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RECOMMENDER SYSTEMS FOR ENGINEERING EDUCATION

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Recommender systems (RS) represent a very important aspect for the Education 4.0, especially for the engineering education that is taking advantage from the new technologies. Personalized e-learning is very connected with this kind of systems, being important for the students but also for the teachers to be evolved in a personalized learning-teaching process. The use of RS has developed a lot for the engineering education and in the last years a lot of online learning environments were created and improved based on the new solution offered by the RS. The purpose of this paper is to offer an overview of the most recent researches from e-learning that are using RS. There are also analyzed the main recommender systems types and their issues and limitations.

1. INTRODUCTION

The development and the improvement of the internet technologies have led in obtaining various ways of data retrieving, storing and extracting. Therefore, the users may have access to a huge amount of data and information, this aspect being a positive one. In the same time, users start often to encounter difficulties in making a choice that has the highest degree of satisfaction for them. In general, this kind of choice implies also important resources like time, money, effort *etc.* For example, a high school graduate wants to choose faculty that will suit best to his expectations. In the selection process of his faculty, faculty that will affect very much his future and his career, the future student will be influenced by his friends, students of that faculty and relatives. Based on their opinions, a choice will be taken.

A very helpful solution in having the best decision in various domains are the so called the recommender systems (RS). RS have started to be used more often in the last decade and the RS based applications are used in many daily activities. The principle of the RS is that it is in the human nature to make any kind of decisions based on the experiences and recommendations of others. In their development, RS benefited by the advantages offered by the Industrial Revolution 4.0, revolution that came with innovative technological solutions in Education, Engineering, IT&C, Commerce, Marketing, Governance, Tourism *etc.*

The present paper presents the main RS types that are most encountered and embedded in different application and solutions, reviewing and emphasizing some of the most recent papers from engineering education, more precisely the technology enhanced learning (TEL).

In the second section of the paper there are mentioned the benefits of the technology-enhanced learning and it is introduced the concept of RS, mentioning also the most important RS types. In the third section there are described the main RS types among with their particularities and issues, and also offered examples from literature of their use from engineering education and not only. The last two sections are the Conclusions and References.

2. BACKGROUND

The RS are different from other classical system techniques and tools like search engines and databases, having particularities that lead to better results and also more relevant for the user [1, 2]. One of the first solution based on RS was made in 1998 [3] and after, the RS have started to be widely used for the e-commerce domain in order to create customized recommendations for users, for examples Amazon (it offered recommendations for other products based on the user profile, his previous acquisitions and his online behavior) and Google (the news recommended by Google were based on the articles that the user has read in the past and the accessed sites).

For the engineering education, one of the first RS was built in 2002 [4] where the author has proposed an agent that uses the web mining techniques in order to be able to recommend on-line learning activities.

Because of the Industry Revolution 4.0, several concepts were born like Education 4.0 [5–7], Industry 4.0, IT&C 4.0, Marketing 4.0 *etc*. Regarding the Education 4.0, it places the learner in the center of the education process and offers him enough flexibility to create his own learning path and customized ways to learn, aiming always the final objectives. This type of education also prepares the learners for future leadership positions within a globalized and very dynamic knowledge society. Regarding the Education 4.0, there are several specific trends [8–10]. Engineering education is a special type of education because it implies a lot of abstract terms, concepts and notions. In order to help the students to understand them better, the technology-enhanced learning is used because [11]: it delivers distance education, it offers virtual learning environments, student's assessment through technology and engineering literacy, learning materials are ease to be updated and recommended, it makes use of the mobile technology. Many of these aspects imply the use of data and information.

As the amount of data and information available increases, the use of RS become a very important solution in identifying the searched content that satisfy best the users' needs. The design and implementation of an RS imply programming skills and knowledge in the field of technologies used in the recommendation process. The results of any RS must meet four requirements [12, 13]: relevance (items that are recommended must be relevant for the user), diversity (recommended items must be similar but also divers), novelty (recommended items must be new for the user), serendipity (the items are new for the user but also unexpected.

According to [14], RS are defined as being "*software*

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tools and techniques that provide suggestions for items to be of use to a user" (from 2011).

Some more recent definitions for RS are:

- from 2017: "*systems that try to identify the need and preferences of the users, filter the huge collection of data accordingly and present the best suited option before the users by using some well-defined mechanism*" [15]

- from 2019: "*RS are an essential part of every consumer-oriented website, being systems that use several techniques (like filtering, exploring and ranking) for a very large amount of data and information based on preferences of the users or similar items*" [16].

Having a closer look to the mentioned definitions, it can be observed that the importance aspect of the RS is growing as the time pass by, RS becoming a key element in understanding and retaining the user.

A more formal definition of the recommendation problem that an RS must to solve is: let be *I* the set of all items that might be recommended, let be *U* the set of all users, and let be *util* an utility function that measure the usefulness of an item *i* for a user *u*, *util:U*x*I->R*, where R is a set that is totally ordered. For each user *u* that belongs to *U*, an *i'* must be chosen in order to maximize the user's utility.

A specific aspect of an RS that makes it different from other systems types like systems for information retrieval (SIR) and search engine (SE) is the personalization aspect. If the SIR and SE offer relevant results based on a query and it doesn't matter who was the person that ran it, the RS offer relevant results based on information that are strictly related to the user.

3. RECOMMENDER SYSTEM TYPES

RS are classified based on several criteria like: the used approaches, application domain for which the recommendations are made, the data mining techniques that are used. Several classifications are presented in [17, 18]. The most encountered RS types are: *Collaborative recommendation, Content-based recommendation, Knowledge-based recommendation, Demographic-based recommendation, Hybrid filter recommendation, Reclusive methods based recommendation.*

3.1 COLLABORATIVE FILTERING (CF) BASED RS

Making decision in a rational way is a process specific to human nature. A person tends to make decisions based on his own experience but also relaying on the experience of a group of people that is well known by that person, people from that group having common concerns with him.

A major role in the decisions making process is played by the collaborative filtering (CF), which is one of the most encountered recommendation technique. The CF approach is using recommendation from several users whose choices are alike or almost the same to the target user. In order to apply this approach, users with similar choices must be identify and then explore their preferences. The RS type based on CF is the most encountered and it offers very good results.

Based on this approach, the results offered by a CF based RS to one or several target user/users are built based on recommendations made by other users, users that are similar with the target user/users. The similarities between a target user and the other users aim the users' profile, users' behavior taking into account the items that are important to them (purchased, selected or rated items) [19]. The clients with similar choices are called "neighbors".

The CF was one of the first approaches for the RS and it was introduced in the early '90s. Based on CF concept an experimental system was made, the Tapestry system. This RS was made by Xerox Palo Alto Research Center and its goal was to filter the emails.

The issues that are specific to CF and that influence the results are [20, 21]: the cold start problem (recommendation of a product/service to a new user about which there are no kind of information), sparsity (in many cases, the users do not rate the product/service, situation that leads to the sparsity of data), scalability (because of the huge amount of data and information, managing so many users and items through the internet and trying to find different kind of similarities between them becomes expensive), gray sheep (unusual user), black sheep, synonym problem.

According to [22] there are three approaches for CF based RS: user-based approach, item-based approach and mode-based approach, approaches that can be used also for engineering education. The first one and the second one may be grouped as memory based technique.

User-based approach – this approach consists in associating to each user a set of neighbors (the nearest/similar neighbors), and then a prediction is made regarding the user's rating on an item based on the rating offered by the nearest/similar neighbors). In general, in order to identify similarities between users, several metrics may be used (*e.g.* Pearson correlation , cosine, Euclidean). For example, for a matrix user-items *A(mxn)* that stores ratings given by *m* users to *n* items, the Pearson correlation (pc) that computes the similarity between two users (target user - *tu* and another user - *au*) is given by the formula (1), where *tu* represents the target user for which a recommendation will be offered regarding a certain item *j*, the *au* is another user that already has offered a rating for the item *j*, *p* ($p < n$) represents the number of the items for which the *tu* and *au* have offered ratings, $r_{tu,i}$ represents the rating offered by the user *tu* to the item *i*, the $\bar{r}_{tu}$ represents the mean of the ratings given by the user *tu*, the $\bar{r}_{au}$ represents the mean of the ratings given by the *au* user.

$$pc_{(tu,au)} = \frac{\sum_{i=1}^{p}\left(r_{tu,i} - \bar{r}_{tu}\right)\cdot\left(r_{au,i} - \bar{r}_{au}\right)}{\sqrt{\sum_{i=1}^{p}\left(r_{tu,i} - \bar{r}_{tu}\right)^2}\sqrt{\sum_{i=1}^{p}\left(r_{au,i} - \bar{r}_{au}\right)^2}}. \quad (1)$$

Item-based approach – this approach consists in associating to each item a set of neighbors (the nearest/similar neighbors). Using the ratings offered by the nearest/similar neighbors for that item, the rating for that item will be predicted. For example, similarities between a pair of items may be identified using similarity metrics. The rating for a certain item *i* for a user *u* ($pr_{u,i}$) may be predicted by using a simple weighted average (2), where *N* represents the number of most similar items rated by the user *u,* the $r_{u,j}$ represents the rating offered by the user to the item *j*,

$w_{i,j}$ represents the similarity between the two items i and j which may be computed using similarity metrics, and $\left|w_{i,j}\right|$ represents the positive value of the $w_{i,j}$.

$$pr_{u,i} = \frac{\sum_{j \in N} r_{u,j} w_{i,j}}{\sum_{j \in N} \left|w_{i,j}\right|}. \quad (2)$$

Model-based approach - the model is based on the clustering process and uses specific algorithms in order to build a set of user groups. The user will be included in one of these groups. Based on the group in which the user is included, the model will predict the rating that the user will give for a certain item, taking into account the ratings offered by the other members of the group for the same item.

3.1.1 TECHNIQUES USED BY CF BASED ON USER AND ITEMS

A classification of the techniques used by the CF based on user and items, may be as follows:

• Rating – this approach has started to be used from mid '90s and is based in obtaining a rating from a certain user for several products. This rating will be used in order to identify better items and to make recommendations to other users. As an improvement from the result accuracy point of view, the researchers have proposed the raking based recommendation approach [23]. In this approach, the ordering information of rating data is analyzed to improve rating prediction accuracy.

In [24] there is done a presentation of the RS for TEL settings, emphasizing their particularities compared to RS for other domains.

In [25] there is proposed an e-learning RS for engineering education based on rating and content filtering in order to recommend the most useful materials to the students and according to the obtained results of their proposed RS, the authors have found that the learners' performance was increased by at least 12 %.

In [26] there is proposed a RS that is incorporated into an existing computer-supported collaborative learning environment.

• Association rule mining (ARM) between preferences of neighbor of users. In [27] is presented the singular value decomposition (SVD) technology during two experiments in order to reduce the dimensionality of the RS databases. An association rule (AR) may be seen as a simplification of a rule A -> B, where A, B are two item-sets, and where $A \cap B = \varnothing$. The AR is modeled as a mathematical model based on four parameters n (number of elements), n_A (cardinality, card(A)), n_B (cardinality, card(B)) and n_{AB} (represents the distribution for A and B). Let suppose that R_{ASS} be a set of all association rules, then it may be presented as the equation (3) [28].

$$R_{ASS} = (n, n_A, n_B, n_{AB}) \left| \begin{array}{l} n_A \le n, n_B \le n, \\ \max(0, n_A + n_B - n) \\ \le n_{AB} \le \min(n_A, n_B) \\ (confidence \ge \min conf). \end{array} \right. \quad (3)$$

In [29] is made a comparison between ARM and other data mining techniques and also a classification framework for them in order to extract the most suitable recommendations to the users based on their interests.

In [30] there is designed a course recommender model for engineering education which has the aim to recommend the most suitable courses based on students characteristics. In order to achieve its goal, the system uses cluster technics to identify similar students (from skills and interests point of view).

In [31] the authors have described a personalized RS that uses ARM for recommending to a student which (next) links to visit within an adaptable educational hypermedia system.

• Similarity between the preferences of different users regarding common items – this approach is usually used when information about ratings there are not enough.

In [32] is proposed a recommendation approach for learning objects (LOs) in ubiquitous e-learning systems. The approach takes into account information from forums and chats, transforming these in information sources and then uses the user-based nearest neighbor recommendation approach. Identifying similarities between social components of the users, the system will generate more accurate recommendations.

• Tagging – this approach offers the results based on: the tags popularity among the group of all users, based on the recent use, or based on the simple heuristics to extract keywords from the uniform resource locator (URL) that is being tagged. URL represents a standardized naming convention for addressing resources available over a computer network.

In [33] it is used the user annotations concept (tagging) to the domain model witch add additional information for the educational materials and help the users to communicate to each other. For the engineering education, communication aspect is very important, students being able to help each other in order to understand the topics and the support materials that usually comprise a lot of abstract concepts. The designed RS helps the students in using and processing the learning resources in effective manner such as recommendations for certain items.

• Choice of individuals for varied items – this approach is used in situation when rating-based strategies do not offer the expected results. The items are recommended based on similarities that exist among the user preferences regarding certain items.

In [34] is debated the topic of the personalized curriculum planning. Students need to choose an appropriate courses selection in order to meet graduation requirements for their degree. An automated course recommender is a solution for scale advices for large group of students. The proposed solution is implemented using deep learning techniques as short-term memory (LSTM) recurrent neural networks.

3.1.2. MODEL-BASED RECOMMENDATION TECHNIQUE FOR CF

This approach offers results based on learned models. According to [35] the predictions and recommendations for the user are made following the next steps: a) the patterns are obtained by training data and analyzing it; b) based on obtained patterns the learned models are designed and build; c) based on the learned models then predictions are made. According to the same source, results from model-based recommendation give better performance on sparse data sets than memory-based methods (user-based and item-based approaches) and have less accuracy in prediction on dense data sets. Techniques from this approach may be classified in two categories: cluster model and bayesian network model.

In [36] in order to build a model-based RS, the authors use the explanations in learning design settings aiming to enhance teachers' acceptance and perceived experience. The conclusion of the authors is that explanations must to be included into a RS that propose learning designs. This may be a good possibility to improve the teacher-perceived experience and also to encourage their wider vision by other teachers.

In [37] is used an existing platform (iCourse) and it is proposed a content-based course recommender model for massive open online courses (MOOCs). The authors' findings show that the prediction precision of the proposed model is much better than a random recommendation. Another factor that influences the results is the descriptive data of the course, the more accurate it is, the better. For the system there are used also demographic data.

3.2 CONTENT-BASED RECOMMENDER SYSTEMS (CB-RS)

This type of RS predicts and recommend items to an user, the items being very similar with the ones that the user has accessed and bought in the past [38]. The specific process of this type of RS is about associating the attributes of a user profile (profile in which are stored information about his preferences) with the attributes of an item that might be relevant for him in order to recommend to the user new items. One of the first CB-RSs was proposed in 1999. The recommendation process follows three steps [39]: content analyzer, profile learner, filtering component. The following researches described below show ways in which engineering education may be improved by using CB-RS.

For an CB-RS, a cosine similarity metric may be used as (4), where w_c and w_s are the term frequency (TF) – invers document frequency (IDF) weight vectors.

$$u(c,s) = \cos(\vec{w}_c, \vec{w}_s) = \\ = \frac{\vec{w}_c \cdot \vec{w}_s}{\|\vec{w}_c\|_2 \times \|\vec{w}_s\|_2} = \frac{\sum_{i=1}^{K} w_{i,c} w_{i,s}}{\sqrt{\sum_{i=1}^{K} w_{i,c}^2}\sqrt{\sum_{i=1}^{K} w_{i,s}^2}}. \quad (4)$$

In [40] is proposed a platform (so called MOVING platform) that contains a very large amount of resources (data, information, support materials, video, social media posts, pictures *etc.*). For this platform it is used a CB-RS. The authors offer solutions that support users in managing in an efficient manner such amount of resources. In order to obtain the results, a hierarchical concept frequency - inverse document frequency (HCF-IDF) model is used. The HCF-IDF model can exploit the hierarchical relationships that exist between the concepts from a thesaurus. The platform recommends the best educational resources to the users based on users' search history.

In [41] a CB-RS is designed in order to realize a degree of order in several e-courses from the content management point of view. The main topic of the paper is related to the blended learning form (BLF) of education (for content creation) and a CB-RS used for e-learning materials. The use of e-courses is based on these two parts. The BLF and the CB-RS are used to obtain the design of RS model that reflects technical requirements of established learning management system for the university. The pilot stage of implementation of the RS model was tested and the model was validated by the reduced failure rate of the students at the final tests.

In [42] it is proposed a CB-RS for an online course that can be used for distance-learning platform (that are also used for students' assessments). In many situations these platforms and also training devices like massive open online courses (MOOCs) do not have recommendation tools and instruments to guide learners during their learning process. For this reason teachers and tutors often cannot realize a representation of learners' activity, they cannot send recommendations, remarks to each learner and to intervene in appropriate time. The authors of this paper propose a CB-RS solution that try help teachers and tutors to analyze the learners' responses in an automatically way. Using this system, they can assess the knowledge level for each student.

The specific issues of this RS type are: overspecialization (restrictions are imposed for the users in order to receive recommendations for items based only on the information that exist in their profile), limited content analysis (there is difficult to make a recommendation if there are not enough information about the user), data sparsity.

3.3 KNOWLEDGE BASED RS (KRS)

The KRS is one of the most important RS type. In [43] KRS is defined as that system that uses the information and knowledge about users and items in order to use a knowledge-based approach for creating recommendations, building also reasoning about the items that have characteristics according to the user requirements. In order to create recommendations by the KBS, there have to be taking into account the needs and preferences of the user.

For creating the user models, several knowledge structures must to be designed. Knowledge structure may be represented by [44]: content, context-aware, cases (case-based reasoning), queries (preferred characteristics for products/services), constraints (constraint-based reasoning), ontologies, social knowledge, matching metrics and knowledge vectors. For engineering education, the solutions that include this type of RS help learners understand better their domain and its particularities, to identify easier the latest discoveries *etc.*

In [45] a KRS is proposed a system called ScholarLite that uses probabilistic topic models for generating recommendations to users in an academic environment. It uses the machine learning to identify different knowledge from several aspects for the faculty member (like themes publications that were published, extract their topics) and combines them with their educational background. Based on this correlation, recommendations are generated regarding the industry-academia collaboration, course that is best to teach, research vision.

In [46] there is presented a new strategy that can be used for the KRS, strategy that integrates knowledge from a certain domain for new users into a machine learning based recommendation system for existing users. This kind of system may help students to receive recommendations regarding the courses that is best to enroll, support materials that are more indicated for a certain topic, colleagues with similar interests *etc.*

In [47] it is proposed a RS for enhanced mobile e-learning. In order to create the system, the authors model and represent the domain knowledge. The knowledge in this context is based on user information (the learner) and on resources (learning resources) and tries to identify the users' learning patterns. Engineering education may benefit a lot using this system because a large number of learners, especially at the beginning, don't have a good method or approach in order to understand the specific concepts and processes of their domain.

The main limitations of KBS [48]: the cost of knowledge acquisition, accuracy of models, constraint-based explicitly defined conditions, case-based similarity to specified requirements, offering recommendations of items that are very similar to those the user already has or is interested, overspecialization taking into account the preferences of other users.

3.4 DEMOGRAPHIC RS (DRS)

The demographic RS type is one of the first RS that were designed. For this type of system the most used techniques are the correlation and similarity measures as metric. This RS tries to identify the similarities between demographic information (like age, education, job, marital status *etc.*) that are stored for the users. When a new client wants to buy a product from a website, the DRS identifies the similarities between demographic information of the new client and the stored demographic information of the existent clients. Recommendations for new items are made taking into account the preferences of the new client and the similarities between his demographic information and the others clients demographic information. This type of system is usually integrated in other RS type (*e.g.* for CF based RS).

For the learning environments that are offering engineering education, this type of RS is very useful because in order to make recommendation (especially for the new learners), these recommendations are made only based on the demographic information that are first collected during the enrollment process.

In [49] is there is presented a RS that make use of the DRS principle. The proposed system contains three modules (a user cluster module, a representative module, and an adaption module). With this approach, the authors try to overtake the cold start problem because first module aims to find groups of users, the second one determines a representative of each group, and the third one handles new users and assigns them appropriately.

Issues for the demographic RS may consist in the difficulty in obtaining the information, often there is not enough information, information is about a narrow area regarding the user.

3.5 HYBRID RS (HRS)

Systems like CF-RS, CB-RS, KBS, DRS and RM-RS usually offer good results but in many cases, because of their issues and limitations, the association of a user with an item is not so appropriate. In order to overtake these problems, combinations of these types have started to be used, creating in this way the most complex RS type, namely the hybrid recommender systems. The HRS have a unitary structure, combining also several recommendation approaches and technics specific to other RS. Because of their characteristics, HRS are more efficient and flexible, offer better results than other RS and are widely spread in vary domains. For example, an HRS may use a knowledge approach if there are no information about a user and a collaborative approach if there are enough information about the user. Engineering education implies a complex learning process and is facing several challenges like the huge number of digital learning resources and the ability to select the most appropriate, low quality results of learning environments to satisfy and understand different needs of learners. For this type of education, HRS are offering good recommendations that in many cases are more accurate and more personalized than other types of RS, trying to take advantage of all the HRS properties like: recommendations are made in a dynamic way and are based on patterns, user preferences are very often updated, they are more adaptive based on the types of RS that are used.

In [50] there is proposed a personalized e-learning RS used to adjust learners' level. The RS uses a HRS that tries to be able to offer a teaching activity that is adapted to the needs and characteristics of the learners. The aim of the authors is to integrate the RS in a major architecture, adding in this way more information for the learner profile. This profile will be the main factor that will influence the recommendations for resources and learning scenarios.

In [51] is proposed an ontology-based hybrid approach in order to recommend customized courses in a framework named ontology based personalized course recommendation (OPCR) framework . The recommended courses must to fit student's personal needs by integrating all available information regarding the courses and supporting students to choose courses based on their career objectives. The OPCR framework is a key element for the created HRS. The designed HRS is available online for learners and researchers.

In [52] is proposed an adaptive HRS for e-learning personalization based on data mining techniques. The system is named LearnFitII and its aim is to automatically adapt to the dynamic preferences of learners. The main features of this system are that it recognizes for learners different learning patterns and habits analyzing their psychological model and their server logs.

In [53] the authors have designed a HRS that tries to undertake two specific problems of RS, namely the cold-start problem and the low model scalability problem. In order to reduce the dimensionality, ontologies are used to integrate the extracted characteristics into topics.

3.6 RECLUSIVE METHODS BASED RS (RM-RS)

The RM-RS is different from CF-RS, and the use of RM-RS it may be seen as complementary to CF. The RM-RS uses an approach that uses the information about the items and, in the same time, imposes their representation. A particularity of these RS is that the recommendations made to the user are made taking into account only the preferences of the user for which the recommendations will be made. The most often encountered techniques and methods used for RM-RS are [54–56]: fuzzy methods set (used for designing and building the recommendation rules), nearest neighborhood, tagging, rating, clustering, Bayesian networks, web mining, genetic algorithms.

In [57] there is presented a personalized courseware recommendation system. The designed system is using the proposed fuzzy item response theory (PFIRT). The aim of this system is to create recommendations for courses that have the difficult level correlated with the learner knowledge background and understanding level. The experiment conducted by the authors has shown that applying the PFIRT to web-based learning can lead to a personalized learning process and to the use of a more efficient learning manner.

In Table 1 are presented the most common advantages and disadvantages for the presented RS types.

Table 1

RS advantages and disadvantages

RS Type	Advantages	Disadvantages
CF	- good results when there are enough information about the user, - quality is improving over time, - it is used a bottom-up approach	- the cold start problem, - sparsity, - scalability, - gray sheep, - black sheep, - synonym problem, - results quality depends by the historical rating of the user
CR-RS	- useful for HRS, - there are offered recommendations from the beginning, - capable to manage new and unpopular items, - no cold start problem (for attributes based techniques)	- overspecialization, - limited content analysis, - data sparsity, - new user problem, - works only with categories, - is not learning.
KRS	- there is no need to provide rating for items because KRS is based on unambiguous knowledge.	- the cost of knowledge acquisition, - accuracy of models, constraint-based explicitly defined conditions, - case-based similarity to specified requirements, - offering recommendations of items that are very similar to those the user already has or is interested, - overspecialization taking into account the preferences of other users.
DRS	- are not depending by the domain, is not facing the cold-start problem	- difficulty in obtaining the information, - often there is not enough information, - information is about a narrow area regarding the user
HRS	- recommendations are made in a dynamic way and are based on patterns, - user preferences are very often updated, - they are more adaptive based on the types of RS that are used, - overcome problems that appear in CF and CR-RS	- the cold-start problem, - the low model scalability problem
RM-RS	- improve results offered by CF based on their different approaches	- the offered results depend very much by the existing information about the user

Table 2 presents the most encountered RS types and for each one, several examples for engineering education and other domains are mentioned.

Table 2

RS types and example for education and other domains

RS Type	Engineering education	Other domains
CF	Rating: [24-26, 58] ARM: [30, 31, 49, 52, 59, 60] Similarity: [32, 61] Tagging: [33] Choice: [34] Model-based: [36, 37]	Rating: [71, 72] ARM: [29, 73] Similarity: [74] Tagging: [75] Choice: [76] Model-based: [77, 78]
CB-RS	[25, 40-42]	[79, 80]
KRS	[45, 46, 47, 62-67]	[48]
DRS	[49, 68]	[15]
HRS	[46, 50-52, 69, 70]	[81, 82]
RM-RS	[56, 57, 63]	[55, 83]

4. CONCLUSIONS

Because of the internet growth, the number of users and the amount of data were highly increased. Form the user point of view, a problem appears when he has to choose an item from thousands. In these situations, recommender systems are offering very good solutions in helping the user to choose the best item for him, item that accomplishes his expectations best.

For the engineering education, RS are offering very good solutions because of the technologies that help improve the learning process in many directions, even if it is about recommend educational resources, recommend certain courses, automatically students' assessment *etc.* RS could have a big impact over the learning activities, playing also a very important educational role taking into account the communication and collaboration between learners and teachers.

In this paper were mentioned the benefits of the technology-enhanced learning (TEL), it was introduced the concept of RS and various RS types were described among with their particularities and issues. Based on the offered classification for the RS, recent researches were described, offering an overview of the use of RS in the engineering education domain.

Based on this overview, the paper will help the researchers and practitioners in understanding the RS and in developing new approaches. An open issue for the RS is the development of assessment frameworks. These kind of frameworks must to consider as many dimensions possible like pedagogical dimensions, learning methods used, communication type *etc.*, and evaluate them using together instruments and metrics.

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