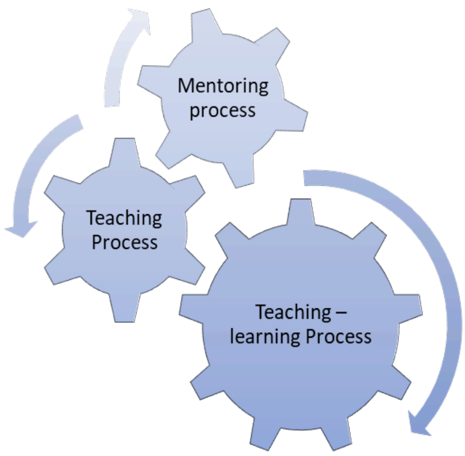

Figure 4: Relationship between educational processes

Thus, it is evident that the ERS are information systems developed in an educational institution or organization with the purpose of recommending to the different actors of the educational environment: students, teachers, researchers or others, educational items:

subjects, careers or departments, exercises, activities, etc. that contribute to improve the quality of education.

Q2. What elements are involved in an ERS?

To understand the architecture of an ERS, it was proposed to know its elements. See figure 5.

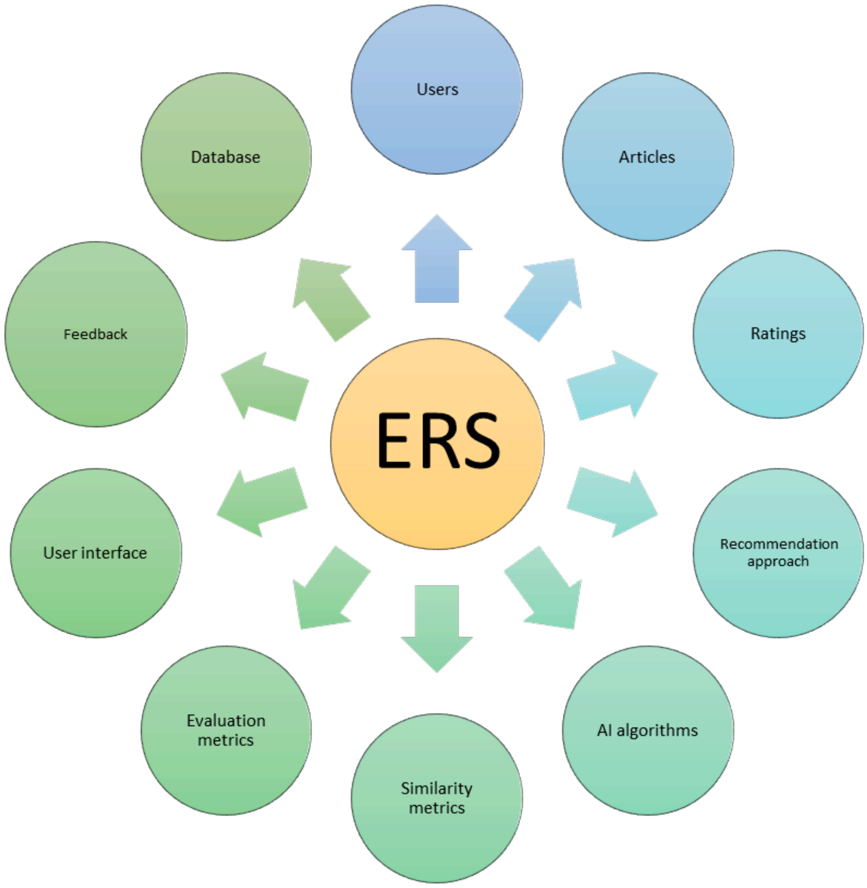

Figure 5: Elements of an ERS

Below is a brief explanation of each element:

- Users: people who use the system and receive recommendations based on their preferences, behavior, and feedback (Li & Zhang, 2021).
- Items: products, services or content that are recommended to users based on their interests and needs (Uddin et al., 2021).
- Ratings: explicit comments (ratings, reviews, preferences) or implicit comments (clicks, views) (Ren, 2023) provided by users on items they have used or consumed, which is used to calculate the similarity between users and items.
- Recommendation approach: is the method or technique used to generate recommendations (Murad et al., 2019).
- AI algorithms: used to analyze data and generate recommendations (Zhou et al., 2018).
- Mathematical formulas: measures used to determine the similarity between users or items based on their ratings (Abed et al., 2020).
- Evaluation metrics: criteria used to measure the effectiveness of ERS, such as accuracy, coverage, diversity, and novelty (Saito & Watanobe, 2018).

- User interface: through which recommendations are presented to the user. It can be a website, mobile application, email or other forms of communication (Liu et al., 2021).
- Feedback: ERS continuously learns and improves by incorporating user comments. This can include explicit comments (ratings, reviews) or implicit comments (clicks, time spent) to refine recommendations over time (Santosa et al., 2021).
- Database: It is where information about users, items and interactions between them is stored (Lazarevic et al., 2022).

Q3. What are recommendation approaches?

The development of RS has a history, they emerged in the early 1990s and used algorithms that identified other users with similar tastes and combined their ratings into a personalized weighted average (Jannach et al., 2011). From there, the first recommendation approach called collaborative filtering appeared. This was followed by the construction of online SRs and in 2006 led to the development of in-context SRs. By 2007, six recommendation approaches were identified: collaborative filtering (CF), content-based filtering (CBF), context- or utility-based filtering, knowledge-based filtering, demographic filtering and hybrid filtering (Burke, 2007). The innovation that has this technology has achieved the emergence of emerging popularity-based and artificial intelligence (AI)-based approaches.

The importance of knowing recommendation approaches lies in the way recommendations are conceived, for example, a collaborative filtering ERS focuses on students' preference similarities or similarity of preferences of educational resources, while a content-based ERS is going to focus on a student's historical preferences, i.e. on the educational resources he/she has already chosen before.

ERS are categorized according to the form and according to the algorithmic approach (Quijano-Sánchez et al., 2020), according to the algorithmic approach based on unknown valuation estimation methods (Palomares & Porcel, 2020) ERS are categorized into: ERS based on heuristics and ERS based on models. Heuristic-based ERS estimate the relevance of items through mathematical formulas such as cosine similarity calculation or item or user correlation, whereas model-based ERS predict the relevance of items through machine learning techniques (Quijano-Sánchez et al., 2020), this indicates that the algorithmic approach will depend on whether AI algorithms are used, or mathematical formulas are used to generate the recommendations. Similarly the metrics to evaluate the accuracy of the recommendations will depend on this algorithmic approach, for example, a metric to evaluate the AI algorithm: classification tree, used in the ERS is the cross-validation (Pesovski et al., 2022), a metric to evaluate the accuracy in the calculation of the cosine similarity in the ERS is the mean average precision (mAP)(W. J. B. de Oliveira & Brandão, 2021).

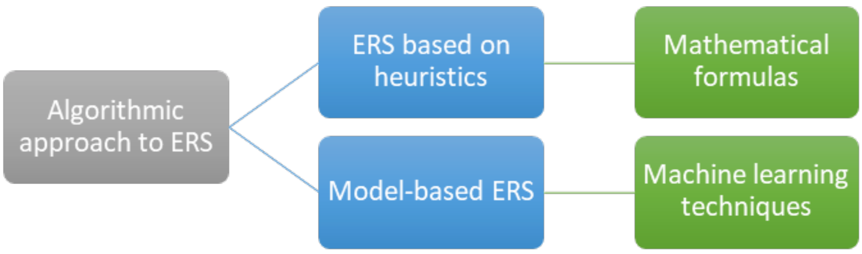

Figure 6: Algorithmic approach to ERS

For (Sunil Kumar Aithal et al., 2023), the most used approaches in ERS are: collaborative filtering, content-based filtering and the hybrid approach. Each of these and the emerging approaches identified in this study are detailed below.

Collaborative Filtering (CF)

For (Cai et al., 2022) collaborative filtering is a recommendation methodology that uses the known preferences of a group of users to recommend or predict the preferences of other users. These are categorized into memory-based collaborative filtering systems and model-based filtering systems (Zhang, 2021). Memory-based collaborative filtering recommendation systems are categorized into user-based filtering and item-based filtering (Rana et al., 2020; Roy & Dutta, 2022).

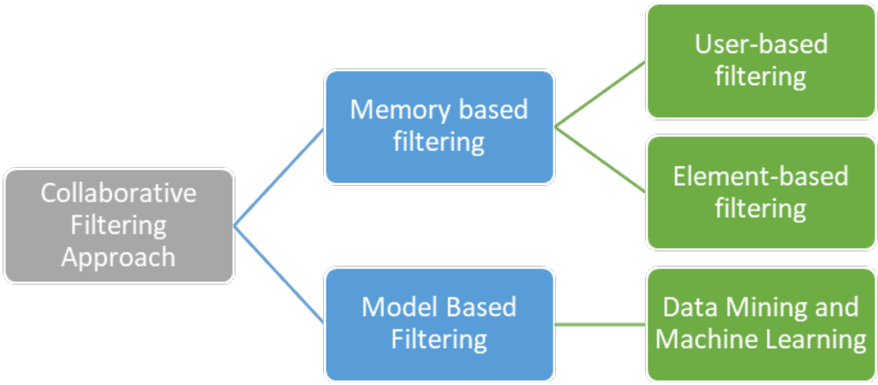

Figure 7: Categorization of the collaborative filtering approach

Memory-based collaborative filtering systems recommend new items by taking into account the preferences of their neighborhood (Xu & Yin, 2022).

In user-based filtering, the similarity between users is rated in relation to a given item. If a new item receives positive ratings from the user's neighborhood, the new item is recommended to the user.

In the item-based approach, the similarity between items is rated, an item neighborhood is constructed consisting of all similar items that the user has previously rated. Then for a new item, the rating is predicted by calculating the weighted average of all the ratings present in a neighborhood of similar items (Palomares & Porcel, 2020).

Model-based collaborative filtering systems use machine learning and data mining to predict user ratings to unrated items (Rana et al., 2020; Roy & Dutta, 2022).

Content-Bbased Filtering (CBF)

These systems use the student's personal information and the characteristics and attributes of the items to generate recommendations like the items the student liked in the past (Mohamed et al., 2019).

Hybrid Filtering

A hybrid recommender system combines two or more recommendation techniques to obtain higher accuracy and improvements in recommendations (Choe et al., 2021).

Popularity-Based Filtering

This approach recommends popular or trending items based on the popularity and demand of the items among users (Mohamed et al., 2019).

AI-Based Filtering

This approach uses AI algorithms for the design of ERSs. To achieve this, supervised and unsupervised learning techniques, such as regression, classification, and clustering, are used to develop recommendation models (Assavakamhaenghan et al., 2021). When having large amounts of data, ERSs use deep neural networks to analyze and extract complex features from student data for more subtle patterns and make more accurate and detailed recommendations (Tahiru, 2021).

Q4. What AI algorithms have been used in ERS?

For (Coca & Llivina, 2021) AI has four basic knowledge cores: knowledge representation, reasoning, uncertainty treatment and learning, furthermore the author indicates that AI is the computer science in charge of applying methods of knowledge representation, processing and extraction, by means of multi-paradigm programming, in the development of computer systems with rational behavior. Table 1 shows the relationship of AI problems related to the four basic knowledge cores.

Table 1: Relationship between AI problems and the basic knowledge cores (Coca & Llivina, 2021)

AI Categories	Problem
Knowledge representation	Tacit knowledge representation Natural language representation
Uncertainty handling	Models for computational decision making
Reasoning	State space search Inference in knowledge-based systems
Machine learning	Data mining Agent autonomy

According to the (European Parliament, 2021) there are two types of AI, that AI developed through software that generates applications such as: virtual assistants, image analysis software, search engines, voice and face recognition systems, recommendation systems and that integrated AI used in robots, drones, autonomous vehicles or in general, in the Internet of Things.

Analyzing the concept of (Coca & Llivina, 2021 and the categorization of (European Parliament, 2021) evidences that behind all software applications developed by AI, there are AI algorithms that belong to different programming paradigms, this determines a change of perspective in software programming and research, due to the fact that some authors indicate that machine learning, deep learning and reinforcement learning are branches of AI (Bagnato, 2023), when in fact, machine learning more than being a basic core of AI knowledge (Coca & Llivina, 2021) becomes one of the main programming paradigms to develop AI software applications, this paradigm contains learning strategies which have a set of techniques and each technique has algorithms that analyze data.

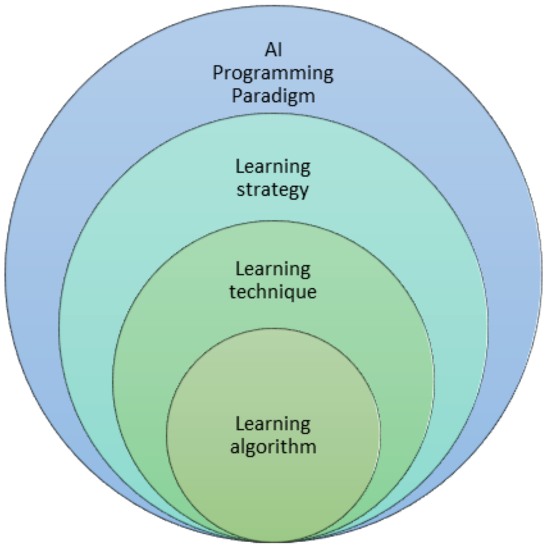

Figure 8: Paradigm, strategy, technique, and algorithm relationship

Machine Learning

This paradigm contains algorithms and statistical models that allow computer systems to learn and make predictions or decisions based on data, without being explicitly programmed (Yongxian et al., 2020).

The main machine learning strategies are supervised learning, unsupervised learning, reinforcement learning and deep learning. Figure 9 shows the main machine learning algorithms.

In supervised learning, the algorithm is trained on labeled examples, where the correct output for each input is known. In unsupervised learning, the algorithm is trained on unlabeled data and must find patterns or structures in the data. In reinforcement learning, the algorithm learns by interacting with an environment and receiving feedback in the form of rewards or punishments. Deep learning involves training generative neural networks to learn from large amounts of data.

The main application areas of deep learning are computer vision, speech recognition, natural language processing (NLP) and recommender systems (Batmaz et al., 2019).

Technological advances in NLP have given rise to what is now called generative artificial intelligence (GIA) which is characterized by using generative neural networks, the work of (Vaswani et al., 2016) presents dominant sequence transduction models which are based on convolutional neural networks or complex recurrent neural networks to develop machine translation and language management tasks.

The multi-paradigm programming of AI allows the combination of algorithms from one paradigm and another in applications, giving rise to artificial general intelligence (AGI). One of the main AGI developments is ChatGPT, which is a natural language processing (NLP) chatbot (Frąckiewicz, 2023) based on the GPT (Generative Pre-trained Transformer) model, which uses generative neural networks and evolutionary algorithms. By using ChatGPT in education, it is concluded that this application is also an ERS.

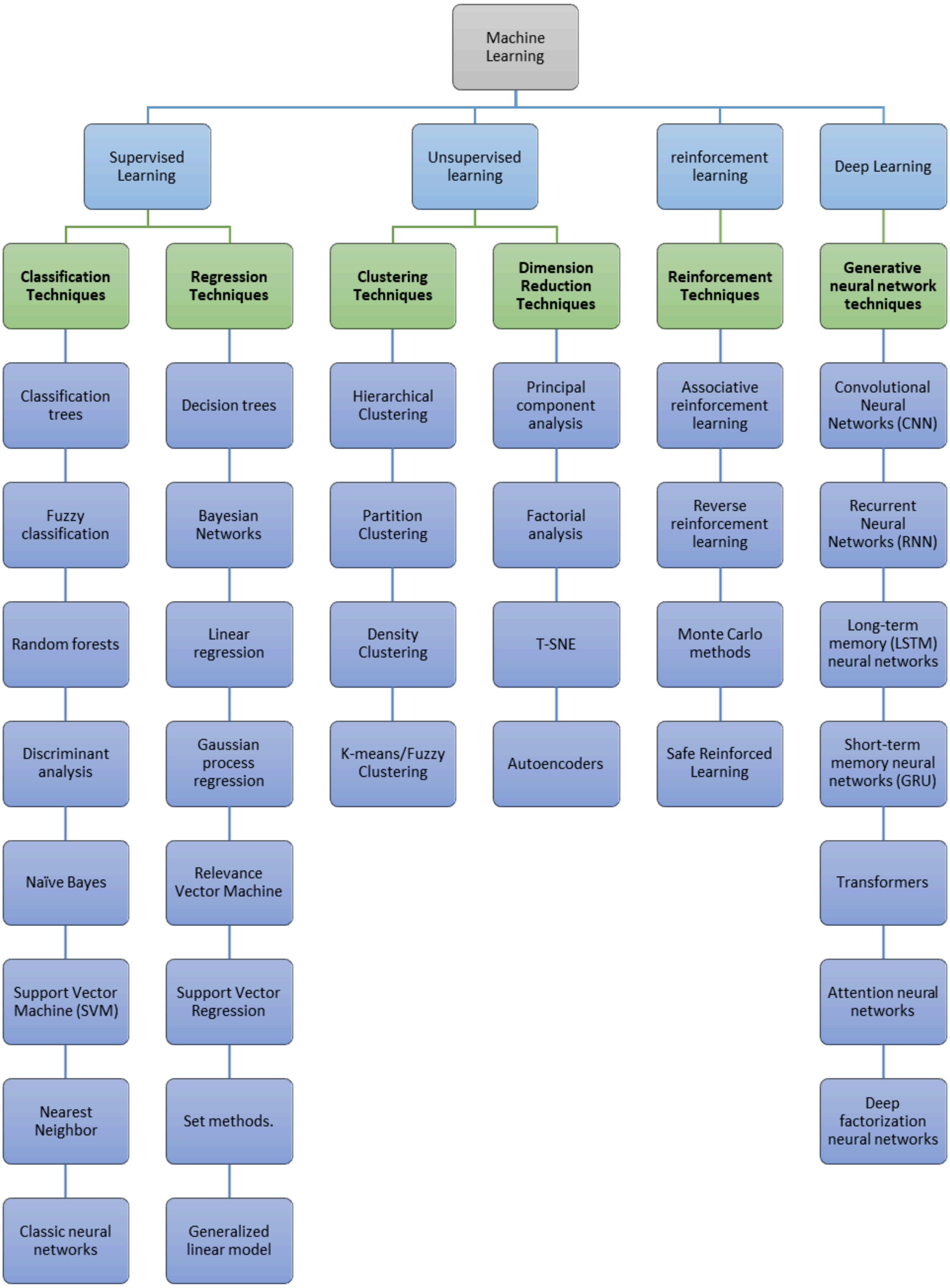

Figure 9: Main machine learning algorithms

Q5. What type of recommendation systems contribute to the educational quality of the different educational centers worldwide?

Knowing the educational context allows directing efforts towards educational quality objectives. The commonly identified educational levels are primary, secondary, higher (da Silva et al., 2022) and postgraduate (Nalawade & Tiple, 2022), however, the U.S. educational system includes K-12 schools, the "K" refers to "Kindergarten", which is the first year of formal education, and the "12" refers to the 12 years of education that includes primary and secondary (Zayet et al., 2022).

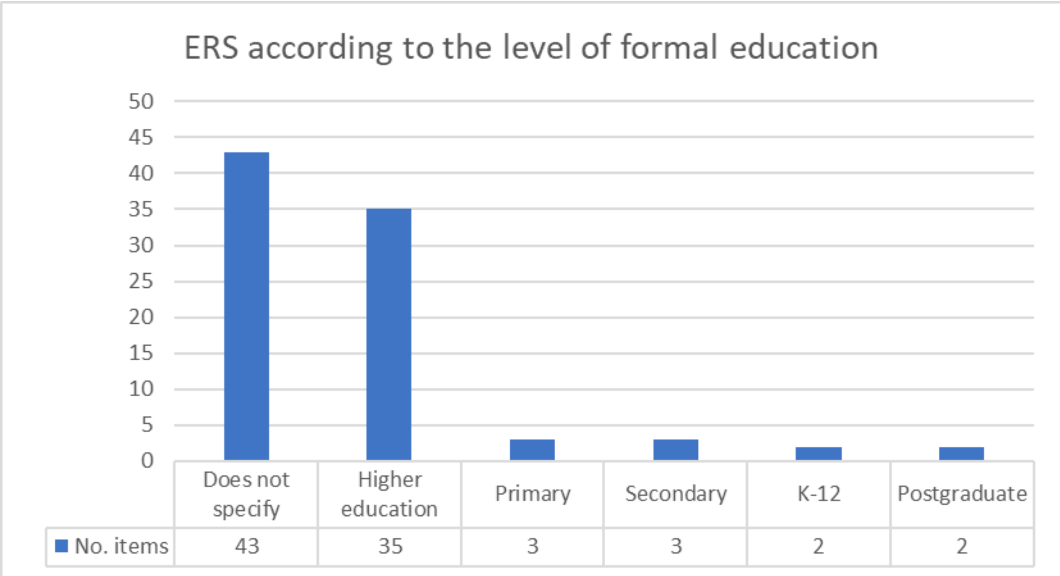

Figure 10: SRs identified according to the level of formal education

For (Charitopoulos et al., 2020) the educational modalities of the ERS are grouped into 8 families, see figure 11.

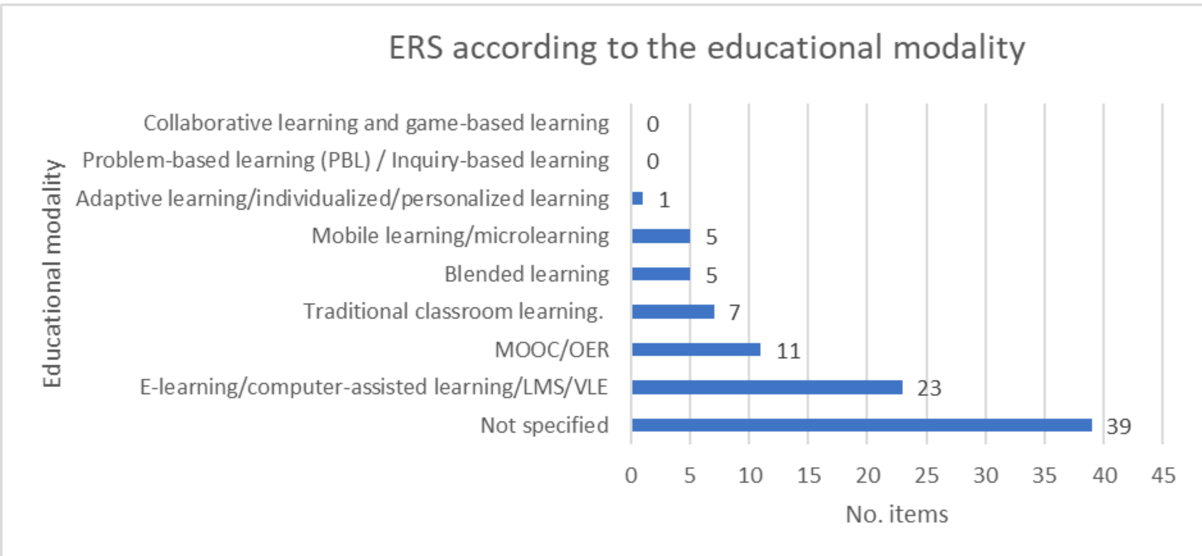

Figure 11: ERS identified according to the educational modality

It should be noted that some ERS were implemented for 2 or more levels and the same happens with educational modalities; some articles indicated that ERS were used in 2 or more modalities.

From the analysis of the 82 scientific works, around 55 ERS were identified focused on development objectives related to educational quality such as:

Table 2: Main contributions of the ERS to educational quality

Dimension	ERS Development Objectives	No. ERS
Learner Characteristics	Motivate student engagement	2
Teaching and Learning	Support student assessment	2
Context	Provide career guidance to suggest relevant career paths, job opportunities, or internships based on students' interests, skills, and educational background(Mansouri et al., 2023)	8
Material and human inputs	Support teachers by providing information about students' preferences, learning patterns and progress(Rahman et al., 2021)	3
	Support faculty in the development of research and outreach activities.	3
	Select and plan appropriate courses, majors, or programs that align with their aspirations and help them make informed decisions based on their interests, career goals, and skill development needs(Lazarevic et al., 2022; Liu et al., 2021).	17
	Provide personalized learning to tailor educational resources and learning activities to each student's individual needs, learning styles(D. Li et al., 2023), and preferences.	16
Results	Support remediation through identification of knowledge gaps and recommendation of remedial resources, tutorials, or personalized interventions(Campos et al., 2022).	4
Total number of articles with specific development objectives		55
Total number of articles without specific development objectives		27
Total number of articles reviewed		82

As can be seen, most ERS have course selection, personalized learning and career guidance as development objectives.

Conclusions

It was determined that ERS improve educational processes and therefore the quality of educational centers. Future research can focus on the multiparadigm programming of AI, the methodology and evaluation methods that ERS have.

The elements involved in ERS were identified: users, items, ratings, recommendation approach, AI algorithms, mathematical formulas, evaluation metrics, user interface, feedback and database. In this work, we only delved into recommendation approaches and AI algorithms, however, future research can study the elements that have not been observed.

Recommendation approaches were identified, the decision to use AI algorithms depends on the recommendation approach selected for an ERS, in addition to the educational objectives and quality criteria required by an educational institution.

So far it was established that the most used algorithms in ERSs belong to the machine learning paradigm, however, they are not the only algorithms used, future research can study algorithms from other AI paradigms such as evolutionary computation, logic programming and functional programming.

It was identified that most of the ERS use the hybrid recommendation approach, the educational contexts respond to the levels of education "Kindergarten" or first year of formal education, primary, secondary, higher and postgraduate. The educational modalities are grouped into 8 families and the types of ERS so far implemented are mainly focused on the objectives of: personalized learning, course selection and career guidance, with the student being the main user of the ERS.

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