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A Systematic Review on Recommendation Systems Developed for the Field of Adult Education

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Today, the changing job performances and the desire of individuals to improve themselves have created the desire of people to quickly reach the content that is suitable for them. The use of suggestion systems designed to identify the needs of individuals and present the most appropriate content is considered as a solution method in this regard. The aim of this systematic study is to determine the trends in the field by making a comprehensive analysis about what kind of suggestions are given in the studies on the recommendation systems used and designed in the field of adult education, in which year the studies were conducted, the research method used, the filtering methods used and the algorithms used, and to identify the trends in this field to establish an up-to-date basis for new entrants. As a result of the review made in various databases, 113 studies were reached, and a systematic analysis of 75 studies that met the inclusion criteria was carried out. As a result of the review, it was seen that the most content suggestions were made, the most publications were made in 2020, the research method focused on determining the system performance and promoting, and a limited number of experimental studies were included. It has been determined that the most collaborative filtering method is used, and content-based and hybrid filtering methods are less preferred. It has been concluded that the K nearest neighbor algorithm is used much more than other algorithms, and besides this algorithm, artificial neural networks, support vector machines, decision trees and newly proposed algorithms by the researchers are also included. In line with the results obtained, investigations were made and suggestions were made for practice and research for future studies.

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Keywords: Recommendation systems, adult education, adult recommendation systems, literature review.

INTRODUCTION

Today, we live in a world where we can reach more products and varieties. We need to make decisions for different purchases from clothes to books, from food to electronic devices, and from cars to homes. The multitude of options for all these products brings difficulties in choosing individuals who do not have time to research in the hustle and bustle of daily life or who are undecided about what they need. In the periods when there were no virtual systems, individuals made their product choices mostly on the recommendation of the best seller or their relatives/acquaintances. The service sector of the developing world also brought about changing habits and enabled the use of Virtual Systems (Ganguly et al., 2010). While there were few products and uses in the beginning, with the increase in the number of items and users over time, it has become difficult for individuals using virtual systems to make decisions. It is seen that similar difficulties are experienced in the field of education.

With the recognition that obtaining information from the Internet saves time and space, there has been an uncontrolled exponential increase in the number of virtual classrooms, courses, and educational materials (Chou & Chen, 2008; Vezne et al., 2023). While MIT, one of the systems providing e-learning services, publishes 2577 courses online in the open course system, UDEMY, which is the most widely used in Turkey, offers more than 185,000 courses, and the Ministry of National Education offers courses with an average of 461,689 different content per year for users of all ages. Access to digital content whose growth rate cannot be controlled is easy for individuals, but this increase also causes serious problems for users in choosing content. These problems reduce the effectiveness and efficiency of the training, the chance of reaching the right training, and the satisfaction rate of individuals from training (Peltier, Schibrowsky& Drago, 2007). Interests, skills, needs, and expectations that vary according to the person require a solution to the problem of presenting online content equally and in the same way to everyone. The most effective method that can be a solution to this problem in online environments is recommendation systems. The main task of recommendation systems is to prevent virtual disappearance by identifying and presenting the most suitable / ones among numerous content (Khanian&Mohd, 2016). Recommendation systems are also preferred by publishers to increase the preference rates of the applications or websites used, to ensure user satisfaction, and to enable orientations to different items (Cheng et al., 2016; Özaydın et al, 2022a, b).

According to Knowles (1978), an adult is defined as a person who has reached the biological reproductive age and is legally capable of voting, obtaining a driver's license, marrying of their own accord, or going to the military. Adult education, on the other hand, can be defined as the process of organized activities in which people who have completed their continuous/formal education participate voluntarily in order to create a change in their understanding of life, knowledge, skills, behavior and understanding. Adults want to meet

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both their own and society's needs throughout their lives. This need may arise not only from the need to know/learn, but also from the need to be valued/prestige or self-actualization, as stated by Maslow (1943) in the hierarchy of needs. Adult students differ from child students. There are no exam requirements that will shape life depending on a certain curriculum (Knowles, 1978). They are at a certain level of educational maturity and have their own intellectual structures. For these reasons, before learning a subject, they want to know why they will learn, how the learned information will affect their lives and where they should use this information. The need to know is inevitable for adult students, not only for themselves, but also for ensuring the development and safety of the individuals they are responsible for (Garrison, 2003). The desire to adapt to the developing and changing world around them, to learn new techniques and to feel adequate for the individuals under the most important responsibilities is the trigger of this desire to learn. Positive support of the educator/education system, organized form of learning objects, and repetitions provide the permanence and continuity of learning to support adult individuals' desire to learn (Wlodkowski, 1999). Considering all these requests and needs, increasing information sets and lack of time, suggestion systems are important for the identification and proposal of needs of adults that are not even aware of themselves. While presenting correctly structured information sets to individuals saves time, it also increases motivation by preventing information overload. The systems in which these information sets are presented to the individual in line with the needs, preferences or navigation of the individuals that they are aware of or not aware of are called suggestion systems. Suggestion systems present the given suggestion to the person, and it is up to the person whether the user prefers this suggestion or not.

This study examines the studies on suggestion systems prepared for adults in the field of education in line with predetermined criteria and presents the results. When the previous literature reviews are examined; Deschênes (2020) examined the studies on recommendation systems in the field of learning between 2008-2018. In the study, investigations were made on what was suggested, which filtering methods were used, and what the dependent variable was. Zang, Lu, and Zang (2021) conducted a study on recommendation systems for their screening e-learning. In this study, the authors focused on determining the filtering methods used in the field. Urdaneta-Ponte, Mendez-Zorrilla and Oleagordia-Ruiz (2021) examined the studies on the use of recommendation systems in learning environments between 2015-2020 in their literature review. In these reviews, it was determined in which countries the subject was studied, the distribution of publications by years, the distribution of studies according to the type of education, the recommendations, and which metrics were used to determine the system performance. In this study, the focus is on the studies on adult recommendation systems in the field of learning between the years 2000-2022. In other studies, what is suggested (Urdaneta-Ponte, Mendez-Zorrilla & Oleagordia-Ruiz, 2021), number of publications by years (Urdaneta-Ponte, Mendez-Zorrilla &Oleagordia-Ruiz, 2021; Deschênes, 2020; Zang, Lu & Zang, 2021) and what the filtering methods are (Deschênes, 2020; Zang, Lu & Zang, 2021) studies have been made on it. However, other studies do not show any restrictions on users. In addition, in this study, unlike other literature reviews in the literature, surveys were conducted on the research methods examined, the algorithms used, and the adult recommendation systems, which is the main focus. When the literature review studies in the literature are examined, it is seen that they are made in the fields of computer engineering, software engineering, business administration and educational sciences.

Conceptual Framework

According to the way they work, recommendation systems can be content-based, collaboration-based, or hybrid-based. According to the type of raw data (user-user, user-item, item-item interaction) to be used for machine learning in recommendation systems, the type of filtering to be used is determined (Ricci, Rokach & Shapira, 2011). After the specified filtering type, machine learning algorithms used in these filtering methods are used in model generation. Suggestions are made to people with the models produced.

Collaborative Filtering

Collaboration-based filtering expression is mentioned for the first time in the literature in 1992 by Goldberg in a study in which the recommendation system called Tapestry was put forward. Collaboration-based filtering is the most preferred method among recommendation systems. Unlike the "Collaborative Filtering - CF" content-based filtering, which we consider as filtering based on common preferences, it works not by the user-item matrix of a single user, but by considering the profiles of users who like similar sets of attributes and showing similar characteristics (Figure 1)(Koren, Rendle & Bell, 2022). The algorithms used in the design are the demographic characteristics, interests, likes, scores given to the previous content, etc. of the users in the system. Collecting information about the criteria ensures that similar users are identified, these users are grouped, and similar content is presented to users in the same group.

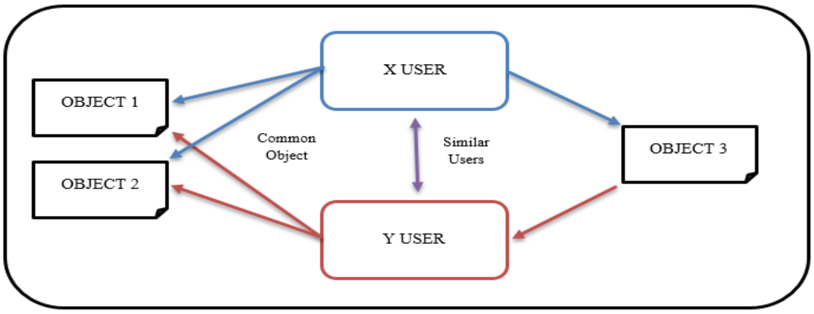

Figure 1. Recommendation process in collaboration-based systems

Creating Collaborative Filtering

Collaborative filtering algorithms consist of 3 separate calculation steps: similarity calculation, neighborhood selection, and prediction calculation.

Collaborative Filtering Methods

In CF filtering, a user-item interest matrix is created for each user in the system, in line with the ratings given to the items. By using this matrix, similarities are calculated with the memory-based or model-based methods.

Memory-based methods, also called neighborhood-based, are user-user (similar users prefer similar items) or item-item-based (similar items are preferred by similar users). They can be constructed using cosine similarity or Pearson correlation.

In the model-based method, rating estimates are made for items that are not evaluated based on the ratings created by users for items. Using decision trees, SVD, MF, Bayesian, rule-based models, or clustering approaches, convergent neighbors are determined and recommendations are presented.

Content-based Filtering

A system using Content-Based Filtering (CBF) analyzes the attributes of one/many items previously rated by user X and ensures that items with similar qualities are offered for the interests of user X (Lops, Gemmis&Semeraro, 2011)(Figure 2). In other words, in the content-based filtering method, it is essential to present a suggestion among the items grouped according to the description of an item in the system, the keywords describing the item or the features that the user prefers about the items. The algorithms used try to suggest items similar to an item a user has liked in the past. Since a new item added to the system is an item group to which it belongs, it does not need to be evaluated by users.

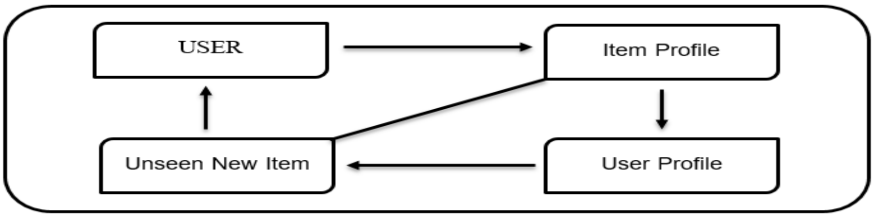

Figure 2. Recommendation process in content-based systems (Sharma and Gera, 2013)

Creating Content-based Filtering

Content-based filtering algorithms consist of 3 separate calculation steps: content analysis, extracting user profiles, and filtering.

Hybrid Filtering

In hybrid-based filtering design, collaboration and content-based filtering can be used together, or it can be developed by combining different techniques. This technique is to combine its advantages with each technique to create a system that works with maximum performance by eliminating its disadvantages (Çano&Morisio, 2017).Burke (1999) classified hybrid methods into seven different types: Weighted, Switching, Hash, Feature Combination, Cascading, Feature Augmentation, and Meta-Level.

METHOD

The aim of this study is to determine the trends in studies on recommendation systems in the field of education for adult individuals through articles, papers, master's theses or doctoral theses. In this direction, the study was carried out as a review study.

Within the framework of the determined aim, answers were searched for the following research questions.

- What types of media have been suggested in the studies?
- What is the distribution of the reviewed studies according to the year they were published?
- What is the studies distribution according to the research method used in the studies examined?
- What is the distribution according to the filtering methods used in the studies?
- What are the machine learning algorithms used for making recommendations?

Study Process

The work process carried out is given in detail in Figure 3 step by step. As seen in Figure 3, the study started with the identification of keywords. Keywords for the purpose were determined as "educational recommender systems, educational recommender systems for adults, and collaborative filtering in education". These keywords were scanned in Turkish and English in EBSCO, ProQuest, ULAKBİM, YÖK National Thesis Center, and Google Scholar studies between 2000-2022.

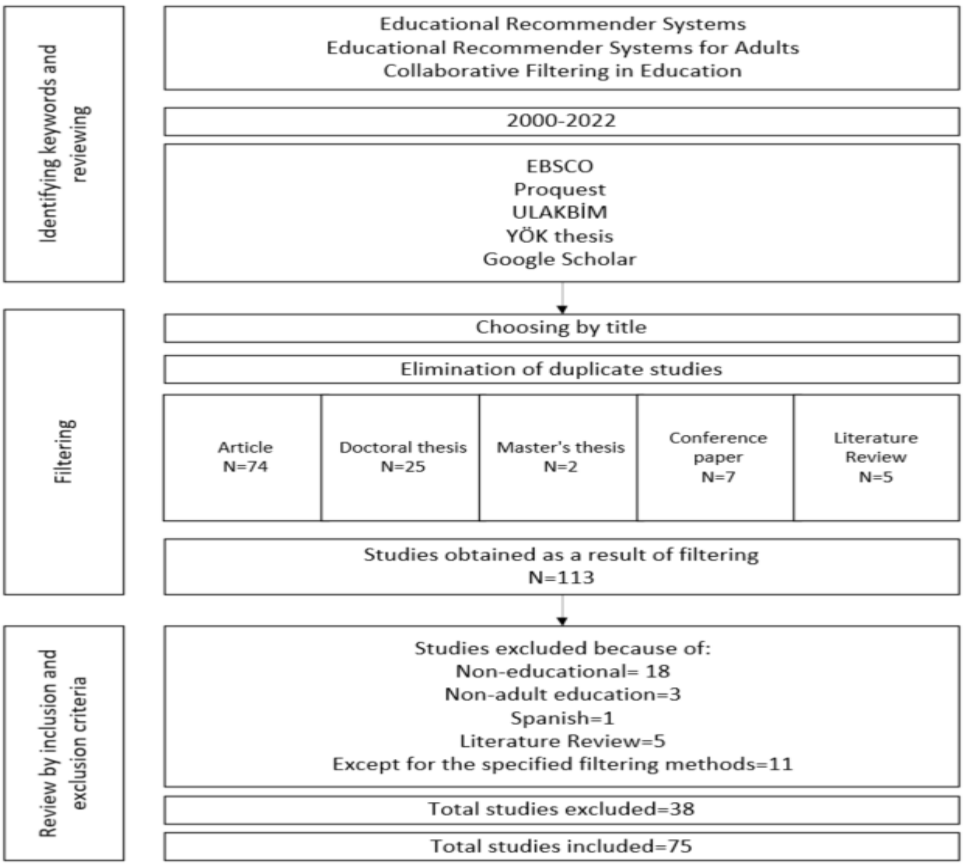

Figure 3. Study process

As a result of the search, a total of 113 studies in the type of 74 articles, 5 literature reviews, 25 doctoral theses, 2 master's theses, and 7 conference papers related to keywords were reached. Before examining the studies in detail, inclusion and exclusion criteria were determined for the study. These criteria are listed in Table 1. A total of 113 studies found in line with the criteria were examined. As a result of the analyses, 18 studies were conducted in areas other than education, 3 studies were conducted outside adult education, 1 study was written in Spanish, 5 studies were published as a literature review, and other techniques other than the filtering techniques in the inclusion criteria were used in other 11 studies. Accordingly, a total of 38 studies were excluded from the detailed review as they did not meet the inclusion criteria. The remaining 75 studies were reviewed in detail by two researchers (Appendix 1). These investigations were carried out to determine the type of suggestion given in the studies, the year of the study, the method used, the filtering meth od used, and the algorithms used. The information is given in the findings section in the form of tables and explanations.

Table 1. Inclusion or exclusion criteria

Inclusion Criteria	Exclusion Criteria
Adult recommendation system for individuals between the ages of 18-64	Studies with individuals under 18 and over 64 years old
Studies using content-based filtering technique	Studies in areas such as non-education, engineering, marketing
Studies using cooperative filtering technique	Studies conducted in languages other than Turkish and English
Studies using hybrid filtering technique	Literature reviews
Studies in the field of education	Studies using knowledge-based filtering technique
	Studies using data mining techniques

FINDINGS

Under this heading, there are findings for the detailed examination. The types of recommendations used in the studies examined are given in Figure 4.

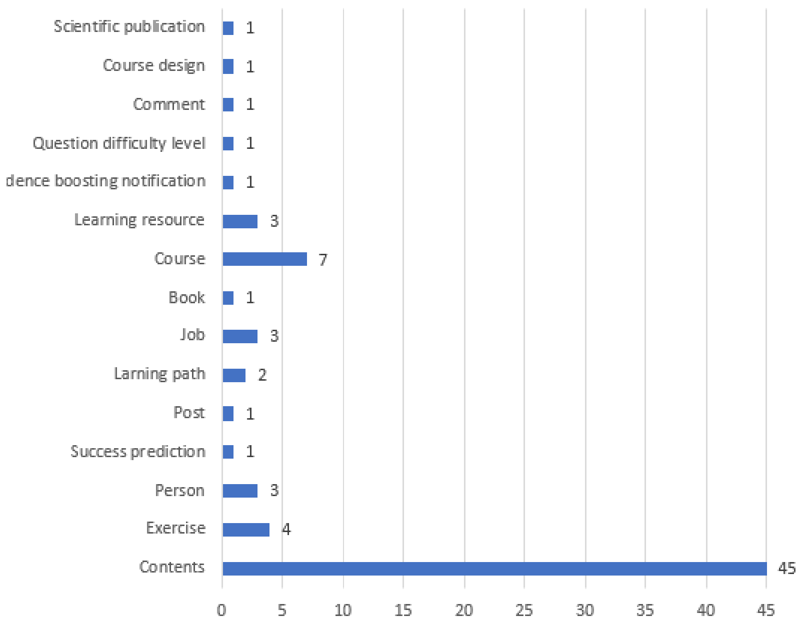

Figure 4. Types of recommendations given to individuals in studies

When the types of suggestions are examined in detail, the most common suggestions are for the content (N=45). Course suggestions (N=7)are the second most suggestive type.

Apart from content and courses, there are also exercises (N=4), learning resources (N=3)(like links, books), job (N=3), people (N=3), and learning paths (N=2) recommendations were also made. When the distribution of the studies by years is examined in detail, the results are given in Figure 5.

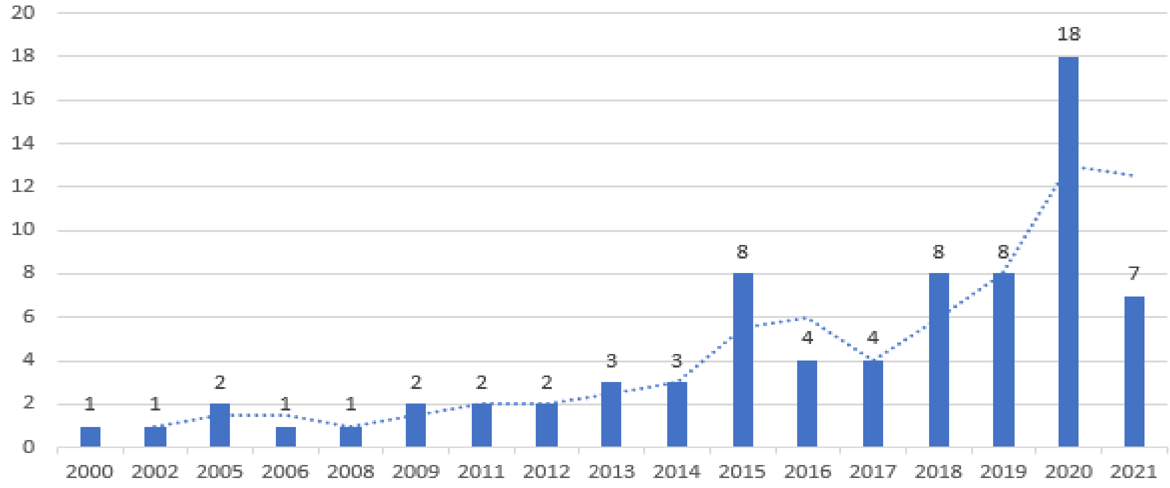

Figure 5. Distribution of the reviewed studies by publication years

According to the literature, the year with the most publications is 2020 (N=18). There were 8 study in 2015, 2018, and 2019, 7 study in 2021, 4 study in 2016 and 2017, 3 study in 2013 and 2014, 2 study in 2005, 2009, 2011, and 2012, and 1 study in 2000, 2002, 2006, and 2008. In 2001, 2003, 2004, 2007, and 2010, a recommendation system study for adults was not found within the framework of the determining criteria. Since both of the 2 studies conducted in 2022 are literature reviews, there are no publications that meet the criteria this year. The findings regarding the study methods used by the researchers in the studies examined are given in Figure 6.

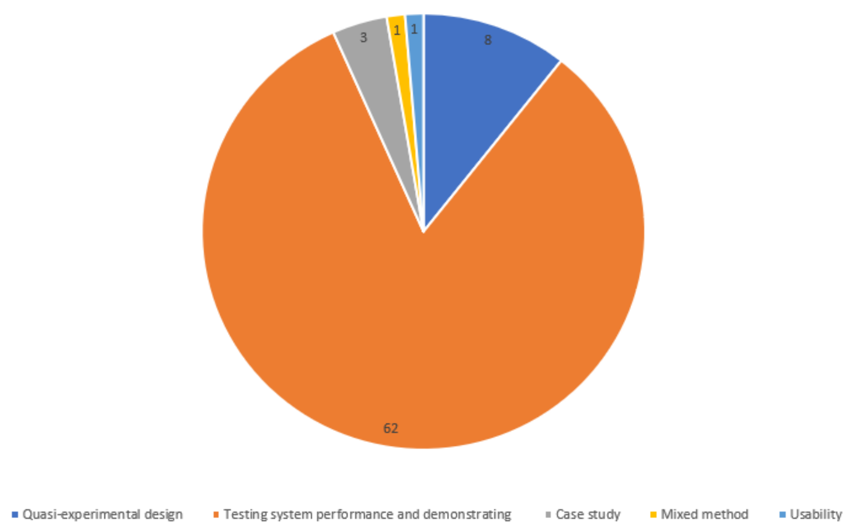

Figure 6. Study distributions according to the method

When the research methods used are examined, the most used method is testing and promoting the system's performance (N=62). In addition, quasi-experimental research design (N=8) and case studies (N=3) are also included in adult recommendation systems studies. In the studies, mixed research and one study in which the usability of the system was tested were found. The results of the investigations according to the filtering method used are given in Figure 7.

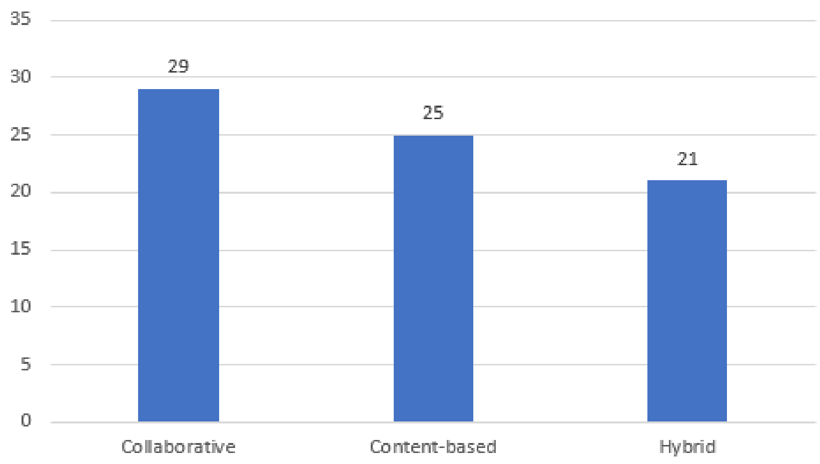

Figure 7. Filtering methods used in studies

When the filtering methods used in the studies examined the most used method is the cooperative (N=29) filtering method. In addition, content-based filtering was used in 25 studies, and hybrid filtering methods in which collaborative filtering and content-based filtering were used simultaneously in 21 studies. The findings regarding the algorithms used in the studies examined are given in Figure 8.

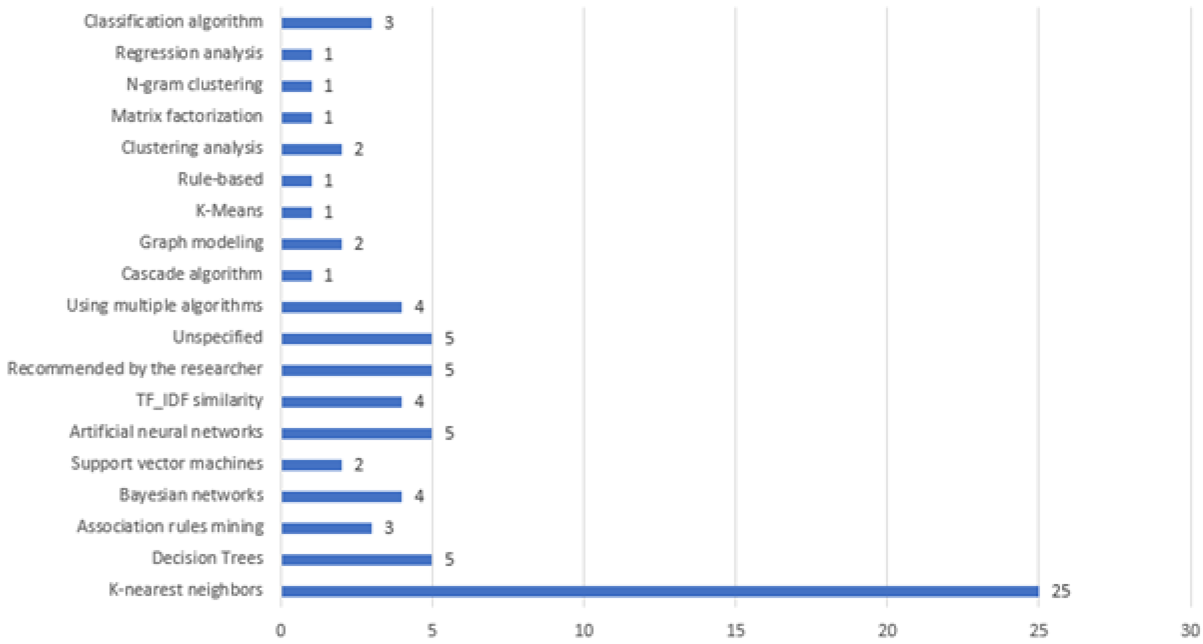

Figure 8. Machine learning algorithms used in the studies

When the algorithms used for machine learning are examined in the studies, it is seen that the K-nearest neighbor algorithm (N=25) is mostly used in the studies. Artificial neural networks and decision tree algorithms were used in 5 studies, the algorithm used in 5 studies was not mentioned, and the algorithms recommended by the researchers were used in 5 studies. More than one algorithm was used in 4 studies, and the TF_IDF similarity algorithm and bayesian networks were used in 4 studies. There are 3 studies in the literature, each using association rules analysis and classification algorithms. In 2 studies, clustering analysis, graph modeling, and support vector machine algorithms are used. Regression analysis, n-gram clustering, matrix factorization, rule-based, k-means, and cascade algorithms were used in each study.

CONCLUSION and DISCUSSION

In this study, 75 studies on recommendation systems in the field of adult education were examined. These 75 studies were analyzed in detail in terms of the types of recommendations made, the year of publication, the research method used, the filtering methods used and the algorithms used. The results of the examination are given in detail in the findings section. When the studies were examined according to the suggestion types, the most content suggestions were made to the people, and the second highest suggestion type was on the suggestion of learning objects. Looking at the years of study, the studies in which adult recommendation systems were used were mostly published in 2020, and the period with the least publication years was the beginning of the 2000s. According to the research methods used, the studies mostly included studies that tested the system performance and introduced the system, as well as studies using quasi-experimental designs, case studies, mixed studies, and usability studies. When the studies under the headings of cooperative, content-based, and hybrid filtering methods are examined, the most used method is cooperative filtering. The second preferred method is the content-based method, and the less preferred method than the other two methods is the hybrid filtering method, which uses cooperative filtering and content-based filtering methods at the same time. When the machine learning algorithms used in the studies are examined, it is observed that the k-nearest neighbor algorithms are mostly preferred. In addition, as algorithm preference; decision trees, bayesian networks, artificial neural networks, new algorithms proposed by researchers, TF_IDF similarity, use of multiple algorithms, classification and clustering algorithms, graph modeling, support vector machines, regression analysis, n-gram clustering, matrix factorization, rule-based, k-mean and cascade algorithms were also used.

When the types of suggestions made to the users were examined, the most content type of suggestions was included in this study. Urdaneta-Ponte, Mendez-Zorrilla, and Oleagordia-Ruiz (2021) concluded in their study in the field of education that learning resources are the most recommended. They also concluded that the course recommendation was the second most recommended recommendation. However, in this study, in the recommendation systems for adults, the second recommendation is the learning object, followed by the course recommendations in the third place. Zhang, Lu, and Zhang (2021), in their study, concluded that the most recommended type is learning materials, ie content, as in this study. In the second place, they concluded that learning objects are the most used type, as in this study. It is thought that the differences in the studies are due to the differences in the database scanned, the differences in the year range, the different classification of the themes by the researchers (for example, Zhang, Lu&Zhang (2021) took the content and learning objects as two separate types in their study “content” type, in this study, the contents and learning objects were grouped under the "content" type), the difference in scope and the differences in the inclusion and exclusion criteria determined. Since multimedia objects (contents) (Deldjoo, Schedl, Hidasi, Wei, & He, 2022) are the most basic and indispensable element of these trainings in online trainings and it is important to provide learners with content suitable for them in terms of individualization of learning, it is thought that the contents are recommended the most. When the study distributions by years are examined, Deschênes (2020) has the most publications in 2018, Rima, Meriem, Najima, and Rachida, (2022) in 2021, Urdaneta-Ponte, Mendez-Zorrilla and Oleagordia-Ruiz (2021) in 2020. have reached their conclusion. In this study, as in the study of Urdaneta-Ponte, Mendez-Zorrilla and Oleagordia-Ruiz (2021), most publications were made in 2020. The reason why Deschênes (2020) came to a different conclusion may be that this study was conducted between 2008 and 2018. In addition, the differentiation of the conclusion reached by Rima, Meriem, Najima, and Rachida (2022) is because the survey includes all studies without the target audience limit that can be reached in the field of education. When the literature review in the field of education is examined, there is no information about the research methods used in these studies. As Jordan and Mitchell, (2015) stated, it can be said that recommendation systems are a new trend in the field of machine learning, and it is due to the focus on the development and performance of systems. Looking at the results of the analysis of the filtering methods used in these scans, Deschênes (2020) concluded that the most used method is content-based filtering, followed by the second most used method, using content-based and hybrid filtering techniques with an equal number of studies. Urdaneta-Ponte, Mendez-Zorrilla and Oleagordia-Ruiz (2021) concluded in their study that the cooperative filtering method was used the most, the hybrid filtering method was used second, and the content-based filtering method was the least preferred one. Zhang, Lu and Zhang (2021) concluded that as in this study, the most collaborative filtering method is used, then content-based filtering is the second most preferred filtering technique, and hybrid filtering is the least preferred method compared to other methods. As stated by Walker (2000), the use of collaborative filtering techniques in recommendation systems generates recommendations based on user-user interaction results. In the first studies conducted in recommendation systems, it was aimed to recommend an object to people who might prefer it more, based on user-user interaction (Jordan & Mitchell, 2015). In this area, different data, based on user-user interaction and suggestions for this interaction were carried out. In addition, the collaborative filtering method also provides the use of simple algorithms (Koren, Rendle & Bell, 2022). These situations bring about more use of cooperative filtering techniques. Urdaneta-Ponte, Mendez-Zorrilla and Oleagordia-Ruiz (2021), and Deschênes (2020) did not review the algorithms used in their studies. Zhang, Lu and Zhang (2021) examined 40 studies in their study and stated that only two of these studies used the k-nearest neighbor algorithm, which was found to be the most preferred in this study. In addition, the results of the use of n-gram, rule-based, graph modeling, artificial neural networks, and decision tree algorithms in this study were also obtained as a result of the investigations by Zhang, Lu and Zhang (2021). The K nearest neighbor algorithm uses classification algorithms. It uses simple calculations such as pearson correlation (Walker, 2002), sinus similarity (Li & Ye, 2020), heuristic similarity (Salehi &Kmalabadi, 2012), and cosine similarity (Rodríguez, Ovalle & Duque, 2015). In addition, the k nearest neighbor algorithm, which is a classification algorithm, supports working with less learning data compared to algorithms using clustering such as artificial neural networks. This explains the reason why the K nearest neighbor algorithm is the most used algorithm. In addition, this algorithm has the feature of being one of the first used algorithms in recommendation systems (Walker, 2002) because of that it is the most preferred algorithm.

SUGGESTIONS

When the methods used in the analyzed studies are examined, it is seen that the experimental studies in which the system performance is tested and introduced are rarely included. Experimental studies can be included in future studies and the effects of these systems in terms of different dependent variables can be examined. In addition, a detailed screening study can be done about the dependent and independent variables that are considered in experimental studies.

When the studies are examined in terms of the filtering methods used, it is seen that the least used filtering method is hybrid filtering. Hybrid filtration systems reduce the cold start problem compared to systems where only cooperative or content-based filters are used. In future studies, studies can be carried out to prevent cold start problems by using the hybrid filtering technique.

When the distribution of studies by year is examined, it is seen that the most studies were carried out in 2020, but this number decreased in 2021-2022. Within the framework of the above-mentioned recommendations, new studies on the effectiveness of recommendation systems can be made to contribute to the literature.

In this study, it was seen that the two types most recommended were contents and courses. Other than these species and the species specified in the study, studies can be carried out to suggest species that are used in educational activities or that can support these activities.

When the algorithms used for machine learning were examined, it was seen that classification algorithms (K-NN, etc.) were preferred more than clustering algorithms (artificial neural networks, etc.) in this study. In future studies, the performance of these methods or their effects on dependent variables can be examined by using methods using clustering algorithms.

LIMITATIONS

This study is limited to studies that are conducted in EBSCO, Proquest, ULAKBİM, YÖK National Thesis Center, and Google Scholar between 2000-2022, with "educational recommender systems, educational recommender systems for adults, and collaborative filtering in education" keywords. Studies outside of these criteria were not included in the review.

Declarations

Conflict of Interest

This study was carried out within the scope of the TÜBİTAK 1001 project entitled 120K927, "Developing a Recommendation System for Increasing Parents' Digital Parenting Competencies".

This study is related to the doctoral thesis entitled "Development, evaluation, and usability of a mobile recommendation system to increase parents' digital parenting competencies".

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Research and Publication Ethics Statement

Hereby, we as the authors consciously assure that for the manuscript "
" the following is fulfilled:

- This material is the authors' own original work, which has not been previously published elsewhere.
- The paper reflects the authors' own research and analysis in a truthful and complete manner.
- The results are appropriately placed in the context of prior and existing research.
- All sources used are properly disclosed.

Contribution Rates of Authors to the Article

This study was conducted in equal collaboration between the four authors.

Acknowledgment

This study was carried out within the scope of the TUBİTAK 1001 project numbered 120K927, and entitled "Developing a Suggestion System for Increasing Parents' Digital Parenting Competencies"

This study is an extended version of the abstract presented at 15th International Computer and Instructional Technologies Symposium.

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APPENDICES

Appendix 1. Reviewed Studies

Study	**Type**	**Recommendation given**	**Method**	**Filtering technique**	**Used algorithms**
Moshrefizadeh (2021)	Article	Learning object	Testing system performance and demonstrating (TSPD)	Content-based	Classification algorithm
Ma, Lu, Taniguchi and Konomi (2021)	Article	Course recommendation	TSPD	Content-based	KNN (K-nearest neighbors)
Bhaskaran, Marappan and Santhi (2021)	Article	Content	TSPD	Hybrid	Clustering analysis
Bulathwela, Pérez-Ortiz, Novak, Yilmaz and Shawe-Taylor (2021)	Article	Video	TSPD	Hybrid	More than one
Althbiti (2021)	PhD Thesis	Content	TSPD	Collaborative	Artificial neural networks
Morales, Gonzalez, Alquerque, Reyes and Sanchez, (2021)	Conference paper	Learning object	TSPD	Hybrid	Unspecified
Yang, Chen, Akçapınar, Flanagan and Ogata (2021)	Article	Learning object	TSPD	Content-based	TF_IDF similarity
Polyzou (2020)	PhD Thesis	Course recommendation	TSPD	Collaborative	KNN
Na, Xiuyuan and Na (2020)	Article	Content	TSPD	Hybrid	Support vector machines
Cheng and Bu (2020)	Conference paper	Content	TSPD	Hybrid	Association rules mining
Gordillo, López-Fernández and Verbert (2020)	Article	Learning object	Usability	Collaborative	KNN
Hidayat, Suwawi and Laksitowening (2020)	Article	Content	TSPD	Collaborative	KNN
Li and Ye (2020)	Article	Course recommendation	TSPD	Collaborative	KNN
Liao, Feng, Sun, Wang, Liao and Li (2020)	Conference paper	Learning object	TSPD	Collaborative	KNN
Wan, Wu, Guo, Yang, Han and Yin (2020)	Conference paper	Learning resource	TSPD	Collaborative	KNN
Tavakoli, Mol and Kismihók (2020)	Article	Job	TSPD	Collaborative	KNN
Wang, Zhu, Zhu, Zhang, Chen and Xiong (2020)	Article	Course recommendation	TSPD	Collaborative	Bayesian networks
Demertzi and Demertzis (2020)	Article	Content	TSPD	Hybrid	Artificial neural networks
Tavakoli, Hakimov, Ewerth andKismihok (2020)	Article	Video	TSPD	Content-based	Classification algorithm
Hikmatyar (2020)	Article	Book	Case study	Collaborative	Recommended by the researcher
Khadka (2020)	PhD Thesis	Scientific publication	Quasi-experimental design	Content-based	Unspecified
Brik and Touahria (2020)	Article	Person	TSPD	Collaborative	Bayesian networks
Ağzıyağlı (2020)	Master's Thesis	Content	TSPD	Content-based	TF_IDF similarity

Zhao, Arya, Orjiand Chan (2020)	Article	Exercise	TSPD	Content-based	Decision trees
Dahdouh, Dakkak, Oughdirand Ibriz (2019)	Article	Content	TSPD	Collaborative	Association rules mining
Huang, Liu, Zhai, Yin, Chen, Gaoand Hu (2019)	Article	Exercise	TSPD	Collaborative	KNN
Jiang, Pardosand Wei (2019)	Article	Content	TSPD	Collaborative	Artificial neural networks
Li, Li, Zhang, Zhong and Cheng (2019)	Article	Content	TSPD	Hybrid	KNN
Shi, Wen, Wangand Ouyang (2019)	Article	Learning resource	TSPD	Collaborative	KNN
Chen, Yin, Li, Rong, Xiong and David (2019).	Article	Content	TSPD	Collaborative	Association rules mining
Mokarrama, Khatun and Arefin (2020)	Article	Job	TSPD	Content-based	Artificial neural networks
Adam,Sulaimanand Soh (2019)	Article	video	TSPD	Content-based	Using multiple algorithms
Zhu, Liu, Tian, Ni, Wu, Chenand Zheng (2018)	Article	Video	TSPD	Collaborative	Recommended by the researcher
Ibrahim, Yang, Ndzi, Yang and Al-Maliki (2018)	Article	Job	TSPD	Hybrid	KNN
Gulzar, Leema and Deepak (2018)	Article	Course Recommendation	TSPD	Hybrid	N-gram clustering
Cai, Han, Li, Zhang, Panand Yang (2018)	Article	Learning object	TSPD	Content-based	Graph modeling
Klašnja-Milićević, Vesinand Ivanović (2018)	Article	Learning object	TSPD	Collaborative	KNN
Zhou, Huang, Hu, Zhuand Tang (2018)	Article	Learning path	TSPD	Collaborative	KNN
Shu,Shen, Liu, Yiand Zhang (2018)	Article	Learning object	TSPD	Content-based	Artificial neural networks
Albatayneh, Ghauthand Chua (2018)	Article	Post	TSPD	Content-based	TF_IDF similarity
Ochirbat and Shih (2017)	Article	Job	TSPD	Collaborative	Regression analysis
El Mabrouk, Gaouand Rtili (2017)	Article	Content	TSPD	Hybrid	Decision Trees
De Meo, Messina, Rosaciand Sarné (2017)	Article	Exercise	TSPD	Collaborative	KNN
Sirisaengtaksin (2016)	Master's thesis	Content	Quasi-experimental design	Content-based	Rule-based
Xu, Xingand Van Der Schaar (2016)	Article	Learning Path	TSPD	Content-based	KNN
Bourkoukouand El Bachari (2016)	Article	Content	TSPD	Collaborative	KNN
Symeonidisand Malakoudis (2016)	Article	Course Recommendation	TSPD	Collaborative	Matrix factorization
Zheng, Chen,Hung, He,Hong and Lin (2015)	Article	Success prediction	Quasi-experimental design	Hybrid	Recommended by the researcher
Tejeda-Lorente, Bernabé-Moreno,PorceGalindo-Moreno and Herrera-Viedma (2015)	Conference paper	Content	Quasi-experimental design	Content-based	KNN

Ye, Tang, Xuand Jin (2015)	Article	Learning object	TSPD	Content-based	Support vector machines
Wu, Lu and Zhang (2015)	Article	Exercise	TSPD	Content-based	Decision trees
Mulholland, Mc Kevitt, Lunney, Farren and Wilson (2015)	Article	Content	TSPD	Content-based	Recommended by the researcher
Montuschi, Lamberti, Gatteschiand Demartini (2015)	Article	Course recommendation	TSPD	Content-based	Bayesian networks
Rodríguez, Ovalle and Duque (2015)	Conference paper	Learning object	TSPD	Hybrid	KNN
Rodríguez Marín, Duque and Ovalle (2015)	Article	Learning object	TSPD	Content-based	Clustering analysis
Tian, Gao, Zhang, Liang, Qianand Zhao (2014)	Article	Confidence-boosting suggestions	TSPD	Content-based	Decision trees
Segal, Katzir, Gal, Shani and Shapira (2014)	Article	Question difficulty level	TSPD	Collaborative	KNN
Pedro, Santos, Almeida, Ramos, Moreira, Almeida and Antunes (2014)	Article	Content	Case study	Collaborative	Unspecified
Salehi (2013)	Article	Learning Object	TSPD	Content-based	Decision trees
Dwivedi and Bharadwaj (2013)	Article	Learning resource	TSPD	Hybrid	K-means
Klašnja-Milićević (2013)	PhD Thesis	Content	Quasi-experimental design	Collaborative	KNN
Walker (2012)	PhD Thesis	Course design	Quasi-experimental design	Hybrid	More than one (KNN, bayesian networks)
Salehi and Kmalabadi (2012)	PhD Thesis	Learning object	TSPD	Content-based	KNN
Santos and Boticario (2011)	Article	Content	TSPD	Content-based	Unspecified
Ghauth and Abdullah (2011)	Article	Content	Case study	Content-based	TF_IDF similarity
Shen, Wangand Shen (2009)	Article	Learning object	TSPD	Collaborative	KNN
Drachsler, Hummel, Van den Berg, Eshuis, Waterink, Nadolski, ... and Koper (2009)	Article	Learning object	Quasi-experimental design	Hybrid	Graph modeling
Wang (2008)	Article	Content	TSPD	Hybrid	Classification algorithm
McNee (2006)	PhD Thesis	Content	TSPD	Hybrid	Bayesian networks
Masters (2005)	PhD Thesis	Comment suggestion	Mixed method	Hybrid	More than one (KNN, Bayesian networks)
Rafaeli, Dan-Gur and Barak (2005)	Article	Person	TSPD	Collaborative	KNN
Walker (2002).	PhD Thesis	Content	Quasi-experimental design	Collaborative	KNN
Burke (2002)	Article	Content	TSPD	Hybrid	Cascade