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The Use of Recommender Systems in Formal Learning. A Systematic Literature Mapping

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Abstract: Recommender Systems provide users with content or products they are interested in. The main purpose of Recommender Systems is to find, among the vast amount of information that is available or advertised on the Internet, content that meets the user's needs i.e., a product or content that satisfies his or her wishes. These systems are being used more and more in many of the services of our daily lives. In this paper, a systematic mapping review that explores the use of Recommender Systems in formal learning stages is presented. The paper analyzes what kinds of items the Recommender Systems suggest, who the users that receive the recommendations are, what kinds of information the Recommender Systems use to carry out the recommendation process, the algorithms and techniques the Recommender Systems employ and, finally, how the Recommender Systems have been evaluated. The results obtained in the review will make it possible to identify not only the current situation in this field but also some of the challenges that are still to be faced.

Keywords: Recommender Systems, Formal Education
Categories: K.3.1, J.1, H.4
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1 Introduction

Everyday, large amounts of data are created, shared and exchanged. This has also affected the way we interact with that data, which is also undergoing a transformation. New ways to interact with data and with other people, groups or products are emerging. Data is becoming increasingly important. In the early nineties, a new kind of application which exploited the information extracted from the interaction of users and systems emerged. These kinds of systems, known as Recommender Systems (RS), came to provide an effective solution in many different areas. An RS provides a user with relevant content with regard to the knowledge elicited from the interaction between users and items [Falk, 2019]. To fulfill their purpose, RSs rely on three main components: items or products, users and interactions.

Although the RSs have their origin and are implanted in numerous consumer systems associated mainly with the area of e-commerce, other areas have also benefited from their advantages, and can continue to do so. This is the case of the educational area, which has also benefited from the irruption of these types of applications. In fact, in the last 10 years researchers from many universities and research institutions have made a huge effort to take advantage of *Recommender Systems in Education*.

Some literature reviews about RSs have been conducted in the last few years such as [Portugal et al., 2018], which analyses the use of machine learning techniques in RSs, or [Villegas et al., 2018], which focuses on a particular kind of RSs, namely, Context-aware RSs. However, to the best of the authors' knowledge, no literature review regarding the use of RSs in formal education has been carried out so far. In [Taurus et al., 2018], a survey of ontology-based RSs for e-Learning is presented. The paper only considers a particular kind of Knowledge-based RSs and the considered period is 2005 to 2014.

This paper aims to explore and analyze the use of RSs in formal learning, in particular in primary, secondary and higher educational stages. To this end, a systematic mapping review that will allow the researchers in the Technology Enhanced Learning (TEL) area to have an insight into how RSs have been used so far has been conducted. Therefore, the research questions addressed in this work, at least some of them, will differ from those considered in previous Systematic Literature Reviews, as they are aimed at discovering the goals the RSs pursue in formal education. Based on the results, research gaps and possible directions for future research in the area of *RSs in Formal Learning* will be identified.

2 Method

The adopted protocol to carry out the study is composed of two main phases: Definition and Execution. In the Definition phase, the research questions, the search queries, the inclusion and exclusion criteria, and the data extraction strategies were defined.

Once the research questions presented below were defined, the search queries were framed following the PICOC criteria, as suggested by Petticrew and Roberts [Petticrew and Roberts, 2006] and by Kitchenman and Charters [Kitchenham and Charters, 2007]. Five digital libraries were selected: ACM Digital Library, IEEExplore Digital Library, Springer Link, ISI Web Of Science, and Scopus.

Subsequently, for each paper, the following exclusion criteria were defined: it does not propose a solution, it is not peer reviewed, it is not written in English, it does not indicate the educational stage that the solution is proposed for or the solution is not intended for formal learning, it does not describe the technique used to make the recommendation, it does not describe the type of data used to make the recommendation.

Finally, the data extraction strategy was defined. The analysis of each paper was based on the next defined research questions: **(Q1)** Is the solution proposed in the paper applied in Primary Education, Secondary education or in Higher education? **(Q2)** Is the solution proposed aimed at students, at teachers or at both? **(Q3)** What kinds of products or contents does the solution presented in the paper recommend? **(Q4)** What information does the RS use to provide the recommendations? **(Q5)** Does the RS use explicit or implicit feedback? **(Q6)** What algorithms does the proposed solution use? **(Q7)** Has the RS been evaluated using offline, online or user studies?

In the Execution phase, the second phase of the process presented above, the query string was executed. Table 1 summarizes the search strings used for each source, together with the number of results obtained, the number of duplicated papers, and the number of papers selected to conduct the final study. This study contains all the publications on Recommender Systems for Formal Learning from 2009 as of November 2020.

Digital source	Search string	Total number of papers	Number of papers duplicated	Number of papers selected
ACM Digital Library	"query": {recordAbstract:(+recommender +system +education)} "filter": {"publicationYear": {"gte":2009, "lte":2020}}, {owners.owner=HOSTED}	492	68	12
IEEExplore Digital Library	(((("All Metadata": recommender system) AND "All Metadata": education) AND "All Metadata": higher education) OR "All Metadata": secondary education OR "All Metadata": primary education)	591	5	6
Springer Link	'recommender AND system AND education'	1668	485	13
ISI Web of Science	TS=(("higher education" OR "university" OR "secondary education" OR "primary education") AND ("recommended system" OR "recommendation system")) or TI=(("higher education" OR "university" OR "secondary education" OR "primary education") AND ("recommended system" OR "recommendation system"))	1012	561	7
Scopus	("higher education" OR "university" OR "secondary education" OR "primary education") AND ("recommended system" OR "recommendation system")	1401	110	42
		5164	1229	80

Table 1: Search strings and number of papers returned

In the duplicate removal stage, 1229 out of 5164 publications were identified as duplicates. In addition, 5083 papers were rejected following the exclusion criteria. Springer and Scopus are the sources that provide the most articles, followed by ISI Web of Science. IEEExplore Digital Library and ACM Digital Library are the sources that provide the fewest articles.

Finally, 80 papers were selected for the thorough read and data extraction phase, in which the answers to the research questions would be obtained (see Section 3). Appendix A summarises the analysed papers along with the names of the described Recommender System, if available.

According to the methodology followed, the papers were reviewed by the three co-authors of the paper at both the selection stage and the data extraction stage. A randomly selected sample of 15 papers was used to determine the inter-rater agreement between the reviewers, to which end the Kappa coefficient was computed. Regarding paper selection, the researchers achieved a perfect agreement (k = 1). The interrater agreement on the data extraction stage was calculated for each data extraction question (Q1: 0.86, Q2: 0.82, Q3: 0.89, Q4: 1, Q5: 1, Q6:1, Q7: 0.88). As can be observed, the agreement is strong in most cases (k > 0,8), and perfect in some questions according to the interpretation stated by [McHugh, 2012]. In the few cases in which there was no initial agreement, the decision was agreed at a meeting in which the 3 reviewers participated.

Again, Springer is the source that provides more papers. Therefore, it seems that this source contains the most educational content.

Considering the publication date of the papers selected for the analysis, the number of publications has increased noticeably over the last few years. In fact, 61.17% of the reviewed papers were published in the last three years and 52% of these have been published in 2020.

3 Results

In this section, the results obtained are summarized and discussed.

3.1 In which education stages are RSs being used?

As Table 2 shows, most of the solutions (65.00%) are implemented at a higher education stage, some solutions are applied only at secondary level (20.00%), and no solution is proposed only for primary level. Besides, 7.50% of the works are oriented to both secondary and higher educational stages, and 5.00% to both the primary and secondary educational stages. Only two papers present solutions for all educational stages 2.50%).

	Educational Stage	Literature	Pct.
1	Higher education	[Almutairi et al., 2017, Angelova et al., 2018, Benhamdi et al., 2017, Bhumichitr et al., 2017, Bourkoukou et al., 2017, Cárdenas-Cobo et al., 2020, Cerna, 2020, Chen et al., 2020, Cobos et al., 2013, Dahdouh et al., 2019, De Medio et al., 2020, Prasertitipong and Srisujjalertwaja, 2018, Dussan-Sarria and Leon-Guzman, 2012, El-Bishouty et al., 2014, Esteban et al., 2020, Faisal et al., 2020, Ferreira et al., 2020, Heras et al., 2020, Hoic-Bozic et al., 2016, Iatrellis et al., 2017, Ibrahim et al., 2020, Isma'il et al., 2020, Jun Liu et al., 2010, Kanika et al., 2019, Kopeinik, 2018, Lin et al., 2018, Liu et al., 2017, Ma et al., 2020, Nho et al., 2020, Nuswantari et al., 2020, Pardos and Jiang, 2020, Pariserum Perumal et al., 2019, Pereira et al., 2018, Porcel et al., 2020, Putri and Zulkarnain, 2020, Sabic and El-Zayat, 2010, Salehi et al., 2014, Sauer et al., 2014, Sobecki, 2012, Syed and Nair, 2018, Tawfik et al., 2020, Troussas et al., 2020, Uslu et al., 2016, Vialardi Sacín et al., 2009, Wan and Niu, 2020, Wang et al., 2017, Wenige and Ruhland, 2018, Yeh, 2015, Zheng et al., 2019, Zhu et al., 2018, Zhu et al., 2020, Zhuhadar et al., 2009]	65.00%
2	Secondary	[Aarthi et al., 2019, Baskota and Ng, 2018, Chang et al., 2011, Ezz and Elshenawy, 2020, Hidayat et al., 2020, Hsu et al., 2013, Janpla and Kularbphettong, 2016, Jiang et al., 2014, Mokarrama et al., 2020, Obeid et al., 2018, Palilingan and Batmetan, 2018, Samin and Azim, 2019, Selvam et al., 2020, Tilahun and Sekeroglu, 2020, Xu, 2019, Yuliansyah et al., 2020]	20.00%
3	Both higher education and secondary	[Dwivedi and Roshni, 2017, García et al., 2009, Ibrahim et al., 2017, Liao et al., 2020, Lin et al., 2019, Sirikayon et al., 2018]	7.50%
4	Both primary and secondary	[Bai and Yang, 2019, Karga and Satratzemi, 2018, Peralta et al., 2018, Zervas et al., 2015]	5.00%
5	Primary, secondary and higher education	[Karga and Satratzemi, 2019, Sergis and Sampson, 2016]	2.50%

Table 2: Classification of Recommender Systems by Educational Stage

3.2 What kind of users is the recommendation aimed at?

It is also important to analyze the population to which the solution was proposed. Initially, three populations were considered in this study: students, teachers and both students and teachers. Students and teachers are the main actors in learning processes. However, some of the analyzed works consider different actors. Table 3 summarizes the results of this classification. It is worth mentioning that most of the solutions are aimed at students (68.75%). However, there are also RSs that provide recommendations to teachers (18.75%) and to both students and teachers (11.25%). There is also a solution aimed at companies that need to identify researchers from universities and a solution for faculty members so that they can advise students about what actions are required to clear their probation.

	Aimed at	Literature	Pct.
1	Student	[Aarthi et al., 2019, Angelova et al., 2018, Baskota and Ng, 2018, Bhumichitr et al., 2017, Bourkoukou et al., 2017, Cárdenas-Cobo et al., 2020, Chang et al., 2011, Chen et al., 2020, Dahdouh et al., 2019, Praserttitipong and Srisujjalertwaja, 2018, Dussan-Sarria and Leon-Guzman, 2012, Dwivedi and Roshni, 2017, Esteban et al., 2020, Ezz and Elshenawy, 2020, Heras et al., 2020, Hidayat et al., 2020, Hoic-Bozic et al., 2016, Hsu et al., 2013, Iatrellis et al., 2017, Ibrahim et al., 2017, Ibrahim et al., 2020, Isma'il et al., 2020, Janpla and Kularbphettong, 2016, Kanika et al., 2019, Kopeinik, 2018, Liao et al., 2020, Lin et al., 2018, Liu et al., 2017, Ma et al., 2020, Mokarrama et al., 2020, Nho et al., 2020, Nuswantari et al., 2020, Obeid et al., 2018, Palilingan and Batmetan, 2018, Pardos and Jiang, 2020, Pariserum Perumal et al., 2019, Pereira et al., 2018, Porcel et al., 2020, Putri and Zulkarnain, 2020, Sabic and El-Zayat, 2010, Salehi et al., 2014, Samin and Azim, 2019, Selvam et al., 2020, Sirikayon et al., 2018, Syed and Nair, 2018, Tawfik et al., 2020, Tilahun and Sekeroglu, 2020, Troussas et al., 2020, Uslu et al., 2016, Vialardi Sacín et al., 2009, Wang et al., 2017, Yeh, 2015, Yuliansyah et al., 2020, Zhu et al., 2020, Zhuhadar et al., 2009]	68.75%
2	Teacher	[Bai and Yang, 2019, Cobos et al., 2013, De Medio et al., 2020, El-Bishouty et al., 2014, Ferreira et al., 2020, García et al., 2009, Jiang et al., 2014, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Peralta et al., 2018, Sergis and Sampson, 2016, Sobecki, 2012, Xu, 2019, Zervas et al., 2015, Zhu et al., 2018]	18.75%
3	Both	[Almutairi et al., 2017, Benhamdi et al., 2017, Cerna, 2020, Jun Liu et al., 2010, Lin et al., 2019, Sauer et al., 2014, Wan and Niu, 2020, Wenige and Ruhland, 2018, Zheng et al., 2019]	11.25%
4	Other	[Faisal et al., 2020]	1.25%

Table 3: Recipients of Recommender Systems's solution

3.3 What kinds of products or contents are recommended?

As Table 4 shows, most of the solutions focus on providing the student with educational resources 51.25%). Educational resources include resources such as LOs, articles, exercises, videos or books. Other systems focus more on providing the student with additional information such as websites, related articles, books,conferences and news. Furthermore, many RSs are designed to suggest courses (28.75%). In some cases, the RS proposes suitable degree programs or Universities (13.75%), and occasionally, the recommendations are generated to aid employment seeking (2.50%) or learning paths (2.50%). Other systems provide other kinds of recommendations such as the allocation of classrooms, peers tutors, solutions to similar problems and thesis supervisor (5.00%).

	Purpose	Literature	Pct.
1	**To recommend educational resources**:		51.25%
	Learning Objects and material	[Bai and Yang, 2019, Benhamdi et al., 2017, Bourkoukou et al., 2017, Cerna, 2020, Chen et al., 2020, De Medio et al., 2020, Ferreira et al., 2020, Heras et al., 2020, Hidayat et al., 2020, Kopeinik, 2018, Liao et al., 2020, Lin et al., 2019, Pariserum Perumal et al., 2019, Peralta et al., 2018, Pereira et al., 2018, Putri and Zulkarnain, 2020, Salehi et al., 2014, Sergis and Sampson, 2016, Wan and Niu, 2020, Wang et al., 2017, Xu, 2019, Zheng et al., 2019, Zhuhadar et al., 2009]	
	Exercises, activities	[Cárdenas-Cobo et al., 2020, Hoic-Bozic et al., 2016, Hsu et al., 2013, Porcel et al., 2020, Troussas et al., 2020]	
	Videos	[Syed and Nair, 2018]	
	Additional material: news, conferences, articles, websites	[Dussan-Sarria and Leon-Guzman, 2012, Kanika et al., 2019, Sabic and El-Zayat, 2010]	
	Books	[Sirikayon et al., 2018]	
	Digital Library Resources	[Wenige and Ruhland, 2018, Tawfik et al., 2020]	
	Learning Designs	[Cobos et al., 2013, El-Bishouty et al., 2014, García et al., 2009, Karga and Satratzemi, 2018, Karga and Satratzemi, 2018]	
	Remote Virtual Labs	[Zervas et al., 2015]	
2	To recommend courses	[Almutairi et al., 2017, Bhumichitr et al., 2017, Dahdouh et al., 2019, Praserttitipong and Srisujjalertwaja, 2018, Dwivedi and Roshni, 2017, Esteban et al., 2020, Faisal et al., 2020, Ibrahim et al., 2017, Ibrahim et al., 2020, Isma'il et al., 2020, Jun Liu et al., 2010, Lin et al., 2018, Nho et al., 2020, Pardos and Jiang, 2020, Samin and Azim, 2019, Sobecki, 2012, Tilahun and Sekeroglu, 2020, Uslu et al., 2016, Vialardi Sacín et al., 2009, Yeh, 2015, Zhu et al., 2018, Zhu et al., 2020, Zhuhadar et al., 2009]	28.75%
3	**To recommend**:		13.75%
	Universities	[Aarthi et al., 2019, Baskota and Ng, 2018, Mokarrama et al., 2020, Obeid et al., 2018, Yuliansyah et al., 2020]	
	Degree programs, careers, majors or departments	[Chang et al., 2011, Ezz and Elshenawy, 2020, Janpla and Kularbphettong, 2016, Nuswantari et al., 2020, Selvam et al., 2020]	
	Collaborators in R&D projects	[Wang et al., 2017]	
4	To recommend jobs or personalized curriculum	[Liu et al., 2017, Palilingan and Batmetan, 2018]	2.50%
5	To recommend learning paths	[Iatrellis et al., 2017, Jiang et al., 2014]	2.50%
6	Other	[Angelova et al., 2018, Faisal et al., 2020, Ma et al., 2020, Sauer et al., 2014]	5.00%

Table 4: Purpose of Recommender Systems in Formal Learning

3.4 What type of data is used?

RSs use different types of data to build the user profiles and provide the recommendations: the interests of students (23.75%), personal data, such as age and gender (26.25%) and academic scores (33.75%) are widely used. User activity and interaction (13.75%), such as web history, navigation and clicks have been successfully used to recommend learning materials or resources. In addition, historical academic data (16.25%), e.g., enrollments, is used to make recommendations for courses or even schools or universities.

In some other cases, additional information such as pedagogical strategies or an evaluation model is required (6.25%). In other papers, user learning style preferences (12.50%) and personality style (2.50%), user's ratings and feedback (10.00%) or social data (8.75%) are used in order to make suitable recommendations to students. Some solutions use the query of the user or the educational resources metadata as input in order to recommend the most appropriate items. The parameters used in the design of the RSs are summarized in Table 5.

	Input	Literature	Pct.
1	User's interests and abilities	[Bai and Yang, 2019, Benhamdi et al., 2017, Chang et al., 2011, Praserttitipong and Srisujjalertwaja, 2018, Heras et al., 2020, Hsu et al., 2013, Ibrahim et al., 2017, Jun Liu et al., 2010, Kopeinik, 2018, Liao et al., 2020, Obeid et al., 2018, Palilingan and Batmetan, 2018, Pariserum Perumal et al., 2019, Pereira et al., 2018, Sabic and El-Zayat, 2010, Salehi et al., 2014, Selvam et al., 2020, Yeh, 2015, Zheng et al., 2019]	23.75%
2	Demographics (gender, age)	[Bai and Yang, 2019, Baskota and Ng, 2018, Cobos et al., 2013, Dussan-Sarria and Leon-Guzman, 2012, Heras et al., 2020, Hoic-Bozic et al., 2016, Ibrahim et al., 2017, Jun Liu et al., 2010, Liao et al., 2020, Liu et al., 2017, Pereira et al., 2018, Putri and Zulkarnain, 2020, Sergis and Sampson, 2016, Uslu et al., 2016, Vialardi Sacín et al., 2009, Wang et al., 2017, Xu, 2019, Yeh, 2015, Zheng et al., 2019, Zhu et al., 2018, Zhu et al., 2020]	26.25%
3	Academic performance (test score, average grades, …)	[Aarthi et al., 2019, Baskota and Ng, 2018, Bhumichitr et al., 2017, Praserttitipong and Srisujjalertwaja, 2018, Dwivedi and Roshni, 2017, Esteban et al., 2020, Ezz and Elshenawy, 2020, Ferreira et al., 2020, Heras et al., 2020, Iatrellis et al., 2017, Isma'il et al., 2020, Janpla and Kularbphettong, 2016, Jiang et al., 2014, Lin et al., 2018, Ma et al., 2020, Mokarrama et al., 2020, Porcel et al., 2020, Sabic and El-Zayat, 2010, Salehi et al., 2014, Samin and Azim, 2019, Selvam et al., 2020, Sobecki, 2012, Uslu et al., 2016, Vialardi Sacín et al., 2009, Yuliansyah et al., 2020, Zhu et al., 2018, Zhu et al., 2020]	33.75%
4	User's activity (navigation, clicks)	[Bai and Yang, 2019, Bourkoukou et al., 2017, Cárdenas-Cobo et al., 2020, Hidayat et al., 2020, Hoic-Bozic et al., 2016, Nho et al., 2020, Peralta et al., 2018, Salehi et al., 2014, Sirikayon et al., 2018, Syed and Nair, 2018, Zhuhadar et al., 2009]	13.75%
5	Historical academic data (enrollments, courses taken)	[Bhumichitr et al., 2017, Chang et al., 2011, Dahdouh et al., 2019, Dwivedi and Roshni, 2017, Iatrellis et al., 2017, Lin et al., 2018, Lin et al., 2019, Liu et al., 2017, Pardos and Jiang, 2020, Sobecki, 2012, Uslu et al., 2016, Vialardi Sacín et al., 2009, Yeh, 2015]	16.25%
6	Teacher's parameters (pedagogical strategy, subject domain, evaluation model, ICT competence, …)	[Cobos et al., 2013, García et al., 2009, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Zervas et al., 2015]	6.25%
7	User's ratings and feedback	[Benhamdi et al., 2017, Cárdenas-Cobo et al., 2020, Hidayat et al., 2020, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Ma et al., 2020, Porcel et al., 2020, Zhuhadar et al., 2009]	10.00%

	Input	Literature	Pct.
8	Social data	[Ferreira et al., 2020, Ibrahim et al., 2017, Liu et al., 2017, Ma et al., 2020, Pereira et al., 2018, Sergis and Sampson, 2016, Wang et al., 2017]	8.75%
9	Student's learning style preferences	[Benhamdi et al., 2017, Chang et al., 2011, Chen et al., 2020, El-Bishouty et al., 2014, Heras et al., 2020, Hoic-Bozic et al., 2016, Kopeinik, 2018, Samin and Azim, 2019, Troussas et al., 2020, Wang et al., 2017]	12.50%
10	Personality and intelligence style	[Nuswantari et al., 2020, Wan and Niu, 2020]	2.50%
11	Educational resources metadata	[Esteban et al., 2020, Peralta et al., 2018, Salehi et al., 2014, Wenige and Ruhland, 2018]	5.00%
12	User's query	[Angelova et al., 2018, De Medio et al., 2020, Ibrahim et al., 2020, Putri and Zulkarnain, 2020, Tawfik et al., 2020]	6.25%
13	Job experience	[Almutairi et al., 2017, Liu et al., 2017]	2.50%
14	Other	[Kanika et al., 2019, Sauer et al., 2014]	2.50%

Table 5: Input of the Recommender System

3.5 Do RSs use explicit or implicit data?

Generally, the data produced by the users when interacting with a system can be classified as explicit data or implicit data [Falk, 2019]. When the system deduces and extracts data by monitoring the behavior of the users and their interactions with the system, it is said to use implicit data. The information directly provided by the user (e.g., a rating for a particular product) is called explicit data. For example, a user can provide explicit feedback in the form of a certain number of stars or any other icon illustrating how much the user likes a product. In the RS community, a five-star scale has been the most often used means to collect this information, although there are systems that use textual information, such as user reviews, to gather the perception of the users about the products [Margaris et al., 2020].

According to the conducted review, in formal learning the combination of explicit and implicit data is the most common feedback type (38.75%), closely followed by implicit feedback (36.25%). Explicit feedback is exclusively used only in 25.00% of the proposals. Table 6 summarizes which solution is used in each analyzed work.

3.6 What kinds of algorithms or techniques are used?

A great variety of algorithms and techniques can be used to develop an RS. At this point, the publications will be classified considering the algorithms and techniques they have used. To fulfill this purpose, the taxonomy proposed by Burke [Burke, 2002] will be used. This taxonomy identifies six recommendation techniques: collaborative filtering, content-based filtering, utility-based, demographic and knowledge-based, and hybrid, which combines different techniques.

CF, CB and KBS are the most popular algorithms in RSs. In fact, these techniques have been used in 35.00%, 11.25% and 12.50% of the publications, respectively.

With regards to CF-based RSs, user-based algorithms have been the most popular approach so far. Other works rely on model-based CF approaches, using techniques such as Matrix Factorization, Clustering, Association Rules, Bayesian Networks and Neural Networks.

CB algorithms rely on metadata associated to the documents (e.g., keywords) to generate recommendations. Usually, the algorithm used to extract metadata and analyze

	Type of data	Literature	Pct.
1	Explicit	[Aarthi et al., 2019, Benhamdi et al., 2017, Chen et al., 2020, Faisal et al., 2020, Ferreira et al., 2020, Hsu et al., 2013, Jun Liu et al., 2010, Kanika et al., 2019, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Kopeinik, 2018, Nuswantari et al., 2020, Palilingan and Batmetan, 2018, Putri and Zulkarnain, 2020, Tawfik et al., 2020, Troussas et al., 2020, Uslu et al., 2016, Xu, 2019, Zervas et al., 2015, Zhu et al., 2020]	25.00%
2	Implicit	[Almutairi et al., 2017, Baskota and Ng, 2018, Bhumichitr et al., 2017, Chang et al., 2011, Dahdouh et al., 2019, Praserttitipong and Srisujjalertwaja, 2018, Dussan-Sarria and Leon-Guzman, 2012, Dwivedi and Roshni, 2017, El-Bishouty et al., 2014, Ezz and Elshenawy, 2020, Iatrellis et al., 2017, Isma'il et al., 2020, Jiang et al., 2014, Lin et al., 2019, Liu et al., 2017, Nho et al., 2020, Peralta et al., 2018, Pereira et al., 2018, Salehi et al., 2014, Samin and Azim, 2019, Sirikayon et al., 2018, Sobecki, 2012, Syed and Nair, 2018, Tilahun and Sekeroglu, 2020, Vialardi Sacín et al., 2009, Wenige and Ruhland, 2018, Yeh, 2015, Yuliansyah et al., 2020, Zhuhadar et al., 2009]	36.25%
3	Both	[Angelova et al., 2018, Bai and Yang, 2019, Bourkoukou et al., 2017, Cárdenas-Cobo et al., 2020, Cerna, 2020, Cobos et al., 2013, De Medio et al., 2020, Esteban et al., 2020, García et al., 2009, Heras et al., 2020, Hidayat et al., 2020, Hoic-Bozic et al., 2016, Ibrahim et al., 2017, Ibrahim et al., 2020, Janpla and Kularbphettong, 2016, Liao et al., 2020, Ma et al., 2020, Mokarrama et al., 2020, Obeid et al., 2018, Pardos and Jiang, 2020, Lin et al., 2018, Pariserum Perumal et al., 2019, Porcel et al., 2020, Sabic and El-Zayat, 2010, Sauer et al., 2014, Selvam et al., 2020, Sergis and Sampson, 2016, Wan and Niu, 2020, Wang et al., 2017, Zheng et al., 2019, Zhu et al., 2018]	38.75%

Table 6: Type of data Recommender Systems collected

the content is Term Frequency-Inverse Document Frequency (TF-IDF), but in the last few years Latent Dirichlet Allocation (LDA) [Blei et al., 2003] is being extensively used.

Regarding KBS, there are three common KBS recommender types: Case-Based Reasoning (CBR), Constraint-based and Rule-based recommenders. Besides the traditional techniques, some other models based on human cognition or Genetic Algorithms (GA) have been used for formal learning.

According to Burke [Burke, 2002], using hybrid approaches, two or more algorithms can work together and therefore, the system will combine the strengths of different recommenders. In addition, Burke classifies hybrid RSs in weighted, switching, mixed, feature combination, cascade, feature augmentation and meta-level [Burke, 2002]. However, none of the reviewed publications specified the kind of hybrid system they presented (considering this taxonomy), and only a few papers provided a detailed enough description of the process that might allow the kind to be inferred. Therefore, instead of categorizing the hybrid RSs considering the taxonomy proposed by Burke, in this work the hybrid RSs have been categorized according to the techniques they combined (e.g., CF+CB …).

Among all the reviewed publications, 37.50% of the proposals present a hybrid system, being those systems based on the combination of CF and CB the most popular. Sometimes, two CF techniques are combined in a hybrid algorithm. Other hybrid systems combine CF and KBS techniques, or CB and KBS systems.

Although Context-Aware (CA) approaches were not considered in the taxonomy of Burke [Burke, 2002], this paper extends the taxonomy by including these approaches because they have become more popular in recent years.

Other techniques such as ontology-based profile design have been used in RSs. The techniques and strategies used in the design of RS are summarized in Table 7.

Type	Approach	Technique	Literature	Pct.
Collaborative filtering (CF)	Memory based	User-based	[Cárdenas-Cobo et al., 2020, Hidayat et al., 2020, Jiang et al., 2014, Jun Liu et al., 2010, Liao et al., 2020, Liu et al., 2017, Sergis and Sampson, 2016, Sirikayon et al., 2018, Uslu et al., 2016, Zhu et al., 2018]	35.00%
		Item-based	[Dwivedi and Roshni, 2017, Faisal et al., 2020, Nho et al., 2020, Porcel et al., 2020]	
	Model based	Matrix factorization (MF)	[Lin et al., 2018, Zheng et al., 2019]	
		Clustering	[Dussan-Sarria and Leon-Guzman, 2012]	
		Association rules	[Chang et al., 2011, Dahdouh et al., 2019, Tilahun and Sekeroglu, 2020, Yuliansyah et al., 2020]	
		Neural networks	[Ma et al., 2020, Pardos and Jiang, 2020, Troussas et al., 2020]	
		Others	[Ezz and Elshenawy, 2020, Isma'il et al., 2020, Nuswantari et al., 2020, Palilingan and Batmetan, 2018, Selvam et al., 2020]	
Content-based filtering (CB)		TF-IDF	[Kanika et al., 2019]	11.25%
		LDA	[Lin et al., 2019]	
		TF-IDF + LDA	[Samin and Azim, 2019]	
		Word embeddings	[Putri and Zulkarnain, 2020]	
		Not specified	[Angelova et al., 2018, Bai and Yang, 2019, Cerna, 2020, Hsu et al., 2013, Mokarrama et al., 2020]	
Knowledge-based (KBS)		Case-based reasoning (CBR)	[Porcel et al., 2020, Sauer et al., 2014]	12.50%
		Constraint-based	[Wenige and Ruhland, 2018]	
		Rule-based	[Aarthi et al., 2019, Iatrellis et al., 2017, Janpla and Kularbphettong, 2016, Vialardi Sacín et al., 2009, Yeh, 2015]	
		Other	[Kopeinik, 2018, Syed and Nair, 2018]	
Context-aware (CA)			[Almutairi et al., 2017, Ferreira et al., 2020, Pereira et al., 2018, Wang et al., 2017, Zervas et al., 2015]	6.25%
Hybrid	CF + CB		[Benhamdi et al., 2017, Cobos et al., 2013, De Medio et al., 2020, Esteban et al., 2020, Ibrahim et al., 2017, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Peralta et al., 2018, Sobecki, 2012, Tawfik et al., 2020, Wan and Niu, 2020, Xu, 2019]	37.50%

Type	Approach	Technique	Literature	Pct.
Hybrid	CF + CF		[Baskota and Ng, 2018, Bhumichitr et al., 2017, Bourkoukou et al., 2017, Chen et al., 2020, Praserttitipong and Srisujjalertwaja, 2018, Dussan-Sarria and Leon-Guzman, 2012, Pariserum Perumal et al., 2019, Salehi et al., 2014, Zhu et al., 2020]	37.50%
	CF + KBS		[García et al., 2009, Ibrahim et al., 2020]	
	CA + CF		[Wang et al., 2017]	
	CB + KBS		[Samin and Azim, 2019, Zhuhadar et al., 2009]	
	CF + CB + KBS		[Heras et al., 2020, Hoic-Bozic et al., 2016, Obeid et al., 2018]	
	Not specified		[Sabic and El-Zayat, 2010]	
Other			[El-Bishouty et al., 2014]	1.25%

Table 7: Used techniques and strategies of RSs in Formal Learning

3.7 How has the RS been evaluated?

In order to test whether the designed RS runs properly, some types of experiments can be carried out. RSs can be evaluated following three different approaches: offline settings, user studies and online experiments [Shani and Gunawardana, 2011]. In the case of offline evaluations, existing datasets are used, and different metrics computed in order to measure the effectiveness and accuracy of the RS. In this kind of evaluation, previously generated datasets, which contain data about users (e.g., ratings, purchases) are usually employed, and the information in the dataset is used to evaluate the results. On the other hand, when the evaluation is online, real user populations interact with the system. This kind of evaluation is the one that provides the strongest evidence about the true value of the system. However, it should be borne in mind that this type of evaluation has an important drawback: in the case that the system provides poor recommendations, the experiment would have a negative effect on the person who is using the RS, as they might lose confidence in the system. Moreover, online experiments are the most expensive to conduct. For this reason, offline evaluations and user studies are conducted before running online experiments. User studies are conducted with a small group of users who have been selected in order to experiment with the system. These users have to be shown how to perform the test and, at the end, they usually fill in a questionnaire about the degree to which they feel the recommendations match their interests. In this way, they can measure the effectiveness of the RS presented.

In the analysis carried out in this study, it can be observed that the most common type of experiment is the offline evaluation (43.75%). Other solutions reviewed conduct a user study (32.50%), and just 8.75% carry out online experiments. Table 8 shows the types of evaluation carried out in the analyzed publications.

	Type of evaluation	Literature	Pct.
1	Offline	[Aarthi et al., 2019, Almutairi et al., 2017, Angelova et al., 2018, Bhumichitr et al., 2017, Bourkoukou et al., 2017, Chen et al., 2020, Dahdouh et al., 2019, Praserttitipong and Srisujjalertwaja, 2018, Esteban et al., 2020, Faisal et al., 2020, Ferreira et al., 2020, García et al., 2009, Ibrahim et al., 2017, Ibrahim et al., 2020, Isma'il et al., 2020, Janpla and Kularbphettong, 2016, Kanika et al., 2019, Lin et al., 2018, Pariserum Perumal et al., 2019, Peralta et al., 2018, Porcel et al., 2020, Putri and Zulkarnain, 2020, Salehi et al., 2014, Samin and Azim, 2019, Selvam et al., 2020, Sergis and Sampson, 2016, Sirikayon et al., 2018, Sobecki, 2012, Syed and Nair, 2018, Tilahun and Sekeroglu, 2020, Xu, 2019, Yuliansyah et al., 2020, Zheng et al., 2019, Zhu et al., 2020, Zhuhadar et al., 2009]	43.75%
2	User studies	[Baskota and Ng, 2018, Benhamdi et al., 2017, Cárdenas-Cobo et al., 2020, Dussan-Sarria and Leon-Guzman, 2012, Dwivedi and Roshni, 2017, Ezz and Elshenawy, 2020, Hidayat et al., 2020, Hoic-Bozic et al., 2016, Hsu et al., 2013, Iatrellis et al., 2017, Jiang et al., 2014, Karga and Satratzemi, 2018, Karga and Satratzemi, 2019, Lin et al., 2019, Ma et al., 2020, Nho et al., 2020, Nuswantari et al., 2020, Pardos and Jiang, 2020, Peralta et al., 2018, Pereira et al., 2018, Sauer et al., 2014, Tawfik et al., 2020, Troussas et al., 2020, Vialardi Sacín et al., 2009, Wan and Niu, 2020, Wang et al., 2017, Zervas et al., 2015]	32.50%
3	Online	[Cerna, 2020, De Medio et al., 2020, El-Bishouty et al., 2014, Heras et al., 2020, Mokarrama et al., 2020, Uslu et al., 2016, Wenige and Ruhland, 2018, Yeh, 2015]	8.75%
4	Both offline and user studies	[Cobos et al., 2013, Kopeinik, 2018, Liu et al., 2017, Porcel et al., 2020, Wang et al., 2017]	6.25%
5	Not specified	[Bai and Yang, 2019, Chang et al., 2011, Jun Liu et al., 2010, Liao et al., 2020, Obeid et al., 2018, Palilingan and Batmetan, 2018, Sabic and El-Zayat, 2010, Zhu et al., 2018]	10.00%

Table 8: Types of evaluation used

4 Discussion

The RS technology has become an important and a very useful technique in many areas of our daily life, including the area of education. In this paper, a systematic mapping review that explores the use of recommender systems in formal learning has been presented. In particular, seven aspects have been analyzed in depth: (Q1) Educational stage at which the RS is aimed; (Q2) Population (*student, teacher*) at which the RS is aimed; (Q3) Type of product the RS recommends; (Q4) Type of data on which the RS is based to make the recommendation; (Q5) Way in which the RS captures the user data (*explicit, implicit*); (Q6) Algorithm or technique on which the RS is based; and, finally, (Q7) Procedure that has been followed to evaluate the systems (*offline, online, user evaluation*).

– Regarding *the educational stage at which the RSs are aimed* (Q1), we can conclude that, in general, through different algorithms, RSs are becoming a useful tool in the area of Education. As this review shows, a wide range of possibilities is available with the aim of both helping students and improving their learning processes and providing strategies for teachers at all stages of formal learning. Note that, in Primary Education, the use of these systems is less common, probably because students do not work with computers as much as in secondary or higher education. Most of the observed systems have been used at the University level, where the interaction between students and computers is high and the use of technology is broader. Figure 1 summarizes the results obtained.

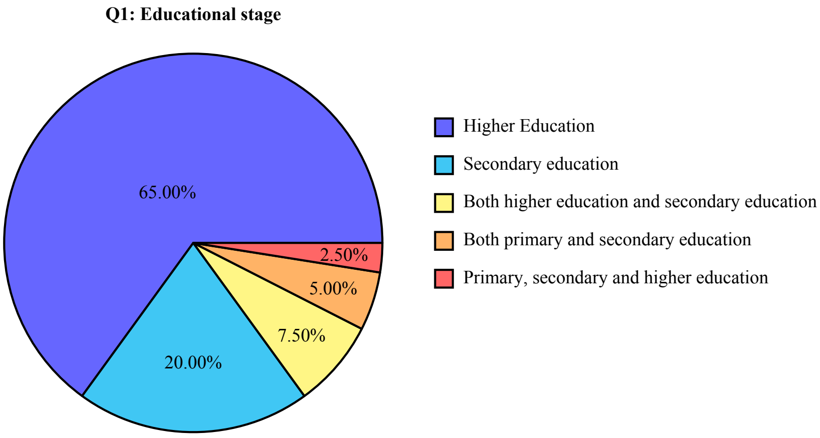

Figure 1: Educational stage RSs are being used at

- The *population at which the RSs are aimed* (Q2) and the *type of product the RSs recommend* (Q3) are closely related aspects. The results obtained are shown in Figure 2 and Figure 3, respectively. Most of the RSs developed are mainly oriented to providing products for students. The purpose of some of these recommendations is to help students by providing learning material such as exercises, videos and books. In addition, there is a group of recommendations that, while they could also help students, their purpose could be to sell a product, such as a university course or degree program. To a much lesser extent, some RSs focus on teachers and, in some cases, on both teachers and students, to whom they are able to provide learning paths or teaching strategies.

  According to [Klašnja-Milićević et al., 2015], a good RS for education should be highly personalized, recommend materials at appropriate times, support continuous learning, and provide high levels of interactivity. Including good pedagogical models into recommendation systems could make the recommendations not only more personalized but also more efficient. Moreover, it must be also taken into account that the learning process is dynamic and changes over time, so learning interests and goals can change according to context and also over time. One way to overcome this problem could be to use sequential patterns. As [Salehi et al., 2014] shows, sequential patterns of learning materials can be identified in the historical access records of the students, and that information can even be used to predict what material is most likely to be accessed by the student in the near future. In the same way, [Frost and McCalla, 2021] present CFLS –Collaborative Filtering based on Learner Sequences, a system which has been designed for an open-ended and unstructured

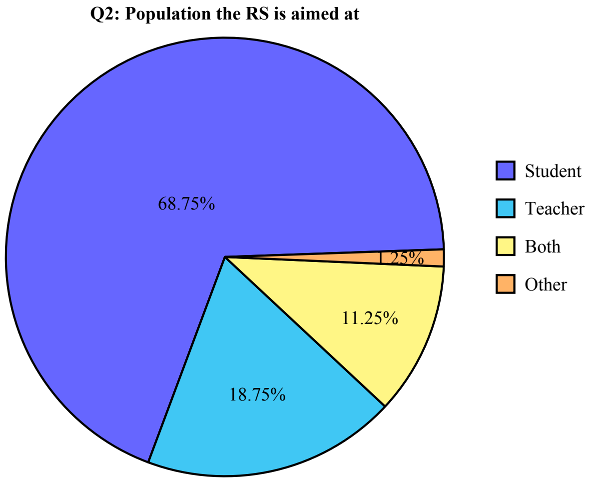

Figure 2: Population the RS is aimed at

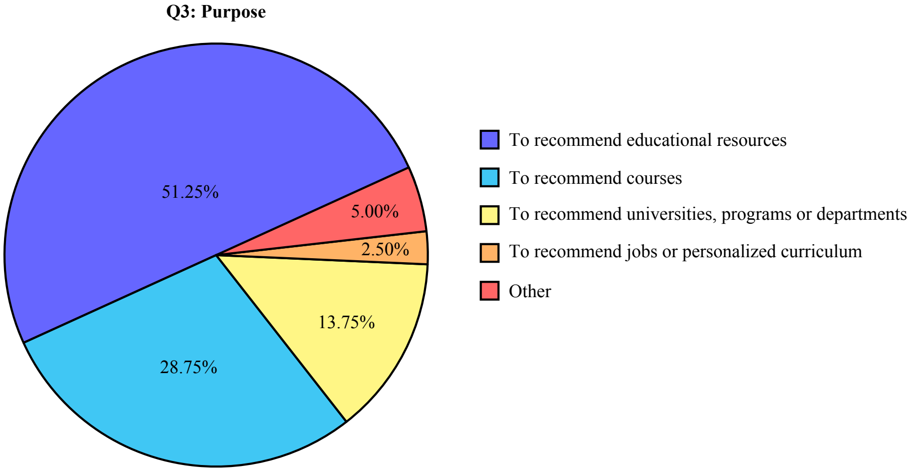

Figure 3: What are RSs being used to

learning environment. This system generates pedagogical plans for a target learner by looking back at the sequence of the most recent learning objects that the target learner has interacted with and finding a neighborhood of other learners who have interacted with a similar sequence of learning objects in the past. We consider that, in order to make adequate recommendations, besides identifying sequential patterns based on the behavior of the students, it would also be convenient to consider the profile of the students to advise them on the contents that better fit their needs.

Additionally, recommendations to teachers pose a great challenge. In fact, according to the results of the literature review, just 18.5% of the studied solutions are aimed at teachers. However, at least 92% of teachers have searched the Internet looking for digital learning resources [Peralta et al., 2018]. Taking into account that the material is not organized, the search and filtering of it takes teachers a considerable amount of time. The organization of the material in repositories together with the inclusion of advanced features would allow the use of these repositories to go beyond mere search engines if recommendation techniques are incorporated [Al-Khalifa, 2008]. RS could also be beneficial for education if they were able to suggest, besides the content, the most appropriate teaching strategies to lecturers so that they can improve their teaching programs or curricula. Only one of the reviewed papers provides this kind of recommendation [Cobos et al., 2013].

In these days, when collaborative or cooperative work is ever more frequent, just one of the reviewed papers presents a RS that has been developed to provide recommendations to groups of users [Ferreira et al., 2020]. RSs could be used in these scenarios, for example, to provide groups with the most appropriate task or strategy considering the profiles of the group members or even helping in the creation of the groups themselves.

– The *type of data on which an RS is based to make recommendations* (Q4) and *the way to acquire it* (Q5) plays a crucial role in any recommendation system. The results for these questions are shown in Figure 4 and Figure 5, respectively.

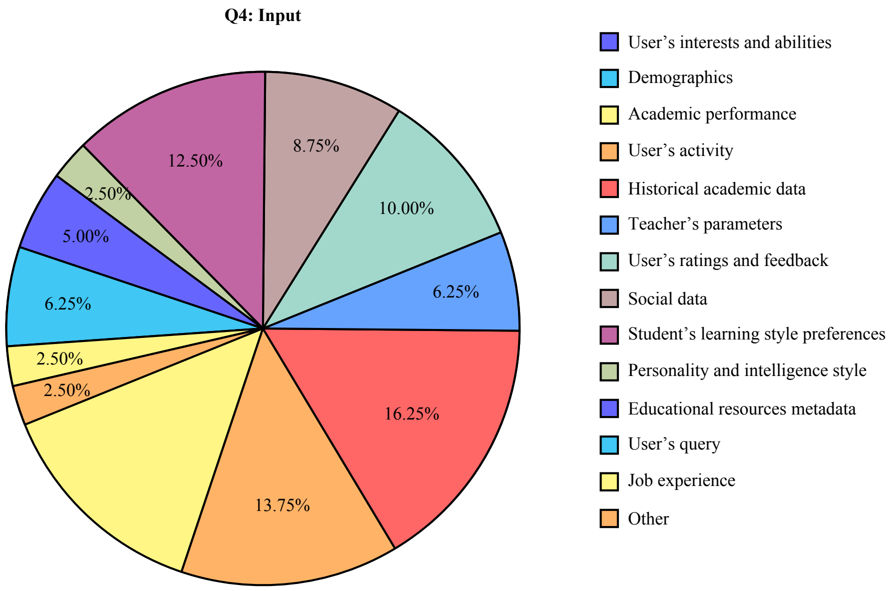

Figure 4: Input of the RSs

Depending on their characteristics, the reviewed RSs process data of different nature (interest and abilities of the users, demographic data, academic performance, data about the activity of the users or historical academic data) that is obtained in a different way. According to the conducted review, in formal learning the most common feedback type provided by the user is implicit feedback (38.2%), closely followed by a combination of explicit and implicit feedback types (37.03%). Only 28.40% of the works use exclusively explicit feedback. Ideally, the data collected should be varied and diverse, and should be collected in many different ways. As far as the acquisition of the data associated to the users is concerned, e.g., their preferences and the contents they are struggling with, non-intrusive ways should be sought. Throughout the entire process of interactions between the user and the system, the user should not feel uncomfortable working with the system. Although explicit feedback might be more trustworthy for the system, as it is directly provided by the user, obtaining this kind of feedback is more intrusive and might lead, in some cases, to users eschewing the system. Implicit data can be continuously recorded while the users interact with the system, but it is sometimes harder to understand what a certain action might represent regarding, for example, the learning process of the student. A combination of explicit and implicit data would be a good choice to determine the preferences of the user. In this way, modelling the user from the collected data is also a big challenge. To find good and appropriate techniques to tackle this task is a big challenge. In addition, it is also worth mentioning that in the papers reviewed, the data collected is about students, never about the group of which the student is a member. We consider that obtaining data in order to study the characteristics of the group could be beneficial to achieve more personalized recommendations. Besides, the use of metadata and algorithms and techniques that allow that metadata to be processed (e.g., Semantic Web or ontologies) will enable new ways of collecting and exploring data to be opened up in order to make better recommendations. In [George and Lal, 2019], the ontology is presented as a way to achieve personalization in order to provide more relevant recommendations and to address some important issues, such as the cold start problem. It also explains some of the drawbacks of an ontology, such as the requirement of knowledge engineering and how time-consuming it can be.

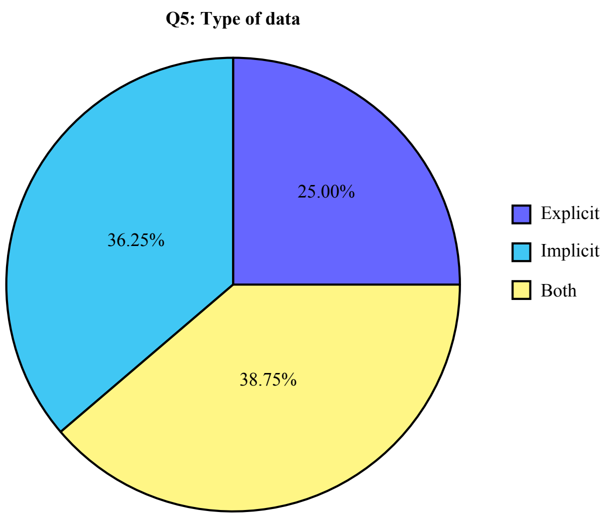

Figure 5: Type of data used

– Regarding the *algorithms used to make the recommendation* (Q6), the CF and CB algorithms do not always take a learner's characteristics into consideration, so introducing other techniques such as KBS or CA recommendations, cognitive models or data mining techniques could improve the recommendations. In addition, modelling how the student learns is necessary to achieve good recommendations [Sergis and Sampson, 2016]. Using Computational models of human cognition and learning could help meet these challenges, but the effectiveness of cognitive models in educational RSs remains poor [Kopeinik, 2018]. Figure 6 shows the usage of algorithms observed in the literature.

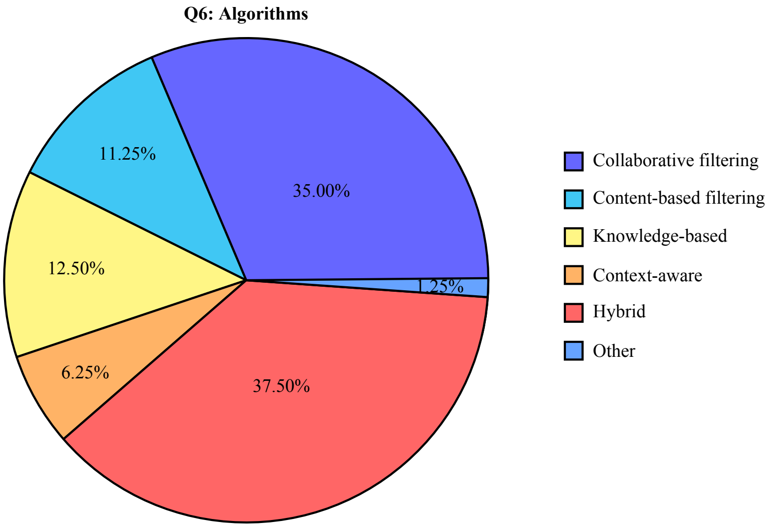

Figure 6: Algorithms used by the RSs

– Evaluation (Q7) is another necessary aspect to be considered in an RS, and surely one of the most complicated to face in an educational environment. Figure 7 summarizes how RSs have been evaluated in the literature. In fact, some proposals from the reviewed solutions were not evaluated, making it impossible to measure the effectiveness of the RS proposed. In [Manouselis et al., 2011] an explanation is presented on why a complementary evaluation is needed besides the classical evaluation. It proposes Kirckpatrick's model [Kirkpatrick, 1994] to measure the success of an RS in a TEL context using four different layers: reaction of the user, learning, behavior and results. Even then, evaluation in an educational environment has methodological and practical difficulties, there is no model available that measures the real impact that a recommender has on the student's learning and therefore this real impact is not measured. To measure this impact adequately, as well as more time, it would take a pedagogical dimension, a combination of a variety of assessment methods, metrics and instruments.

Despite RSs being helpful for education, the analyzed papers do not provide sound evidence of positive effects. In many cases, the algorithms have been tested on existing datasets in offline experiments. Besides, many of the proposals are aimed at recommending complete curricula to the students or even which studies fit better with their profiles. The effectiveness of these suggestions is hard to evaluate (Should the performance of the students after finishing the studies be considered? Should their opinion and satisfaction be considered?) In any case, RSs have proved to be helpful to find and acquire the contents the user is interested in and, hence, should be appropriate to help students find contents that allow them to improve their learning process or to determine the studies in which they will be more successful. Providing evidence in this regard is still an open research line.

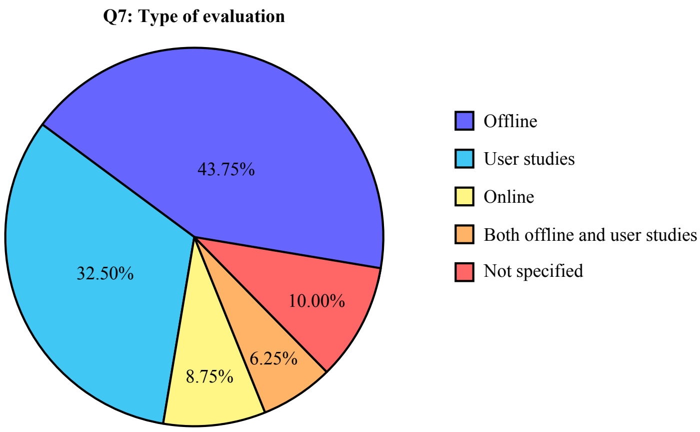

Figure 7: Type of evaluation conducted

In addition, we also consider two other open lines of research that have been omitted from this review: the integration of the RS in a Learning Management System (LMS) (e.g., Moodle or BlackBoard) and ethical issues in Learning Analytics environments. On one hand, there is the chance that the teacher or the student is able to supervise the whole process of teaching and learning with the same tool. The work presented in [Kopeinik, 2018] implements some plugins which are embedded in Moodle. Moreover, recently, unlike an LMS, a new tool for designing, managing and delivering online collaborative learning activities (LAMS) is used in [Karga and Satratzemi, 2018]. On the other hand, there is particular concern about how educational data is collected and analyzed, including aspects such as transparency regarding the data collection process [Slade and Prinsloo, 2013]. To this end, work done in the Learning Analytics area should be considered [Ferguson et al., 2016].

This review was limited in that it examined articles from five databases: IEEExplore, ISI Web of Science, Scopus, ACM Digital Library and Springer, from 2009 to 2020. The articles in these databases are considered to have a high impact on the field. It is worth mentioning that this Systematic Literature Mapping is mainly aimed at researchers moving from the Recommender Systems area to the Technology Enhanced Learning area, in particular, for formal learning. Therefore, the review does not include works that do not focus on formal learning or papers published in the Artificial Intelligence in Education area, although systems such as Intelligent Tutoring Systems have similar goals and might even implement similar algorithms [Manouselis et al., 2011, Paiva et al.,2014, Penteado et al.,2018, Bel Hadj Ammar et al., 2020, Fotoporlou et al., 2020, Lin et al., 2020].

In any case, it seems that several research communities still maintain interest and continue to work on RSs in Education in order not only to achieve better recommendations but also to widen their possibilities of use. In fact, the number of publications in this area has been almost doubled in the last year. Besides, new techniques and algorithms are being adopted and combined to build recommender systems. Some examples are the use of Neural Networks [Pardos and Jiang, 2020], and platforms such as YouTube which are including Deep Learning techniques into their recommendation engine [Zhang et al., 2019].

Acknowledgements

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A List of analysed papers

This appendix displays the 80 papers that were analysed in the Systematic Literature Mapping along with the names of the Recommender System they present, when available (see Table 9).

Scientific Paper	Recommender System
[Aarthi et al., 2019]	—
[Almutairi et al., 2017]	—
[Angelova et al., 2018]	—
[Bai and Yang, 2019]	—
[Baskota and Ng, 2018]	—
[Benhamdi et al., 2017]	NPE_eL (*New multi-Personalized Recommender for eLearning*)
[Bhumichitr et al., 2017]	—
[Bourkoukou et al., 2017]	—
[Cerna, 2020]	—
[Chang et al., 2011]	—
[Chen et al., 2020]	AROLS (*Adaptive Recommendation based on Online Learning Style*)
[Cobos et al., 2013]	RSPP (Recommendation System of Pedagogical Patterns)
[Cárdenas-Cobo et al., 2020]	CARAMBA
[Dahdouh et al., 2019]	—
[De Medio et al., 2020]	MoodleREC
[Dussan-Sarria and Leon-Guzman, 2012]	—
[Dwivedi and Roshni, 2017]	—
[El-Bishouty et al., 2014]	—
[Esteban et al., 2020]	—
[Ezz and Elshenawy, 2020]	—

Scientific Paper	**Recommender System**
[Faisal et al., 2020]	—
[Ferreira et al., 2020]	UbiGroup
[García et al., 2009]	CIECoF (*Continuous Improvement of E-Learning Course Framework*)
[Heras et al., 2020]	C-ERS (*Conversational Educational Recommender System*)
[Hidayat et al., 2020]	—
[Hoic-Bozic et al., 2016]	ELARS (*E-Learning Activities Recommender System*)
[Hsu et al., 2013]	—
[Iatrellis et al., 2017]	EDUC8
[Ibrahim et al., 2017]	—
[Ibrahim et al., 2020]	FBRS (*Fog Based Recommendation System*)
[Isma'il et al., 2020]	—
[Janpla and Kularbphettong, 2016]	—
[Jiang et al., 2014]	—
[Jun Liu et al., 2010]	—
[Kanika et al., 2019]	KELDEC
[Karga and Satratzemi, 2018]	MENTOR
[Karga and Satratzemi, 2019]	
[Kopeinik, 2018]	—
[Liao et al., 2020]	—
[Lin et al., 2019]	—
[Lin et al., 2018]	—
[Liu et al., 2017]	BH-JRS
[Ma et al., 2020]	MPTRS (*Machine learning-based Peer Tutor Recommender System*)
[Mokarrama et al., 2020]	—
[Nho et al., 2020]	—
[Nuswantari et al., 2020]	—
[Obeid et al., 2018]	—
[Palilingan and Batmetan, 2018]	—
[Pardos and Jiang, 2020]	—
[Pariserum Perumal et al., 2019]	—
[Peralta et al., 2018]	—
[Pereira et al., 2018]	BROAD-RSI (*Recommender System based on Social Interactions*)
[Porcel et al., 2020]	—
[Praserttitipong and Srisujjalertwaja, 2018]	—
[Putri and Zulkarnain, 2020]	—
[Sabic and El-Zayat, 2010]	—
[Salehi et al., 2014]	—
[Samin and Azim, 2019]	ScholarLite
[Sauer et al., 2014]	—

Scientific Paper	Recommender System
[Selvam et al., 2020]	—
[Sergis and Sampson, 2016]	—
[Sirikayon et al., 2018]	—
[Sobecki, 2012]	—
[Syed and Nair, 2018]	—
[Tawfik et al., 2020]	—
[Tilahun and Sekeroglu, 2020]	IPCAM (*Intelligent Personalized Course Advising Model*)
[Troussas et al., 2020]	—
[Uslu et al., 2016]	Mecanin
[Vialardi Sacín et al., 2009]	—
[Wan and Niu, 2020]	SI IFL
[Wang et al., 2017]	—
[Wenige and Ruhland, 2018]	—
[Xu, 2019]	—
[Yeh, 2015]	CRIS (*Course Recommendation Intelligent System*)
[Yuliansyah et al., 2020]	—
[Zervas et al., 2015]	—
[Zheng et al., 2019]	—
[Zhu et al., 2020]	—
[Zhu et al., 2018]	—
[Zhuhadar et al., 2009]	

Table 9: Papers analysed in the Systematic Systematic Literature Mapping

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[Bai and Yang, 2019] Bai, H. and Yang, S.: "Research on the sustainable development model of information technology literacy of normal students based on deep learning recommendation system"; Proc. 4th International Conference on Mechanical, Control and Computer Engineering (ICMCCE), (2019), 837–8373.

[Baskota and Ng, 2018] Baskota, A. and Ng, Y.-K.: "A Graduate School Recommendation System Using the Multi-Class Support Vector Machine and KNN Approaches"; Proc. IEEE International Conference on Information Reuse and Integration (IRI), (2018), 277–284.

[Bel Hadj Ammar et al., 2020] Bel Hadj Ammar, W., Chaabouni, M., Ben Ghezala, H.; "Recommender System for Quality Educational Resources"; In: Kumar V., Troussas C. (eds); Proc. Intelligent Tutoring Systems ITS 2020 (2020), 327-334.

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