INDIVIDUALIZED RECOMMENDER SYSTEMS FOR TEACHING: A SYSTEMATIC LITERATURE MAPPING

SISTEMAS DE RECOMENDAÇÕES INDIVIDUALIZADAS PARA O ENSINO: UM MAPEAMENTO SISTEMÁTICO DA LITERATURA

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Abstract. This paper aims to comprehensively study the current research in individualized recommender systems for education. The study uses a systematic mapping method to classify and organize the literature on this topic. The analysis is based on the frequency of publications within the classification scheme, using 1583 articles from the leading scientific databases of the last five years. The main techniques, tools, and strategies employed in creating and implementing these systems will be identified through this study. Understanding the present status of research in this field is crucial to support these systems' future development.

Keywords: individualized recommender systems; education; systematic mapping; literature classification; future development

Resumo. Este artigo tem como objetivo estudar de forma abrangente o estado atual da pesquisa na área de sistemas de recomendação individualizados para educação. O estudo utiliza um método de mapeamento sistemático para classificar e organizar a literatura sobre esse tema. A análise é baseada na frequência de publicações dentro do esquema de classificação, utilizando 1583 artigos das principais bases de dados científicas dos últimos cinco anos. As principais técnicas, ferramentas e estratégias utilizadas na criação e implementação desses sistemas serão identificadas por meio deste estudo. Compreender o estado atual da pesquisa nesse campo é crucial para apoiar o desenvolvimento futuro desses sistemas.

Palavras-chave: sistemas de recomendação individualizados; educação; mapeamento sistemático; classificação da literatura; desenvolvimento futuro

1. INTRODUCTION

Individualized recommender systems have gained popularity in education (Zhang et al., 2021). These systems aim to provide personalized recommendations to learners based on their preferences, learning style, and past performance. Implementing these systems can potentially improve the effectiveness of teaching and learning by offering learners resources tailored to their specific needs (Alamri et al., 2021).

The field of individualized recommender systems for education has developed rapidly in recent years, and research on developing and implementing these systems has increased substantially (Guo et al., 2020). Despite this increase, the lack of a comprehensive and systematic literature review addressing individualized recommendations (Muñoz et al., 2022) rather than just e-learning systems (Hammad, 2018) is notable. This article aims to fill this gap by providing a systematic literature mapping of state of the art in individualized recommendation systems for education.

This study is prompted by the increasing attention to personalized learning and the desire for a deeper understanding of the technologies, methods, and techniques used in the development and execution of individualized recommendation systems for education. This paper aims to provide a comprehensive overview of this area's current state of the art and highlight key trends and challenges in developing and implementing these systems.

The methodology used in this study is based on the PICOC (Population, Intervention, Comparison, Outcome, and Context) framework (Mengist et al., 2020). The population of this study includes students, teachers, and professors, and the intervention is the use of individualized recommendation systems in teaching and learning. The comparison includes traditional teaching and learning methods and other systems such as Artificial Intelligence (AI), Machine Learning (ML), and User Experience (UX). The outcome of interest is the effectiveness of the systems in improving individualization and planning in the context of virtual, school, and college education.

The remainder of this article is organized as follows. First, a detailed literature mapping of the current state of the art in individualized recommender systems for education is provided. It also covers the concepts of recommender systems and individualized recommender systems and their application in the educational domain, especially in virtual learning environments and non-virtual environments. Then, the methodology used is presented based on the PICOC framework. Also, explain the search term, item selection process, and final refinement summary. Conclude with a detailed analysis of all articles showing the current state of the art in individualized recommendation systems for education. Finally, the main findings were summarized, and the implications of this research and directions for future research were discussed.

In essence, the primary goal of this study is to perform an in-depth examination of the status of research in the area of personalized recommendation systems for education. By examining a total of 1583 publications, 84 of which were chosen for in-depth research, the study intends to identify the key trends and obstacles in developing and deploying these systems. This study's overarching objective is to present a comprehensive overview of the field's research status and promote the future growth and development of personalized recommendation systems in education.

2. RECOMMENDATION SYSTEMS APPLIED TO EDUCATION

Recommendation systems in diverse domains, such as e-commerce, entertainment, and education, constitute a specific category within information filtering systems (Schafer et al., 1999). These systems are designed to provide personalized recommendations to users based on their preferences, behaviors, and past performance (Tian et al., 2019). The main goal of recommendation systems is to help users find items that match their interests and needs (Kale et al., 2022).

One example of a use case would be a high school student preparing for college entrance exams who has varying strengths across subjects. To create a tailored study plan, a personalized recommendation system could analyze the student's past performance, learning style, and interests. For instance, if the student excels in mathematics but struggles with chemistry, the system might suggest more interactive chemistry tutorials and additional practice problems while recommending advanced mathematics problems to keep the student challenged.

They can be divided into three main types: content-based, collaborative, and hybrid (Sun et al., 2016). Content-based recommendation systems use item features to recommend similar items to the user (Gemmis et al., 2015). Collaborative recommendation systems use the preferences of other users with similar interests to the current user to recommend items (Cui et al., 2020). Hybrid recommendation systems combine the advantages of content-based and collaborative systems to provide more accurate recommendations (Afoudi et al., 2021).

Content-based recommendation systems are based on the idea that users prefer items similar to those they have previously liked (Kale et al., 2022). These systems use item features to recommend similar items to the user (Sun et al., 2016). For example, in a movie recommendation system, a content-based system would recommend movies with similar characteristics (e.g., genre, actor, and director) to the movies the user previously liked (Kale et al., 2022). Content-based recommendation systems have the advantage that they do not require a large amount of data about users, but they may not recommend new and different items that the user might like (Guo et al., 2020).

Collaborative recommendation systems are based on the idea that users with similar preferences will have similar preferences in the future (Liu et al., 2011). These systems use the preferences of other users to recommend items to the current user (Rashid et al., 2002). For example, in a movie recommendation system, a collaborative system would recommend movies liked by other users with similar preferences to the current user (Ansari et al., 2000). Collaborative recommendation systems have the advantage of recommending new and different items that the user might like, but they can suffer from the cold start problem that occurs when a new user enters the system, and there is not enough data about their preferences (Rashid et al., 2002).

Hybrid recommendation systems combine the advantages of content-based and collaborative systems to provide more accurate recommendations (Afoudi et al., 2021). These systems use item characteristics and other users' preferences to recommend items to the current user (Tewari, 2020). For example, in a movie recommendation system, a hybrid system would recommend movies with similar characteristics to the movies that the user has previously liked and that has also been liked by other users with similar preferences to the current user (Mohamed et al., 2020). Hybrid recommendation systems have the advantage of not suffering from the cold start problem and can recommend new and different items that the user might like (Wei et al., 2021).

In recent years, individualized recommendation systems have attracted much attention in the educational domain (Hui et al., 2022). These systems are designed to provide personalized recommendations to learners based on their preferences, learning styles, and prior performance. These systems can potentially improve the effectiveness of teaching and learning by providing learners with tailored resources based on their individual needs (Agarwal et al., 2022).

Based on their learning progress, interests, and learning styles, these systems may propose learning materials such as videos, articles, and quizzes to learners. Furthermore, personalized recommendation systems may be used to suggest learning activities such as assignments and projects to learners based on their previous performance and interests.

2.1.Individualized Recommendation Systems for Education

Individualized recommendation systems are a type of information filtering system that provide users with personalized recommendations based on their preferences, behaviors, and past performance (Hui et al., 2021). These systems are designed to help users find items that match their interests and needs (Chen & Wang, 2021). In recent years, individualized recommendation systems have gained significant attention in education (Hui et al., 2022) because they have the potential to improve the effectiveness of teaching and learning by providing learners with tailored resources based on their individual needs (Muñoz et al., 2022).

Learning materials like videos, articles, and quizzes may be recommended to students based on their academic achievement, hobbies, and learning preferences using personalized

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

recommendation systems (Zhong & Ding, 2022). In addition, these systems can also be used to recommend learning activities such as assignments and projects for learners based on their past performance and interests (Hui et al., 2022). Also, this can increase learner engagement, motivation, and learning success (Chen & Wang, 2021). Besides, individualized recommendation systems can help reduce learners' cognitive load by providing resources tailored to their learning style (Muñoz et al., 2022).

By providing students with materials specifically suited to their requirements, personalized recommendation systems for education can potentially increase the efficacy of both teaching and learning (Kadirbergenovna, 2022). In addition, these systems can also personalize the learning experience for learners by customizing learning activities and resources based on their learning progress and needs (Hui et al., 2021). In addition, individualized recommendation systems can also help educators identify the learning needs of their students and provide them with appropriate resources and activities (Zhong & Ding, 2022).

However, implementing individualized recommendation systems for education also brings several challenges (Muñoz et al., 2022). One of the major challenges is the cold start problem, which occurs when a new learner enters the system and there is not enough data about their preferences and performance (Hui et al., 2022). In addition, there are also challenges related to learner data privacy and security (Hui et al., 2021). Therefore, it is important to consider these challenges when implementing individualized recommendation systems for education. It is also important to ensure that these systems are developed and evaluated based on evidence-based research to ensure their effectiveness in improving learning outcomes (Hui et al., 2022).

Due to its potential to increase teaching and learning efficiency by connecting students with resources based on their unique requirements, personalized recommendation systems are becoming increasingly common in education. However, it is important to consider the challenges and limitations of these systems, such as the problem of cold start, privacy, and security, and ensure that they are developed and evaluated based on evidence-based research. Future research should address these challenges and evaluate the effectiveness of individualized educational referral systems in improving learning outcomes.

2.1.1. Application in Virtual Learning Environments

Virtual Learning Environments (VLEs) are online platforms that allow learners to access learning resources and activities (Kim et al., 2022). These environments have become increasingly popular in recent years as they provide learners with flexibility and convenience in learning (Choudhury & Pattnaik, 2020). Using individualized recommendation systems in VLEs can enhance the learning experience by providing learners with personalized resources and activities tailored to their needs.

One of the main applications of individualized recommendation systems in VLEs is the recommendation of learning resources (Valverde-Berrocoso et al., 2020). These systems can recommend videos, articles, and quizzes to learners based on their learning progress, interests, and learning styles. They are helping learners find relevant and appropriate resources that meet their learning needs (Choudhury & Pattnaik, 2020). In addition, individualized recommendation systems can also be used to recommend learning activities, such as assignments and projects, for learners based on their past performance and interests (Rodrigues et al., 2019). They can help learners find challenging yet achievable activities aligned with their learning goals.

Another application of individualized recommendation systems in VLEs is to personalize the learning experience (Kim et al., 2022). These systems can match learning resources and activities to learners' needs and preferences in real time based on their learning progress and performance (Rodrigues et al., 2019). They can increase learner engagement, motivation, and learning success (Valverde-Berrocoso et al., 2020). Individualized recommendation systems

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

can also help reduce learners' cognitive load by providing resources and activities tailored to their learning style (Choudhury & Pattnaik, 2020).

However, implementing individualized recommendation systems in VLEs also poses some challenges (Valverde-Berrocoso et al., 2020). One of the major challenges is the cold start problem, which occurs when a new learner enters the VLE and there is not enough data about their preferences and performance (Kim et al., 2022). In addition, there are also challenges related to the privacy and security of learners' data in VLEs (Rodrigues et al., 2019). Therefore, it is important to consider these challenges when implementing individualized recommendation systems in VLEs. It is also important to ensure that the recommendations of these systems are consistent with the learning objectives and curriculum of the course (Choudhury & Pattnaik, 2020). It is also important to ensure that recommendations are culturally and socially sensitive and avoid bias against specific learners (Rodrigues et al., 2019).

Another challenge in implementing individualized recommendation systems in VLEs is the need for robust evaluation methods to assess their effectiveness in improving learning outcomes (Kim et al., 2022). They require developing appropriate evaluation metrics and collecting data on learner performance and preferences (Choudhury & Pattnaik, 2020). It also requires ensuring that evaluation results are used to improve the design and functionality of individualized recommendation systems (Valverde-Berrocoso et al., 2020).

Implementing personalized recommendation systems in VLEs can improve learning by giving students access to materials and activities specific to their requirements. The difficulties and limits of these systems, such as the cold start issue, privacy concerns, security concerns, and cultural and societal sensitivity, must be considered. Additionally, it is critical to make sure that recommendations align with curricular objectives and standards and that systems are rigorously tested for their ability to enhance learning outcomes. Addressing these issues and assessing the efficiency of customized recommendation systems in VLEs should be the main objectives of future research.

2.1.2. Application in Non-Virtual Learning Environments

Individualized recommendation systems are not limited to virtual learning environments; they can also be used in non-virtual learning environments. These environments include traditional classrooms, educational institutions, libraries, and museums (Khan et al., 2022). Using individualized recommendation systems in non-virtual learning environments can improve the effectiveness of teaching and learning by providing learners with tailored resources based on their individual needs (Kuka et al., 2022).

One of the main applications of individualized recommendation systems in non-virtual learning environments is the recommendation of learning resources (Alzahrani & Alhalafawy, 2022). These systems can recommend books, articles, and other materials to learners based on their learning progress, interests, and learning styles (Kuka et al., 2022). They can help learners find relevant and appropriate resources that meet their learning needs (Khan et al., 2022). In addition, individualized recommendation systems can also be used to recommend learning activities, such as assignments and projects, for learners based on their past performance and interests (Alzahrani & Alhalafawy, 2022). They can help learners find challenging yet achievable activities that align with their learning goals (Kuka et al., 2022).

Another application of individualized recommendation systems in non-virtual learning environments is to personalize the learning experience (Alzahrani & Alhalafawy, 2022). These systems can tailor learning resources and activities to learners' needs and preferences in real time based on their learning progress and performance (Kuka et al., 2022). They can increase learner engagement, motivation, and learning success (Alzahrani & Alhalafawy, 2022). In addition, individualized recommendation systems can also help reduce learners' cognitive load by providing them with resources and activities tailored to their learning style.

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

However, implementing individualized recommendation systems in non-virtual learning environments also presents challenges (Jannach & Zanker, 2022). One of the major challenges is the need for accurate data collection and analysis about learner preferences and performance (Alzahrani & Alhalafawy, 2022). In addition, there are challenges related to integrating these systems into existing teaching and learning practices (Jannach & Zanker, 2022). Therefore, it is important to consider these challenges when implementing individualized recommendation systems in non-virtual learning environments. It is also important to ensure that implementing these systems aligns with the curriculum and learning objectives (Alzahrani & Alhalafawy, 2022).

Individualized recommendation systems in non-virtual learning environments have the potential to increase teaching and learning efficacy by providing learners with personalized resources that are suited to their specific requirements. However, the obstacles and limits of these systems, such as proper data collecting and analysis and integrating these systems with existing teaching and learning processes, must be considered. It is also critical to verify that the implementation is consistent with the curriculum and learning objectives. Future research should concentrate on overcoming these obstacles and assessing the efficacy of personalized recommendation systems in non-virtual learning contexts.

3. MATERIAL AND METHODS

The methodology used in this study is systematic literature mapping following the PICOC framework (Mengist et al., 2020). This methodology was chosen because it provides a comprehensive and rigorous review of the existing literature on individualized referral systems in education. A comprehensive search strategy was developed to identify relevant articles from academic databases such as the ACM Digital Library, IEEE Digital Library, ISI Web of Science, Science@Direct, Scopus, and Springer Link. Inclusion and exclusion criteria were established to ensure the relevance and rigor of the selected articles. Articles were first filtered based on their title and abstract and then evaluated based on questions about their content. Based on this rating, all articles above the standard deviation were selected for mapping. The data were analyzed, clustered, and summarized to identify key trends, challenges, and opportunities in the field of individualized recommendation systems for education.

The PICOC method is a widely used framework for conducting systematic literature mappings or reviews in the health and social sciences (Mengist et al., 2020). PICOC stands for Population, Intervention, Comparison, Outcome, and Context. This method is used to define the key elements of a research question and to identify the relevant literature for a systematic review:

- Population: In this research, the population of interest is students, teachers, and professors. This population will be the main focus of the study as they are the main users and beneficiaries of individualized recommendation systems.
- Intervention: The intervention of interest in this study is individualized recommendation systems. These systems are designed to provide personalized recommendations to users based on their preferences, behavior, and past performance.
- Comparison: The comparison in this study is between systems, artificial intelligence, machine learning, and user experience. The comparison will help to identify the specific features and characteristics of individualized recommendation systems that are most effective in improving the effectiveness of teaching and learning.
- Outcome: The outcome of interest in this study is individualization and planning. This outcome will be measured by evaluating the effectiveness of individualized

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

recommendation systems in providing personalized resources and activities that align with the needs and preferences of the users.

- Context: The context in this study is virtual, school, and university. The context will be considered to understand how individualized recommendation systems are used in different learning environments and to identify any specific challenges or limitations that arise in these environments.

The search string is a specific tool for searching relevant literature in a systematic literature mapping using the PICOC framework. The search string was developed by combining keywords related to each framework element with Boolean operators such as AND, OR, and NOT.

In this work, the search string was developed by identifying keywords related to population (students, teachers, professors), intervention (individualized recommender systems), comparison (systems, AI, artificial intelligence, machine learning, user experience), outcome (individualization, planning), and context (virtual, school, college). These keywords were combined with Boolean operators and resulted in the following search string: *("professor" OR "student" OR "teacher") AND ("recommendation systems") AND ("artificial intelligence" OR "AI" OR "machine learning " OR "systems" OR "user experience") AND ("individualization" OR "customized" OR "differentiated" OR "planning").*

The search term was applied to the above databases to identify relevant articles for SLM. The search focused exclusively on articles published within the past five years (2018 to 2022). The five-year search period was chosen to ensure the selected articles reflect the most recent and relevant advancements, trends, and challenges in the field, providing up-to-date insights for current and future applications. This search yielded a total of 1583 results. Initially, 19 articles identified as duplicates were screened out, leaving 1564 articles. These results were then filtered. To this end, two researchers independently searched for the title, abstract, and keyword fields using an article identification guide.

The filtering aimed to identify articles whose title, abstract, or keywords were related to "Recommender Systems," "Education," "Personalization of Teaching," "Personalized Recommendation Systems," or "Personalized Recommendation Systems in Education." After the filtering was completed, the data generated by the two researchers were compared, and a similarity of 322 articles was found. Researcher A filtered 332 articles, and Researcher B filtered 338 articles. After a joint analysis of the 36 articles that did not fall into the intersection, three articles were selected to compile the total set for evaluation.

The quality assessment evaluated 325 items. For an item to fall within the scope of the search, five basic questions had to be answered. These questions were: Is the research applied in the field of education? Does the research relate to a referral system? Does the study address individualized recommendations? Does the study present a model? Does the study include an evaluation of the proposal?

The question "Does the research relate to education?" referred to whether the research involved an application to education or aimed to solve a research problem in education. The question "Research involving some type of referral system?" referred to whether the research involved some referral system. Including studies that focused on the referral system and in which the referral system was only a tool or method. In answering the question "Does the study address individualized referrals?" was also considered whether the work involved some individualization of referrals.

To answer the question "Does the study represent a model type?" each model type proposed by the authors was identified, and an attempt was made to evaluate each model type in the study to determine whether or not it was a recommendation system model. Furthermore, the

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

question "Does the study include an evaluation of the proposal?" examined whether the study included an evaluation of the method, model, or methodology presented.

Each question was answered with a score between 0 and 1 in an interval of 0.5 as follows: 0 corresponds to "No", 0.5 corresponds to "Partially", and 1 corresponds to "Yes" Thus, each item could be scored with a minimum of 0 and a maximum of 5 points.

The total number of points was 1247.5, corresponding to an average score of about 3.84. That allowed the calculation of the standard deviation of the scores, which was 4.36. Therefore, all articles with scores above the threshold determined by the standard deviation were selected for the study. It resulted in a total number of 84 articles.

4. RESULTS

Of the 84 works selected through the methodology used, the classification of the works into relevant subtopics of the literature on classification systems in education was performed. A total of ten possible categories were established for classifying the works. Two researchers independently categorized all works. The data were then compared, and a similarity of 92.92% was found. The differences were compared and discussed so the works could be placed back into their respective categories. The defined categories were the following:

- Adaptive Learning: These papers are based on systems that adapt learning content and pace based on student performance and learning style.
- Content Recommendation: These papers are based on systems that recommend learning resources such as videos, articles, and quizzes for students based on their learning progress and interests.
- Course Recommendation: These papers are based on systems that recommend courses to students based on their interests, past performance, and learning goals.
- Gamification: These papers are based on systems incorporating game-like elements into the learning process to increase engagement and motivation.
- Hybrid Recommender: These papers are based on systems combining different recommendation techniques to provide more accurate recommendations.
- Open Educational Resources (OER) Recommendation: These papers are based on systems that recommend open educational resources to students, teachers, and researchers based on their needs and interests.
- Partner Recommendation: These papers are based on systems that recommend learning partners or collaborators to students based on their learning needs, goals, and preferences. They can be used for project work, group discussions, or peer-to-peer tutoring.
- Personalized Learning: These papers are based on systems that tailor learning experiences to students based on interests, abilities, and learning goals.
- Theoretical or Review: These papers recommend research papers, books, or articles that provide theoretical background or an overview of the current state of the art in a particular field.
- Tutor Recommendation: These papers are based on systems that recommend learning paths for tutoring students based on their learning needs and preferences.

Several of these items could be placed in more than one category. However, it was determined that each of them should be classified into only one category. Therefore, a classification priority was defined from least comprehensive to most comprehensive. So, for example, if an article belongs to a more comprehensive category and a less comprehensive category, it will be classified in the least comprehensive category.

In this way, it is possible to see a dominance of the Personalized Learning category with 18 categorized articles due to the wide range of its content spectrum. The Partner

Recommendations category, on the other hand, has only one categorized article due to its high specialization.

4.1.Personalized Learning

Personalized learning systems in education are an emerging trend that aims to provide students with personalized learning experiences based on their characteristics, preferences, and learning goals. These systems use various techniques, such as data mining, machine learning, and AI, to tailor the content, pace, and feedback of learning to the student's needs.

In recent years, research has focused on personalized and adaptable e-learning systems (APELS). Aeiad and Meziane (2019) describe the development of an architecture for an APELS that aims to provide users with a personalized and adaptive learning environment that leverages available resources on the Internet. Zhou et al. (2018) propose a new recommendation model for complete learning paths that uses clustering and machine learning techniques based on a similarity feature metric and a long-term memory model to predict learning and performance paths.

Xiao et al. (2018) provide an overview of intelligent learning recommendation technology in distance education and propose a personalized intelligent learning recommendation system based on a combinatorial algorithm. Wang and Lv (2022) aim to construct knowledge systems of different disciplines and provide personalized learning approaches for students by using the distributed computing method of the Internet of Things and the clustering algorithm of Deep Learning.

Chen and Wang (2021) provide an overview of the current research investigating the relationships between individual differences and personalized learning. The results suggest that learning style is an essential individual difference considered in work on personalized learning, and current work is moving toward considering multiple individual differences. Learner models are often employed to create personalized learning for numerous individual characteristics. It is a current trend to examine emotion detection in the context of personalized learning.

Tilahun and Sekeroglu (2020) propose an intelligent and personalized course guidance model by analyzing, selecting, and modifying effective course guidance technologies. Dhaiouir et al. (2022) aim to improve distance learning courses by enabling teachers and learners to work under better conditions using Resource Description Framework (RDF), Ontology, Web Ontology Language (OWL), and RDF Query Language (SPARQL). Shin and Bulut (2022) present an intelligent recommender system that uses a reinforcement learning approach to determine the optimal number and timing of tests for each student. Zhang et al. (2019) propose personalized learning guidance for students with Massive Open Online Courses (MOOCs) based on multi-source data analysis.

One key benefit of personalized learning systems is that they can adapt to a student's learning style, preferences, and level of understanding, leading to greater engagement and motivation. In addition, personalized learning systems can provide personalized feedback, improving learner self-regulation and metacognition.

Several studies have been undertaken to understand better the idea and use of customized learning in the workplace. Fake and Dabbagh (2020) conducted an interview-based study with education and training leaders to determine the definition of personalized learning and identify barriers and opportunities for its implementation from an organizational perspective.

Ontologies were explored as a means of personalizing recommendation systems in e-learning. George and Lal (2019) provided a comprehensive review of ongoing research on the use of ontologies for the personalization of recommender systems, noting that ontologies have the advantages of reusability, reasoning capability, and support for inference mechanisms that can provide improved recommendations. In the e-learning field, personalized learning mechanisms have been proposed that use knowledge points from the curriculum as recommended objects and employ collaborative filtering methods and cognitive diagnosis methods to develop tailored learning mechanisms. Tomashevskiy et al. (2021) proposed such a mechanism and conducted experiments to confirm its feasibility.

In addition, Intayoad and Temdee (2020) have proposed a personalized, dynamic, and continuous recommendation method for online learning systems based on contextual bandits and reinforcement learning problems, considering students' past behavior and current state as contextual information. Jeske et al. (2021) suggest that new tools such as learning analytics and intelligent tutoring systems can support learners with different reading difficulties, from learners whose native language is not the language of instruction to those with difficulty due to a learning disability. They suggest general steps needed to effectively implement existing literacy tools into tutoring and learning management systems and the need for multidisciplinary collaboration to meet learners' diverse support needs, emphasizing personalizing learning.

Personalized learning systems can be implemented in various ways, including adaptive learning, intelligent tutoring, and gamification systems. Adaptive learning systems adjust the content and pace of learning based on learner performance, while intelligent tutoring systems provide personalized feedback and guidance. Gamification systems incorporate game-like elements into learning to increase engagement and motivation. However, these specializations are discussed in the following subsections.

In their study, Lalitha and Sreeja (2020) proposed a personalized recommendation system for self-directed learning to solve the e-learning recommendation problem. First, they categorized e-learning materials into introductory, moderate, and advanced levels using content-based and collaborative filtering tools. Then, they assessed learners' needs and requirements using surveys to assess their skills and background. By combining these two modules, the study created precise, personalized recommendations for self-directed learners. Lin et al. (2021) proposed a hybrid method that combines personality traits and demographic characteristics with traditional rating-based similarity calculation using the myPersonality application. This approach addresses the new user problem by accurately predicting user similarity by categorizing personality information into five features.

Pan et al. (2022) proposed two innovative personalized route recommendation methods that utilize probability learning of user behavior through matrix decomposition and kernel density estimation. They addressed the route recommendation problem by transforming it into a shortest path problem using a Bayesian probability model and behavior graph, with experiments on real datasets confirming the effectiveness of these methods. Meanwhile, Sherbakova et al. (2020) explored the core principles of design education, identifying its key features and advocating for an additional educational program. Their research, combining theoretical literature analysis and empirical methods, concluded that fostering a mindset in young people that views design as a transformative creative process is essential for mastering the fundamentals of the design approach.

Despite the wide range of applications, personalized learning systems also have limitations. One of the main challenges is ensuring the quality and relevance of the personalized content and adequately supporting the learner's learning process. In addition, ensuring the privacy and security of the learner's data is essential, which is crucial for the trust and acceptance of these systems. In summary, personalized learning systems in education promise to increase engagement, motivation, and learning outcomes. However, more research is needed to explore the challenges and limitations of these systems and how they can be used most effectively in different educational contexts.

4.2.Content Recommendation

Content recommendation systems are a technique used to recommend items (such as movies, music, and news) to users based on their past preferences and behaviors. These systems use machine learning algorithms to analyze user data and create personalized recommendations. There are different recommendation systems, such as collaborative filtering, which uses similarities between users and their interests to recommend items, and content-based filtering, which uses similarities between items to recommend similar items. These systems are used in various domains, including e-commerce, media, and entertainment.

Bel Hadj Ammar et al. (2020) propose recommending quality educational resources to improve the quality of student learning according to their learning progress and individual needs. They propose an integration of quality assessment with the recommendation process to judge the quality level of resources. To make better decisions and improve analysis, they use the AI technique of Fuzzy Logic to simulate the human reasoning process and help to deal with uncertain data in engineering.

Cerna (2020) and Cerna and Borkovcova (2018) explore blended learning education, emphasizing an innovative approach to content creation and a recommendation system for learning materials in e-courses. Their research analyzes two interrelated parts of e-courses for theoretical and practical purposes, resulting in a recommender system tailored to the learning management system used at their college. This system aims to enhance student learning by actively involving students in creating, presenting, and evaluating materials, supported by virtual tools for communication, navigation, and assessment. The approach integrates virtual and face-to-face assessments, aligning with the blended learning concept. The pilot implementation, tested over the last academic year, demonstrated the model's effectiveness, as evidenced by a reduced failure rate in final exams.

Dias and Wives (2019) present a recommended approach for learning objects in ubiquitous e-learning systems: social learning networks where students interact through forums or chats. In these systems, learners make various decisions about what, how, and with whom to learn, and the approach developed by the authors uses these decisions as information sources. This method extends the user-based recommendation approach, rooted in the nearest-neighbor search problem, and incorporates users' social cues, interests, and preferences. Combining these elements allows the system to identify users similar to active learners, generating more accurate recommendations. Experimental evaluation demonstrated that this approach provides statistically significantly higher accuracy in usage prediction than baseline methods, varying accuracy depending on the combination of user selections.

The approach to the challenges of eLearning recommendation systems is presented by Kulkarni et al. (2020). The authors state that eLearning's challenges are information overload and relevant information. Moreover, ideally, there should be a common platform for eLearning students. eLearning was introduced many years ago using teaching principles. Many colleges, universities, companies, and organizations worldwide offer students distance learning courses, online certifications, and online degrees to promote eLearning. However, the amount of information available makes this process difficult. The authors present possible solutions to these problems based on content recommendation systems.

These systems can help students discover and learn new content. One application example is using recommender systems to tailor a curriculum to individual student needs and interests. That can help increase student motivation and engagement and improve academic performance. Another application is used to help students find and select relevant learning

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

materials. For example, a recommender system could analyze a student's learning history and recommend books, articles, or other materials that might be useful in preparing for an exam, helping to save time and effort and increase learning effectiveness.

In their research, Zhu et al. (2020) propose deep learning in a Deep Sequence Fusion Network based on the fusion of multiple sequential data, which is considered more effective in recommending learning features than any other field. They use the mechanism of self-awareness as the main ingredient to design the auxiliary subnetwork and the prediction subnetwork to fuse different sequential data. The model proposed by the authors works with joint training and highlighted prediction. The two subnetworks work during training and compress the sequential data in the self-observation mechanism. Then, the sequences generated by the self-observation layer flow through different feedforward neural networks to generate the expected targets. Experimental results have shown that this model proposed by the authors improves the accuracy and recognition by 20.5% and 13.6%, respectively, compared to the traditional user-based collaborative filtering algorithm.

Xiong and Li (2021) analyzed eleven types of open online courses in various learning activities. The learning activities were grouped to identify trends in learning behavior. They found that active student participation better-reflected attendance; therefore, predicting performance based on the type of learning activities that could be grouped was possible. The relationship between self-assessment and the effectiveness of teachers' perceptions of classroom behavior was investigated in Portuguese teachers. English teachers realized that the relationship between classroom conditions misleads process analysis through mediating and moderating variables in cloud classroom management.

Lin et al. (2021) show through an in-depth analysis of the existing learning resource recommendation system at their college that it is inadequate and unable to recommend learning resources to students accurately. The authors analyze the key technologies, build a new learning resource recommendation system based on the identification technology, and combine the resource analysis of these technologies to show the operation of this system in detail.

Pique, a web-based recommendation system that uses word embedding and a sequence generator to present students with a set of science article recommendations tailored to their background and interests, was described by Mohseni et al. (2019). They show that natural language processing (NLP) in learning materials allows students to be presented with content matching their background knowledge and interests. Pique aims to provide students with content that stimulates their curiosity to learn more by presenting work sequences with increasingly innovative content. The system has been tested with students to assess their reactions to the recommended sequences.

Murad et al. (2020) developed a hybrid recommendation system that combines rule-based and collaborative filtering methods to provide educational recommendations. The system predicts student performance and links relevant materials using learning outcomes and contextual information. Initial data from admission tests allow for early recommendations. Testing with BINUS datasets showed that overall performance was similar with or without contextual information, the system's ability to offer early recommendations was a key advantage.

Pariserum Perumal et al. (2019) proposed a new recommender system offering suitable content by refining the final frequent element patterns obtained using the recurring pattern mining technique and then classifying the final content into three levels using fuzzy logic. It was achieved by generating frequent patterns after consolidating interest changes to the user with an extended error quotient. In addition, fuzzy rules were used to consider all types of learners when applying rules to pattern tables. In this way, the authors developed a method that aims to detect the preferences of data streams in windows of the same size and to consider the changes in users' interest values over time.

Sunil and Doja (2020) present a new approach in their work, a framework for building an architecture for a recommender system for an e-learning environment considering students' learning styles and knowledge levels. Since each student's learning style and knowledge level differ, the authors re-emphasize the importance of understanding students' needs and providing recommendations based on their needs. Finally, the content-based filtering approach is used to preprocess the data to generate an appropriate list of recommendations and predict student performance.

Tang and Zhang (2022) developed a decision support system that extracts user preference features and weights music tracks using hidden factors from a semantic model. This approach intelligently processes audio resource values to enhance music teaching and learning efficiency. Experiments demonstrated that their personalized recommendation algorithm, especially when combined with a Deep Belief Neural Network, offers high accuracy and scalability. The model's recommendation coefficient outperformed actual ratings, indicating its broader applicability beyond the original user group and music library.

Research in educational content recommendation systems has primarily focused on developing algorithms to deliver relevant content to students. Some studies further incorporate behavioral and environmental factors to reduce bias and enhance recommendation effectiveness. These systems assist in selecting appropriate courses and majors by analyzing student preferences and play a crucial role in personalizing curricula. These systems boost motivation, engagement, and overall academic performance by helping students find relevant learning materials and make informed educational decisions.

4.3.Tutor Recommendation

Tutor recommendation systems are software tools that match students with the most appropriate tutors based on their learning needs and preferences. These systems have attracted much attention in recent years because they can improve tutoring effectiveness and increase student engagement.

One of the biggest challenges in developing tutoring recommendation systems is accurately modeling student preferences and learning needs. It can be accomplished by collecting data about the student's performance, learning style, and background and using machine learning techniques to analyze that data. For example, collaborative filtering, k-nearest neighbors, and decision trees can match students with tutors with similar characteristics.

Cárdenas-Cobo et al. (2018) present a book chapter that focuses on improving computer programming in students. To do so, they use Scratch, a visual programming language, as an informal learning tool. However, they find challenges in using Scratch by college students, such as a mismatch between the learning approaches used by teachers and those used in the classroom and the lack of motivation of some students due to programming exercises that do not match their interests. To address these issues, the authors propose an integrated approach that includes a web application with a Scratch project editor and a system for recommending exercises. Initial results indicate a positive impact of this proposal.

Zakharova et al. (2022) examine the challenges and opportunities presented by the digitization of education. The authors note a contradiction between the growing amount and variety of data collected in the educational process and the lack of appropriate analytical tools to use this data. The research aims to develop a scanning method for EIT support that uses explainable AI to analyze students' digital footprints and predict educational outcomes. The study uses a combination of intellectual analysis of natural language text, clustering, classification, and regression models built using machine learning methods. The authors proposed a methodology for EIT digital support and developed a recommendation system that includes services for students, professors, tutors, and administrators.

Research presented by Dwivedi et al. (2018) addresses the issue of curriculum sequencing in e-learning systems and proposes an effective learning path recommendation system (LPRS) for personalized e-learning. The authors argue that a more efficient e-learning experience can be achieved by recommending a sequence of learning materials, called a learning path, tailored to the learner's preferences. Factors such as the learner's knowledge level and learning style are also considered. To achieve this, the authors propose a variable-length genetic algorithm that can adapt the recommended sequence length to the specific needs of each learner. Experimental results in an e-learning environment demonstrate the effectiveness of the proposed LPRS.

Vagale et al. (2020) present research on learning process management in an e-learning system using a personalized adaptive e-learning system in their article. The system includes three different sequences for topic acquisition: teacher-guided, student-guided, and optimal sequences. The search allows students to switch between these sequences and stores data about the learning process. The results of the data analysis show that more than half of the students used the teacher-guided sequence, while students who chose the student-guided or optimal sequence performed better. The study results were used to improve the optimal sequence method, and an algorithm for developing the recommended learning path was proposed. The course topics and the links between them are represented as a weighted directed graph, and the recommended learning path is determined as the lowest weighted path found in the search.

Another important aspect of tutoring recommendation systems is using adaptive algorithms to adjust recommendations based on student progress. These algorithms can consider factors such as student performance, engagement, and feedback and use this information to provide more accurate recommendations. For example, an algorithm that considers student feedback can make more accurate recommendations by considering how the student rates the quality of tutoring.

Zhu et al. (2018) propose a new map-based learning path recommendation algorithm with multiple constraints to address the challenge of e-learners facing many learning resources and balancing limited learning time with multiple learning objectives in different environments. The main contributions of the paper include testing two hypotheses about the different learning path preferences of e-learners using a questionnaire-based statistical analysis, proposing a model for recommending learning paths with multiple constraints that take into account the different learning path preferences, the organization of learning resources, and fragmented time, describing the design and implementation of a numerous constraint learning path recommendation algorithm based on the proposed model and knowledge map, and demonstrating the effectiveness of the proposed algorithm using survey results from more than 110 e-learning students, confirming the similarity between the students' self-assessed organized learning paths and the recommended learning paths.

Silva et al. (2020) study proposes a hybrid recommendation filtering method to improve computerized adaptive testing. The technique combines collaborative and content-based filters and reduces bias by considering students' historical performance. The authors use item

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

response theory and clustering techniques to create objective recommendations for selecting activities and building an assessment pathway. The article highlights the importance of the grouping task and provides charts and metrics to help professionals make decisions.

Shi et al. (2020) tackle the issue of fragmented learning content in e-learning by proposing a model that extracts and organizes content to meet specific learning objectives, particularly for non-specialists. Using a multidimensional knowledge graph structure, this solution arranges learning objects in a meaningful sequence. The model categorizes learning objects into classes and employs six key semantic relations to generate and recommend customized learning paths tailored to various learning requirements. Experimental results demonstrate that this approach effectively improves personalized learning paths, enhancing the learning experiences of e-learning students.

Vanitha et al. (2019) propose an adaptive e-learning system aimed at improving students' academic performance by providing personalized learning paths. The system focuses on optimizing the combination of individual characteristics and learning content sequences. The study introduces a hybrid algorithm that combines ant colony optimization with genetic algorithms to create these personalized paths. By leveraging the stochastic nature of ant colony optimization and the exploration capabilities of genetic algorithms, the approach constructs optimal learning solutions. Qualitative and quantitative experiments demonstrate that this hybrid algorithm outperforms traditional methods in providing effective personalized learning paths.

Kim et al. (2021) tackle the issue of low retention rates in MOOCs by proposing a personalized learning content recommendation system that enhances adaptability, improves the learning experience, and boosts retention. Their method utilizes deep learning, knowledge tracking, and reinforcement learning, where a student's knowledge level is first assessed using a deep learning-based model, and then a deep reinforcement learning approach is employed to train a recommendation policy. The recommendations are further refined by considering the cognitive levels of Bloom's taxonomy. A user study confirmed the model's effectiveness as a tool for supporting effective learning.

In online learning environments, tutor recommendation systems have shown great efficacy. These environments allow for extensive data collection on student behavior, preferences, and performance, which enhances the accuracy of recommendations. Additionally, the adaptability of online platforms enables real-time adjustments based on student progress. Muñoz et al. (2022) conducted a systematic mapping study of 44 research papers to explore how recommender systems support various educational areas. Their study highlights the techniques and algorithms used, identifies research gaps, and suggests future directions, including the integration of data mining and AI to improve the personalization of academic decisions.

Liu and Li (2020) focus on using data from an online learning platform to uncover hidden patterns in student behavior to improve educational resource recommendations. The study specifically addresses the problem of poor-quality recommendations for inexperienced or less active students. They are proposing a new method called LPCRLN, which combines complex network technology with learning data to build networks of courses and students. Students are then classified into three types, and recommendations are made based on their learning data in different scenarios. The study includes a series of experiments, and the results show that this method significantly improves the accuracy and efficiency of recommendations for different types of students.

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

Mejia et al. (2021) present a career recommendation system that considers students' abilities and interests. The system is based on Gardner's popular Multiple Intelligence Test, which measures brain performance in nine domains and helps understand students' strengths and learning styles. Family variables and scores on a basic knowledge test were also considered. The system was validated against a standard occupational test and showed a success rate of 88.2% in recommending the top five occupations and 93.3% in recommending the chief occupations.

Tomashevskiy et al. (2021) propose technologies to improve digital learning in higher education institutions, considering students' abilities. They investigate using individual learning scenarios based on student models and user knowledge gap maps. The student model includes parameters for readiness levels and cognitive resources that can be used to create individualized schedules for subject repetition, individualized forgetting processes, and adaptive testing scenarios. The approach is implemented in a simple adaptive learning system tested and used in Ukrainian universities.

To improve tutoring effectiveness and increase student engagement, recommendation systems are essential for tutors. By collecting data on student preferences and learning needs and using machine learning techniques to analyze this data, these systems can provide accurate recommendations to match students with the most appropriate tutors. In addition, using adaptive algorithms and the flexibility of online learning environments can improve the accuracy of recommendations and provide a more personalized learning experience.

4.4.Course Recommendation

Course recommendation systems have become very popular in education because they aim to match students with the most relevant and beneficial courses for their needs and interests. These systems use various methods and algorithms to make recommendations, such as collaborative filtering, content-based filtering, and hybrid approaches. One of the main advantages of course recommendation systems is the ability to personalize the learning experience for each student. Considering students' past performance, interests, and goals, these systems can suggest courses tailored to individual needs. It can lead to greater student engagement and motivation and improved academic performance.

The traditional system of research and course selection is a time-consuming and uninteresting activity, which not only seriously affects students' academic performance but also affects students' learning experience and makes it challenging to select relevant learning resources due to information overload. Rahhali et al. (2022) present in their work a model for a recommendation system for e-learning platforms that provides recommendations to students and motivates them to select courses according to their needs.

By proposing an architecture that uses virtual agents to generate semantic recommendations based on users' needs and preferences, Ali et al. (2022) attempt to help academics find appropriate courses in a real-world environment. The virtual agent-based recommender system not only improved user learning but also facilitated course selection based on user interests and preferences, as shown by experimental and statistical results. The main goal is to create a system that intelligently suggests courses, considering various viewpoints, to improve students' skills and knowledge and address the lack of online support from providers, which is known to be the leading cause of many difficulties.

Amrutkar et al. (2021) address the challenges faced by students in India in selecting courses in a credit-based semester curriculum. The application system makes it difficult for students to

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

find courses that match their interests. The study suggests that students often make choices based on recommendations from peers and friends, which may not always be the best choice for them. The authors suggest that a recommender system can help students find courses that interest them, similar to how recommender systems are used on commercial websites to help users select products based on their preferences. The recommender system aims to provide students with recommendations they find valuable and accept.

One of the biggest challenges in developing course recommendation systems is dealing with the problem of data scatter. It refers to the fact that many students do not have sufficient data (e.g., prior course performance) to make accurate recommendations. Researchers have proposed several techniques to address this problem, such as using demographic information or folk wisdom.

Ezz and Elshenawy (2020) proposed an adaptive recommender system to predict appropriate educational paths for students in a college preparatory year. Adaptability is achieved by applying various data mining techniques to extract relevant features and build customized models for each educational path. The problem is a binary classification problem with multiple labels and classes. The system predicts students' academic performance at the Faculty of Engineering, AL-Azhar College. The results show that the proposed model can highly accurately recommend the best machine learning algorithm and relevant data for each subject area. The system can be applied to other educational datasets in the future.

Sánchez-Sánchez and Jaimez-González (2022) presents a system that helps students to select courses. It considers the courses that are already taken and their grades based on information from other students who have already taken them. The system uses an approach that identifies course sequences, predicts courses students can take based on attributes, and estimates the student's grades through regression. This system is designed to help students meet the challenge of curriculum flexibility in universities, where students can shape their life paths and professional training.

In the study by Rafiq et al. (2021), the authors investigate the potential of detailing query/question information in e-learning systems such as online lectures or courses. Includes organizing, parsing, and sorting query/question messages through surface content processing, AI strategies, and predefined applicable content from resource language files. The study aims to improve problem assessment in online courses by developing query optimization systems. The results show that the proposed method increases the accuracy of action verb classification and outperforms traditional methods. The study also offers a new way of measuring the relationship between action verbs, question verbs, and learning outcome statements.

Nguyen et al. (2021) present the development of a course recommendation system for students based on their current academic performance. The study applies various data mining and learning analytics techniques to predict students' learning outcomes for the upcoming semester. The study also compares the effectiveness of predictive learning methods based on collaborative filtering and finds that the matrix factorization method is the most effective. The study also suggests ways and constraints that apply to different curricula. The study suggests appropriate and adequate courses for each student based on their academic performance, aiming to expand and improve the model in the future.

Another issue that must be considered when designing course recommendation systems is the potential for bias. If the system is not properly designed, it can inadvertently lead to the exclusion or underrepresentation of specific student groups in recommendations. To mitigate

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

this, researchers have suggested methods such as incorporating diversity metrics and using algorithms that take impartiality into account.

Li et al. (2018) explore the problem of high dropout rates in MOOCs and the difficulty of understanding users' learning needs and interests and propose using personalized course recommendation technology. The paper focuses on developing a user modeling method that learns the user's latent interests through the interactive course recommendation framework (ICRF) by directly querying the user's interests via lookup tables or questionnaires. The proposed ICRF algorithm for capturing user interests combines representative sampling and an interest propagation algorithm to capture user interests cost-effectively. Experiments with real MOOC course enrollment datasets demonstrate the method's effectiveness.

Lin et al. (2020) present a convex optimization-based framework incorporating L0 regularization and student feature constraints for recommending educational content to students. The proposed approach considers students' goals, interests, and career aspirations and is shown to be more accurate than previous recommendation techniques. The study also shows the importance of assessing students' personal goals in course recommendation systems. The study also contributes by accounting for missing course data and using formatted and unformatted data.

In their research, an intelligent recommendation algorithm for adult education courses was developed by Liu and Li (2020). This algorithm considers the tag information in a library of educational resources and uses the LDA topic model to build a topic model for the resources. The user's interest is then considered more comprehensively by combining the project's topic distribution and the user's project evaluation matrix. The proposed algorithm also reduces the user's project evaluation matrix's size, reducing the algorithm's computational complexity. Research has shown that the proposed algorithm effectively provides personalized recommendations and manages information overload.

Song et al. (2022) present a solution for an e-learning curriculum adaptation system based on a modularized curriculum. This system aims to optimize the curriculum using information systems, knowledge management, and data mining techniques. The research addresses the difficulty of curriculum adaptation due to the complex relationships and constraints between modules, curriculum, and curriculum systems. The solution is significant in the COVID-19 pandemic because e-learning has become an important way for modern busy people, especially students, to acquire knowledge due to its convenience and efficiency.

Course recommendation systems can improve the student learning experience by providing personalized recommendations based on individual needs and interests. However, some challenges, such as data sparsity and bias, must be addressed. These challenges can be addressed through various techniques, such as leveraging the wisdom of crowds, incorporating diversity metrics, and using algorithms that pay attention to fairness. More research is needed to improve the effectiveness of these systems and ensure that they provide equal opportunities to all students.

4.5.Hybrid Recommendation

Hybrid recommendation systems for education have grown in popularity in recent years due to their ability to integrate the qualities of many recommendation methodologies. It can provide individualized suggestions for students, and these systems often include collaborative filtering, content-based filtering, and knowledge-based approaches.

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

Baidada et al. (2019) propose a hybrid approach for recommender systems in online learning environments that considers both the student's personal preferences and other students' preferences. The study aims to improve the relevance of recommended content by considering individual and collective perspectives. The proposed approach is tested using experiments. Future work includes consideration of student performance and impairments to refine the recommendations further.

Bhaskaran and Marappan (2021) focus their research on designing and analyzing a novel adapted transductive support vector machine-based hybrid recommender system for public machine learning datasets. The proposed model aims to improve the performance of a hybrid recommender system through novel strategies. These include a modified single-source noise reduction approach, a modified optimization strategy for anarchic societies, an improved and generalized sequential pattern strategy, and a vector machine. They have improved transductive support. The proposed model has been tested on several public datasets. The results show that it performs better than other methods in expected absolute error, accuracy, classification results, detection, and precision measurements. The accuracy of the proposed datasets ranges from 82 to 98%, and the MAE metric ranges from 5 to 19.2% for the simulated datasets.

Esteban et al. (2020) present a hybrid recommendation system for college courses that combines collaborative and content-based filtering using different student and course information criteria. The system uses a genetic algorithm to find the optimal configuration with the most relevant standards and parameters. Accurate data from a computer science course was used for the study. The results show that the proposed model performs excellently compared to previous models. The results show that the proposed model performs excellently compared to previous models. The study also provides directions for future work in constraining recommendations, social network analysis, and incorporating more course and student data to improve offers.

One of the main advantages of hybrid recommender systems is their ability to overcome the limitations of individual recommender approaches. For example, collaborative filtering methods suffer from the cold start problem, i.e., they have difficulty providing recommendations for new users or articles with little or no historical data. Content-based filtering methods, on the other hand, may not be able to account for changes in student interests or preferences over time. By combining these methods, hybrid systems can overcome these limitations and provide more accurate and robust recommendations.

Another advantage of hybrid recommender systems is the ability to incorporate domain-specific knowledge into the recommendation process. Knowledge-based methods such as rule-based or case-based reasoning can incorporate information about curricula, course prerequisites, and other educational factors into the recommendation process. This way can be ensured that recommendations are aligned with educational goals and that students receive appropriate and relevant learning materials.

Ezaldeen et al. (2022) propose a framework called Enhanced e-Learning Hybrid Recommender System that provides appropriate e-content with the predicted higher levels of assessment that meet the student's specific needs. It develops a new model for automatically inferring the learner's semantic profile, adaptively assigning learning patterns and rules depending on the learner's behavior, and semantic relations computed in the semantic matrix that links the e-learning materials and concepts. It also employs a semantics-based approach to concept expansion using DBpedia and WordNet ontologies. It integrates multiple sentiment analysis models to predict the ranking of e-learning resources based on text scores.

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

Lhafra and Abdoun (2022) focuses on improving the efficiency of e-learning systems by integrating AI and the concept of adaptive learning. The study proposes a hybrid approach that uses recommender systems and machine learning to perform adaptive correction based on the deficiencies identified in the assessment phase. The applied method is based on classifying defects using the Naive Bayes algorithm and recommending the most adaptive corrective action through collaborative filtering. The proposed architecture consists of five steps: data preprocessing, defect detection, difficulty identification, collaborative filtering, and disciplinary action recommendation. The researchers plan to continue the study and implement this approach to compare it with other AI technologies.

Shanshan et al. (2021) developed an improved hybrid ontology-based approach for recommending online learning resources, combining collaborative filtering and sequential pattern mining techniques. The ontology is used for knowledge representation to address cold start and data starvation issues. The hybrid algorithm predicts and provides personalized learning resource recommendations, evaluated in an online learning application for students with varying profiles. Future research will focus on integrating this approach with learning platforms and examining the impact of each attribute on learning preferences using real-world data.

Tian et al. (2019) propose a hybrid algorithm to help users select appropriate books from a library with many books. The algorithm combines collaborative and content-based filtering techniques and is implemented on the Spark Big Data platform. The personalized book recommendation system improves the resource usage rate. The article describes the system's architecture and compares its performance with purely collaborative and content-based methods. In the future, the authors plan to explore new technologies to improve system performance and solve the users' cold-trunk problem.

One potential drawback of hybrid recommender systems is that they can be complex and challenging to implement. It is especially true when integrating multiple data sources such as student profiles, learning materials, and educational goals. In addition, the choice of weighting schemes and parameters can significantly impact system performance, and determining the optimal settings can be challenging.

The article by Vedavathi and Anil Kumar (2021) proposes an efficient recommender system for e-learning based on a hybrid optimization algorithm. The system uses a deep recurrent neural network and an improved whale optimization algorithm to classify student types and analyze their preferences and behaviors. It allows the system to recommend relevant content for each student instead of the student having to search for content themselves. The proposal was validated on several e-learning platforms and proved more efficient and accurate than traditional recommendation systems.

Zheng (2022) addresses differentiated pedagogy, the flexible and organized adaptation of teaching and learning that considers that students have differences in their learning dispositions, interests, understanding styles, experiences, and life circumstances. A personalized education system based on hybrid AI recommendations is proposed, focusing on guiding for implementing integrated standard curricula to create flexible and differentiated educational programs that meet the individual needs of each student. The study proposes an unprecedented algorithm in the literature, with a high degree of convergence and positive experimental results. Future research includes full automation of the recommender system, automatic questionnaire optimization, and fuzzy logic technologies.

Djeghri et al. (2021) developed a recommender system for students' daily campus activities. The goal is to recommend tasks for students throughout the day to help them plan their daily activities. The recommendation system is based on artificial neural networks and matrix factorization and is being tested with the StudentLife student dataset at Dartmouth College. The recommendation is validated using a portion of the dataset, and the results are presented.

Despite these limitations, hybrid recommender systems can significantly improve educational content recommendations' effectiveness. By combining the strengths of different approaches, these systems can provide learners with more accurate, robust, and contextually relevant recommendations. Future research should focus on developing methods for effectively integrating and weighting different recommendation approaches and evaluating the effectiveness of hybrid systems in real-world educational settings.

4.6.Adaptive Learning

Technology in adaptive learning enables personalized learning experiences for students, making it an innovative educational approach. This approach is based on the idea that each student has unique needs and abilities and that personalized instruction can lead to better learning outcomes.

Alvarez and Geoffre (2020) present a method for monitoring and evaluating the effects of adaptive learning in the teaching and learning French for various students. The web platform development is described in detail, including the didactic basis. The unified experimental design developed for the testing phase is presented. Four groups of students with different profiles, including those with special needs, will participate. This way, the evaluation of the potential of adaptive learning to meet all requirements will be systematically documented.

Sridharan et al. (2021) have developed an adaptive learning management system to solve the challenge of selecting the most appropriate resources for each student. It creates a personalized course for each student based on their knowledge level and preferred learning method and continuously updated the system based on their learning speed. Material is filtered from a dynamically updated knowledge base using data scraping and assessed based on student feedback on the relevance and quality of each material. The assessment is both quantitative and qualitative and is validated through statistical analysis.

Dai et al. (2021) utilize Petri nets to create knowledge graphs for adaptive learning diagnosis and recommendation in life science and engineering education. The study focuses on understanding how course structure, teacher motivation, and support systems influence learning transformation and the teaching of life sciences. It also explores how external factors affect the absorption and application of professional knowledge by educators. The research aims to enhance the educational process through these adaptive learning recommendations.

Adaptive learning can provide personalized instruction to students. Adaptive learning systems can use technology to track student progress and adjust instruction accordingly to ensure that each student receives instruction tailored to their specific needs. It can lead to more efficient and practical learning, as students can focus on the material they need to learn rather than spend time on material they already understand. In addition, it can provide real-time feedback to students. Using technology to track learning progress and provide immediate feedback, adaptive learning systems can help students identify areas where they need to improve and take corrective action. It can lead to faster learning and better retention of material.

Gumbheer et al. (2022) review recent context-aware personalized and adaptive mobile learning (PACAML) studies. The review provides researchers with an overview of recent

DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

advances in adaptive mobile learning technologies. Essential aspects of learning contextual information are discussed, and infrastructural requirements are identified. The application of mobile learning technologies in education is also discussed, and critical methods for context adaptation are listed and classified. Further research on PACAML approaches related to pedagogical strategies and psychological aspects is needed to improve the mobile learning experience.

Kolekar et al. (2018) present an approach to identify learning styles to adapt them according to the Felder-Silverman Learning Style Model (FSLSM). For this purpose, an e-learning application based on the Moodle framework was developed to collect student usage data and group them according to the learning categories of the FSLSM model. The portal can be customized by creating an adaptive interface for each student based on their FSLSM learning style. The impact of customization on learning was determined through statistical analysis. Current trends indicating that students prefer online instruction to traditional face-to-face instruction were considered in the development of the portal.

Santoso (2021) proposes an adaptive framework for education that uses a rule-based system to orchestrate student interaction and provide personalized resources in e-learning repositories. In addition, the framework can be used by visually impaired students with an adapted user interface. When searching for educational resources, the student's profile is considered to identify and translate individual characteristics into more suitable leisure needs. This adaptation model can also be used under other standards if the adaptation rules are modified.

Despite its strengths, adaptive learning also has some limitations. One of its most significant weaknesses is its reliance on technology. Adaptive learning systems require reliable Internet access and adequate technology infrastructure for high-speed information and high availability. In addition, these systems can be expensive to implement and maintain, which can be a barrier for some schools and districts.

Ling and Chiang (2022) propose a recommendation system for online programming that provides students with personalized guidance and step-by-step learning planning. The system includes front-end and back-end guidance for web development and can create customized learning paths to provide students with a sense of achievement. In a study, the plan was developed based on data and feedback from 41 professional web designers and used C4.5 decision tree methods to build a model for programming learning recommendations. The test group consisted of 13 novice programmers, and the results showed that the system's effectiveness was acceptable. However, the sample size is small, and future studies should focus on increasing the accuracy of the recommendation.

Maravanyika and Dlodlo (2018) developed a framework for adaptive recommendation systems in e-learning platforms, focusing on differentiated instruction. Through a literature review, they identified 40 personalized learning attributes and used Multiattribute Utility Theory to select the top 10 for inclusion in the system. A sample of 200 students was chosen, with 103 responding to a questionnaire. The identified attributes included culture, emotional/mental state, socialization, motivation, learning preferences, prior knowledge, educational background, cognitive style, and education goals. These attributes were used to derive an adaptive framework for personalized learning platforms.

Nafea et al. (2020) present new algorithms to track students' learning behavior patterns, capture their learning styles, and maintain dynamic student profiles in a recommendation system. In addition, a new method for extracting features that characterize student behavior is proposed to identify learning styles in the FSLSM. Tests were conducted on a dataset of actual

Br. J. Ed., Tech. Soc., v.17, n.3, Jul-Sep, p.878-908, 2024
DOI http://dx.doi.org/10.14571/brajets.v17.n3.878-908
ISSN 2316-9907

students to demonstrate how the proposed algorithm can effectively model a dynamic student profile and adapt to different learning behaviors. The results show that students can efficiently increase their learning efficiency and quality when their learning styles are identified and appropriate recommendations are provided.

Despite these limitations, adaptive learning can potentially revolutionize how education is delivered. It can improve learning outcomes and increase student engagement by providing personalized instruction. In addition, these systems can help ensure that students from disadvantaged backgrounds, who may not have had access to quality instruction in the past, have equal opportunities. As technology advances, adaptive learning is likely to become an increasingly important tool in education to help students reach their full potential.

4.7.Others

Several other approaches have emerged in the research on recommendation systems for education. However, few articles have been published on these topics. Among these approaches, gamification, open educational resources, and partner recommendations stand out. In addition, literature reviews and dialectical works have emerged during this study's investigation.

Gamification in education has emerged as a powerful tool to enhance student engagement and motivation by incorporating game-like elements such as rewards, points, and leaderboards into the learning process. Studies like those by Bennani et al. (2020) and Khoshkangini et al. (2021) have demonstrated that when these elements are customized to fit individual learning experiences, they can significantly improve outcomes such as knowledge retention and problem-solving skills. However, maintaining player interest and adapting challenges to keep them relevant remains a critical challenge that needs to be addressed to maximize the effectiveness of gamification in educational settings.

Open Educational Resources (OER)-based systems provide a solution to the accessibility challenges faced by many students, particularly those in developing regions or with financial constraints. By offering free, openly licensed educational materials, these systems can democratize access to high-quality content. Research by Brahim et al. (2020) and Campos et al. (2020) highlights how OER systems can be tailored to meet the specific needs of users, including those with disabilities. These systems broaden access to education and support personalized learning, allowing students to select and engage with resources that best suit their learning styles and needs.

Personalized curriculum systems, utilizing AI and deep learning, have been developed to meet the diverse needs of students at different educational levels. Liu and Guo (2020) and Tavakoli et al. (2022) have shown that these systems can analyze vast amounts of student data to recommend tailored learning paths and resources, enhancing education's relevance and effectiveness. By aligning learning materials with students' individual goals and performance levels, these systems help improve educational outcomes and student satisfaction. However, further research is needed to verify their effectiveness across diverse educational contexts.

Peer mediation strategies leverage the power of collaboration by pairing students with similar learning goals and preferences, fostering a supportive learning environment. Pereira et al. (2018) demonstrated that such approaches can enhance engagement and academic achievement by allowing students to motivate and assist each other. By using social networks and other tools to personalize recommendations, peer mediation supports learning and helps build a community of learners who can share resources and knowledge effectively.

However, these innovative approaches face several challenges in realizing their full potential. Standardizing terminology and evaluation methods is crucial for advancing research and application in educational technology. As highlighted by Pelánek (2022) and further examined by Rahayu et al. (2022) and Raj and Renumol (2022), inconsistencies in terminology and a lack of standardized evaluation metrics can hinder the development and adoption of these systems. Clearer definitions and more robust evaluation frameworks are needed to implement these technologies effectively and deliver meaningful educational benefits.

5. CONCLUSION

This systematic literature mapping analyzed state-of-the-art individualized educational referral systems using the PICOC framework. The population included students, teachers, and professors, and the intervention used individualized recommendation systems in teaching and learning. The outcome of interest was the effectiveness of the systems in improving individualization and planning in virtual, school, and college education. The study's goal was to provide a comprehensive understanding of the current state of research in this area and to identify critical trends and challenges in developing and implementing individualized recommendation systems for education.

After analyzing 1583 articles, 84 were selected for in-depth analysis, and key findings were summarized. The results indicate that individualized recommender systems for education can potentially improve the effectiveness of teaching and learning by providing tailored resources that address learners' individual needs. However, there are several challenges in developing and implementing these systems. These include the need for a comprehensive and systematic literature review, the difficulty of providing accurate and relevant recommendations, and the need to balance personalization with privacy.

In summary, this systematic literature mapping provides a comprehensive overview of the current state of the art in individualized recommendation systems for education. It highlights these systems' potential benefits and challenges and provides insight into future research directions. Further research is needed to address the challenges and improve the effectiveness of individualized recommender systems in education. Potential future research topics include developing more accurate and relevant recommendation algorithms, investigating privacy concerns, and developing methods to protect privacy, and evaluating the impact of individualized recommender systems on learning outcomes.

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