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Competence-based recommender systems: a systematic literature review

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Competence-based learning is increasingly widespread in many institutions since it provides flexibility, facilitates the self-learning and brings the academic and professional worlds closer together. Thus, the competence-based recommender systems emerged taking the advantages of competences to offer suggestions (performance of a learning experience, assistance of an expert or recommendation of a learning resource) to the user (learner or instructor). The objective of this work is to conduct a new Systematic Literature Review (SLR) concerning competence-based recommender systems to analyse in relation to their nature and assessment of competences an others key factors that provide more flexible and exhaustive recommendations. To do so, a SLR research methodology was followed in which 25 competence-based recommender systems related to learning or instruction environments were classified according to multiple criteria. We evaluate the role of competences in these proposals and enumerate the emerging challenges. Also a critical analysis of current proposals is carried out to determine their strengths and weakness. Finally, future research paths to be explored are grouped around two main axes closely interlinked; first about the typical challenges related to recommender systems and second, concerning ambitious emerging challenges.

Keywords: Recommender system; Systematic literature review; Competence-based learning; Adaptive learning; Emerging challenges.

1. Introduction

New technologies have given rise to different types of learning environments or, even, merging several of them in a more sophisticated nature, such as Intelligent Virtual Environments for Training/Instruction (IVETs), where the complexity of Intelligent Tutoring Systems and 3D technology

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coexist. All these learning environments are applied in very various domains as effective means to achieve positive learning experiences for students. This diversity of environments and domains often requires the use of powerful student modelling whose representation formalism allows us to incorporate all the sources needed to provide increasingly adaptive learning. Moreover, Internet and technological progress have become two key drivers in the advances of educational field. Nowadays, learning is more accessible than ever before as: (1) people from different countries, age or knowledge's level can simultaneously perform, for example, the same massive course, (2) the Learning Management Systems (LMS) are meaningful for the sharing and communication between instructors and learners. The use of Internet in learning has mainly contributed to focus on the student figure since many data from the learning process is collected in the LMS. In these, courses are usually organized following an instructional design used to describe the method that allows students the achievement of learning objectives by performing a set of activities and using the environment resources (Amorim et al. 2006).

Currently, most of the learning activities are based on competences or learning outcomes. Competences are suitable for relating learning and work as they represent the combination between knowledge, skill and performance and learning outcomes can be easily assessed and observable (Paquette 2007). Likewise, the students have got particular learning needs in accordance with their profile or according his/her state (e.g., state of knowledge objects -acquired or not acquired-, degree of achievement of the knowledge objectives or completion state of instructional design units). For this reason, the personalised recommendation as an assistance tool throughout the learning process is nowadays a research field of special interest in education. In learning scenarios, students or teachers can be recommended in several ways. It is very common that tutors advise learners to review a resource, to perform an activity, to enrol in a course, etc.

Ricci et al. (2010) defined recommender systems as software tools platforms or modules that aim to propose useful suggestions for the user. In this line, we intend to analyse the most relevant competence-based recommender systems and their key features.

The main motivation which encourages us to conduct a survey on competence-based recommender systems is to bring light to emerging challenges which promote the improvement in the development of such systems. To this end, it must be analysed to what extent the recommender systems are adapted to new or more evolved learning environments, theories (Reigeluth 2016) and strategies (Marzano, Pickering, and Pollock 2001). Additionally, we need to study how they address problems such as: (i) *cold start* (how to recommend elements to new users); (ii) *black sheep* (how to recommend elements to users with opposite preferences to those of the majority); (iii) *sparsity* (which element should be recommended to a user when the amount of elements is huge and it is difficult that different users coincide in the recommendations); (iv) *over-specialisation* (the more a user assesses elements from a category, the larger the number of recommendations about the category the user will receive and consequently, recommendations will become more specific); and (v) to assess the usefulness of the recommendations provided to the target user and just in time. The latter is particularly complicated when information is provided to the recommender system only at the end of the learning experience (Rafaeli et al. 2004). In short, we aim to analyse the flexibility of current competence-based recommender systems. This flexibility comprises factors such as the recommendation target (tutor or learner), types of knowledge modelling in the environment and specially in the student model (e.g., based on ontologies, traditional databases or none) or the detail level of suggestions (fine-grained or coarse-grained recommendations).

In this work we carried out a systematic literature review (SLR) of current learning recommender systems in order to check how they are adapted to the competence-based education approach. To do so, we followed the formal steps needed to carry out a SLR. We first describe the main features of competences and recommender systems. Second, SLR research questions need to be defined. Third, it is advisable to determine the keywords related to competence-based recommender systems to improve the quality of the literature searches. Fourth, an initial search about previous SLRs related to our topic allowed us to mainly focus on last years. Fifth, a second search in most popular publisher web pages and academic search engines shall be carried out to identify new proposals. The search criteria will be defined by using the keywords of third phase and the years determined in the fourth phase. In the sixth phase, a merging process of all works will be performed to delete duplicates and a general reading of the papers will allow us the filtering of interesting works for this survey. Next, an analysis of the selected proposals to answer the research questions from first phase will be conducted. Finally, we will present a discussion to describe the strengths and weakness of current competence-based recommender systems to encouraging the emergence of new proposals.

The rest of this paper is organized as follows. Section 2 describes main characteristics concerning competences including definition, standards and assessment. Section 3 reviews the main features of recommender systems including a general classification, properties and common pitfalls. Section 4 defines the search process carried out to identify the most prominent proposals. Section 5 describes the competence-based recommender systems obtained from the SLR. In Section 6, the results are deeply discussed and, on this basis, some emerging challenges are raised. Finally, we draw conclusions and present the future lines of work in Section 7.

2. Competences in learning

In the related literature there is a wide variety of definitions of the term "competence" since it was proposed by McClelland (1973) as "the knowledge, skills, traits, attitudes, self-concepts, values, or motives directly related to job performance or important life outcomes and shown to differentiate between superior and average performers" (McClelland 1973). Later, the IMS RDCEO defined the concept as "the combination of knowledge, abilities, tasks and learning outcomes" (Cooper and Ostyn 2002). In 2005, González and Wagenaar defined competence in the Tuning project as a "dynamic combination of knowledge, understanding, skills and abilities" (González and Wagenaar 2005). Paquette (2007) considered that "a competence is a combination of knowledge, skill and performance". Although we consider some of the most relevant definitions of competence, it is possible to find many others in current research works (Idrissi, Hnida, and Bennani 2017).

The competences are generally classified as generic, if they are necessary for the proper performance of any profession or specific, if they encompass in a number of thematic areas (González and Wagenaar 2005). Besides, there are some works on learning recommendation systems (see Section 5.2) that cover, in isolation or together with competence, another terms strongly related with this one such as objectives and learning outcome. Mathew and Kumar (2017) define learning objective as "statements that define the expected goal of a curriculum, course, lesson or activity in terms of demonstrable skills or knowledge that will be acquired by a student as a result of instruction". In a similar way, the European Qualification Framework (EQF)[1] defines learning outcome as "a statement of what a learner knows, understands, and is able to do on completion of a learning process". Given the close relationship between competences and objectives, in this work, we consider both terms indistinctly, taking as reference the matching established by Paquette (2016).

[1] https://ec.europa.eu/ploteus/search/site?f%5B0%5D=im_field_entity_type%3A97

2.1. *Standards of competence modelling*

Regarding the standards and specifications which describes the modelling of competences, an analysis was carried out and summarised below. The IMS RDCEO data model is a minimalist and extensible proposal that allows the specification of competences or educational objectives. Each competence in this data model is represented by an identifier, a title, a description and a definition (Cooper and Ostyn 2002). HR-XML[2] includes, in addition to similar tags as IMS RDCEO, the evidence (e.g., test results or certificates) and weight elements to substantiate a competence with a numeric value. IMS RCD is the evolution of IMS RDCEO proposal which focuses on providing a data model for defining and describing competences for e-learning systems (IEEE-Learning-Technology-Standards-Committee 2008). The EQF transforms the qualification from different countries into a common European qualification with the aim of helping to communication and comparison between qualification systems in Europe. This framework distinguishes eight common reference levels that describe learning outcomes from basic knowledge or skills obtained in Pre-vocational basic qualification to the most advanced knowledge skills obtained in the third cycle. The European e-Competence Framework[3] (e-CF) is an European standard that provides 40 competences concerning Information and Communication Technology (ICT). This framework provides the users with a common language in order to describe competences at five proficiency levels. The competences in e-CF are classified into *plan*, *build*, *run*, *enable* and *manage* areas. Sitthisak et al. (2008) developed the Comba Model, which intended to model learner's knowledge in a subject content matter. This model was built upon many components. However, *capability*, *attitude* and *subject matter content* were the most interesting for the learner's competence assessment. Marques et al. (2010) proposed an ontological bottom-up approach for modelling competences. The model differentiated two constructs: entities, i.e., things which have physical existence, and relationships which are links between entities. Besides, it also used the *competency*, *task*, *goal*, *action* and *resource* components to define the competences. The Competency Based Knowledge Space Theory (CbKST) model aimed to assess latent skills from the problems the student was able to solve (Albert et al. 2012). It was based on precedence relations (competences structure that uses prerequisites relations), competence state (result of connecting single competences) and competence structure (current competence's level and following competences to learn). Paquette (2007) proposed the Modelling with Object Types (MOT) framework for competence self-management.

[2] http://hropenstandards.org
[3] http://www.ecompetences.eu/

It was based on the components knowledge, skill and performance. The knowledge represents a cluster of concept, procedure or principles. The skill is defined by means of a 10-level scale from *pay attention* to *self-control*. Finally, the performance uses a 4-level scale from *aware* to *expert*.

2.2. *Competence assessment*

In relation to the evaluation, most authors distinguish at least three assessment types in accordance with the time when the assessment is carried out (Romero et al. 2015).

- The *diagnostic* assessment has the purpose of determining, prior to instruction, the knowledge, skills, strengths and weaknesses of each student.
- The *formative* assessment happens during the instruction process with the aim of identifying learning needs and adjust teaching.
- The assessment type responsible for measuring the student's achievement at the end of the instruction is known as *summative*.

Besides, in some works (Reynolds, Livingston, and Willson 2009; Idrissi, Hnida, and Bennani 2017), other classes of assessment are mentioned, such as norm-referenced (compare students' performance), criterion-referenced (measures a student's performance against an objective) or competence-based assessment (measurement of student's competence against a standard of performance). For example, Paquette (2016) uses the criterion-referenced assessment class to measure the progress in the reached student's competences along the learning process. In this proposal, the author specifies the *complexity*, *scope*, *context*, *frequency* and *autonomy* criteria to evaluate the performance level of a competence. With this objective in mind, the instructors first define accurately the criteria to achieve the competence and second, assess the student performance level of each competence following the previously-defined criteria.

Regardless of the type of assessment, the UNESCO (2016) suggests that the evaluation of specific competences raises a number of questions of relevance (use of authentic assessment or integration situations if possible), feasibility (resources limit such as time, money or context must be taken into account), reliability (integration situations are more reliable than non-integration ones concerning the student's knowledge but correcting these situations, in which open questions are regular, is more complex) and validity (testing resources in real-life situation, mobilizing central resources rather than secondary, etc.). With reference to validity, the initiative on modelling and measuring competences in higher education belonging to the KoKoHs research program (Leutner et al. 2017) also considers that validation is of paramount importance for competence assessment. Therefore, they focus on the validation criteria of test content, internal structure, response processes and relations to other variables (Zlatkin-Troitschanskaia, Shavelson, and Kuhn 2015). The barriers produced by lack of valid assessment criteria, i.e., criteria that represent what the student is able to do and what the student has to do, such as clearly communicate standards of practice or address the needs of students who do not meet the expectations, are described in a Delphi-survey study (Embo et al. 2017).

At this point, it is worth noting that there are multiple approaches to evaluate the achievement level of a competence reached by the learner. In this line, Idrissi et al. (2017) intensify their research in competence-based assessment approaches in e-learning systems, such as e-Portfolio, simulation-based, project-based or video recording. Drisko (2014) identifies measures that may not fully capture competences such as self-efficacy (own ability to learn), self-report surveys or course evaluations. The author also proposes the use of standardised tests composed of multiple-choice, short-response, short-answer and open-response questions to properly evaluate the competence's achievement level. Moreover, most of the authors coincide with the importance of measuring each competence multiple times and by different means. Authors also recommend the activities to be centred in multiple criteria, i.e., a group of competences instead of a unique competence in an attempt to approximate to real situations (Drisko 2014). In order to assess a competence, it is necessary to determine who is going to be the evaluator and how the competence is scored. In relation to the evaluation process, the person who assesses the student can be: (1) the student himself/herself in the case of auto-evaluation, (2) another student in case of peer assessment or (3) an expert in the remainder cases. In any case, the evaluators should have been previously trained to perform a suitable and uniform assessment. Many competence-based learning proposals usually divide each competence into multiple levels in accordance with the degree of achievement and the cut scores determine who have master the competence and those who have not. Special attention should be paid to establish the cut score values since false positives (pass students who should have failed) or false negatives (fail students who should have passed) can easily happen (Zieky and Perie 2006).

3. Recommender Systems

In order to conduct a survey of competence-based recommender systems, this paper dissects previously the recommender system entity.

3.1. *Classification and properties of Recommender Systems*

As previously stated, recommender systems are software tools responsible for providing suggestions to the user. Most of the experts in the area consider, at least, the following recommender system architectures (Ricci, Rokach, and Shapira 2010):

- Content-based: these systems search similarities between the element's properties to recommend items that are akin to the ones that the user liked in the past (e.g. recommend a product to a customer by considering the information of previous purchases). Some authors consider demographic as a variant of content-based architecture which uses demographic information instead of element's properties.
- Collaborative filtering: they establish the recommendations based on the relationships between users and elements (e.g. recommend TV series to a user by considering favourite series from similar users).
- Knowledge-based: they combine the user's preferences, user's needs and the element's properties to recommend products in complex domains (e.g. recommend a four-door electric vehicle). Some authors identify also the utility-based architecture as a variant of knowledge-based system, in which the users are responsible for defining the desired features.
- Hybrid: They are based on the combination of the above-mentioned architectures to benefit from their advantages. Burke (2002) defines a set of hybridization methods, for instance, weighted, mixed or cascade which provide the hybrid recommender system with more flexibility in the recommendation process.

Regardless its architecture, every recommender system must be reliable and robust. This entails to provide the users with good recommendations and to show interesting information about the recommendations (e.g. explanations, details, etc.), respectively. Moreover, the elements recommended by these systems should: (1) be easy to identify by the user, (2) be easy to evaluate/correct, (3) contain easy to understand ratings and (4) be accompanied by explanations that facilitate the evaluation of the recommendation. Another key property for every recommender system is flexibility.

This property includes that the user can modify its profile and, accordingly, the recommendations (adaptivity). It also implies that new types of recommendations can be easily applied in future (scalability). The flexibility in recommender systems should also facilitate the reusability and the maintainability since the recommender system can be later embedded in more complex systems.

3.2. *Problems in Recommender Systems*

As a previous step, and before performing the survey of competence-based recommender system, we will explain the common pitfalls that may arise in recommender system.

The best known is the *ramp-up* or *cold start problem*. In fact, this pitfall refers to two different but they are closely related problems: give recommendations to new users and recommend new elements (Burke 2002). In order to solve the problem referred to the user, most of the systems recommend popular elements or force the users to fill out a survey, a test or a profile. The new product problem is often solved by encouraging the user to assess the elements. Slightly related to *cold start* problem, it has been identified the problem of *collecting demographic information* because in certain domains, the need to have information about the user's profile is opposite to the ease of obtaining this type of information. A very frequent pitfall in content-based and demographic recommender systems is the *overspecialisation*. These systems use the previously assessed items to give recommendations. Thus, if a user has only assessed elements from a category, the system will recommend elements of that. The quality of unexpected elements advising is known as serendipity and is very common of collaborative filtering recommender systems (Su and Khoshgoftaar 2009).

Additionally to the above problems, there is another group of pitfalls related to the recommendation quality. In this line, the *sparsity problem* happens when the amount of elements is huge and it is very difficult that two users coincide in the recommendations (Solanki 2015). The existence of a high number of elements or users can lead to the *scalability problem*. This pitfall arises when the computational cost to determine the set of similar users is too high causing a too long wait to do the recommendation (Su and Khoshgoftaar 2009). In the *portfolio effect*, the quality of recommendation is reduced whether the system is not able to differentiate two similar but different elements (Burke 2002), and the opposite effect happens in the *problem of synonymy* when two potentially recommender elements are not advised because they have different names (Su and Khoshgoftaar 2009). Quality may be also affected if *shilling attacks* are produced (Solanki 2015), i.e., if a provider employs unethical behaviours to increase its own ratings (*push attack*) or decrease the ratings of rival providers (*nuke attack*). Finally, quality is reduced for those users with unusual preferences. In this sense, the *grey sheep problem* affects to users who can not benefit from recommendations since their preferences does not correspond to the preferences of other groups (Claypool et al. 1999) and the *black sheep problem* happens when a group of users has got the opposite preferences to those of the majority (Gemmis et al. 2009).

4. Research methodology

After a brief description of the main features of competences and recommender systems, we focus on the research methodology of the SLR process. We follow the *Guidelines for performing Systematic Literature Reviews in Software Engineering* to carry out this SLR (Kitchenham and Charters 2007).

4.1. *Research questions and data sources*

Table 1 lists the research questions and the related motivation to achieve the objectives defined in the introduction (see Section 1).

Table 1. SLR research questions.

SNO	Research Questions	Motivation
RQ1	What criteria allow us the analysis of recommender systems and how these criteria can be assessed?	- To identify the criteria (*coverage*, *scalability*, etc.) that allow us to evaluate the quality of the recommender system.
RQ2	What is the nature of competences in the current competence-based recommender systems?	- The aim is to identify the implication's level of competences in the proposals.
RQ3	What are the emerging challenges related to competence-based recommender systems?	- To research the difficulties that competence-based recommender systems are nowadays facing.

Once the research questions are defined, we set out below the data sources for this survey. In this paper, we use the following digital libraries and search engines:

(1) IEEE XPLORE (`http://ieeexplore.ieee.org/`)
(2) ACM Digital Library (`http://www.acm.org/`)
(3) SpringerLink (`http://www.springerlink.com/`)
(4) Elsevier Science Direct (`http://www.sciencedirect.com/`)
(5) Google Scholar (`http://scholar.google.com/`)

4.2. *Search strategy and study selection*

In addition to the data sources, in this third step, it is important to explicitly state the selection criteria (inclusion criteria) for this work. A proposal will be included in our SLR if it meets the following conditions: (i) it must propose a learning recommender system; (ii) competences, learning objectives or learning outcomes should be involved in the recommendation process; and (iii) it must be written in English, and published between 2007 and 2017. Equally relevant is the analysis of the exclusion criteria. A work will be excluded from this research if (i) competences are not relevant to the system, (ii) any information about the recommender system can be identified in the research work (iii) it does not specify in a detailed way, at least, three out of five common features to analyse in a recommender system (i.e., coverage, risk, robustness, adaptivity and scalability) or (iv) the same authors published a subsequent and more comprehensive research work about the same proposal.

The following step in our research methodology consists of determining the more suitable keywords concerning the proposed objectives. Throughout this step, the searching process will be refined. Hence, many irrelevant proposals will be quickly discarded. In the context of this work, authors can indistinctly employ various terms. For instance, learning, instruction or training are frequently used terms to specify the different types of processes for acquiring knowledge, skills, attitudes and competences in different instructional environments. Consequently, special attention was paid to define the search query (see Formula 1).

$$\begin{aligned} Title: (Recommender\ system)\ AND \\ (Learning\ OR\ Training\ OR\ Instruction)\ AND \\ (Competency\ OR\ Competence) \end{aligned} \tag{1}$$

4.3. *Data extraction and data synthesis*

In the next step, the initial search is carried out. By means of this process, we search the surveys of the state of the art related to learning recommender systems. For this purpose, the terms *survey* and *systematic literature review* have been incorporated to the searching query. Since we want to analyse recent works, this search has only taken into account last five years (2012-2017). After carrying out this search in the digital libraries and search engines, many SLR are located. Verbert, Manouselis, Drachsler and other colleges reviewed the technology enhanced learning (TEL) recommender systems and the future challenges (Verbert et al. 2012; Manouselis et al. 2013; Drachsler et al. 2015). These authors identified more than 80 different proposals between the years 2000 and 2014, grouped these works into seven clusters (recommending resources, improving CF algorithms, constraints in the recommendation process, recommendation not based on CF, context in the recommendation process, assessing the impact of recommendations and recommending courses) and performed an exhaustive analysis to classify the items according to supported tasks, user model, domain model or personalization characteristics. Champiri et al. (2015) carried out a SLR focusing on the academic context-aware recommender systems. This survey was conducted considering proposals from 2000 to 2013. As a result, the authors selected 80 proposals which were classified concerning the contextual information (user, document or environment). Furthermore, Klašnja-Milićević et al. (2015; 2017) performed a revision of the e-learning recommender systems developed between the years 2000 and 2014. These authors classified the main proposals in accordance with the employed recommendation technique. Later, Dascalu et al. (2016) considered 14 criteria (detailed in Section 5.1) to analyse 25 educational recommender systems between the years 2000 and 2015. This proposal facilitates the comparison and analysis of different recommender systems. Likewise, it includes a new proposal of recommender system. Tarus et al. carried out a review of ontology-based recommender systems for e-learning (Tarus, Niu, and Mustafa 2017). The authors selected 36 papers from 2005 to 2014 and categorised them in accordance with the recommendation technique, ontology type, ontology representation language and recommended learning resources. Finally, Khan et al. (2017) analysed 94 studies of cross domain recommender systems up to 2016. The authors classified the proposals according to the employed algorithm (clustering, semantics, graph based approach, probability distribution, factorization and tags-based association), evaluation metrics (classification, prediction and ranking), contribution (*accuracy*, *sparsity*, *modelling*, *confidence*, *cold start*, *diversity*, *trust*, *utility*, *scalability*, *privacy*, *novelty*, *serendipity*, *robustness*, *risk*, *adaptivity*), etc.

From all previous described SLRs, we identify 344 proposals related to learning recommender systems. As we are interested only in competency-based recommender systems, a second filtering process has been carried out to exclude those works which are not connected with the topic. After finishing this process, six works were selected (see Table 2).

As stated above, the next phase in the research methodology consists of identifying the proposals not collected in previous SLRs. This second search was implemented by considering main digital libraries, publisher sites and academic search engines. At this stage, the keywords identified in Formula 1 were applied to conduct the survey. Also, only proposals from last decade were included in this search. Initially, we identified 154 proposals but after a general reading, the number of works

Table 2. SLR Filtering process.

SLR	Identified works	General reading	Reading full text	Merging
(Drachsler et al. 2015)	82	8	3	6
(Champiri, Shahamiri, and Salim 2015)	80	4	2	
(Klašnja-Milićević et al. 2017)	27	3	1	
(Dascalu et al. 2016)	25	5	2	
(Tarus, Niu, and Mustafa 2017)	36	6	2	
(Khan, Ibrahim, and Ghani 2017)	94	5	2	

was reduced to 64 (see Table 3).

Table 3. Digital libraries and academic search engines filtering process.

Search engine	Identified works	General reading	Reading full text	Merging
IEEE	35	12	4	24
ACM	33	3	1	
SPRINGER	25	10	6	
SCIENCE DIRECT	29	6	4	
SCHOLAR GOOGLE	102	34	16	

Last step in the research methodology consists of merging the identified proposals in the two searching process to avoid repetitions and reading the full text in order to exclude proposals which are not related to this survey. At the end of this phase, 25 different works were selected.

5. Results

Once the proposals to analyse were selected, it is suitable to put them in a broader context where it is possible to identify relevant information. For instance, contextual information can describe if the topic is gaining interest (see Figure 1). In this sense, the 52% of the proposals were presented between 2015 and 2017 and only the 20% of the works were published between 2007 and 2011. As far as the type of publication is concerned, 48% were conference publications, 40% journal's publications, 8% book sections and 4% thesis.

Regarding the demographic information, the selected publications were from institutions of 15 different countries (see Figure 2). Most of the proposals were carried out in Europa, specifically, main author from 15 proposals was affiliated in an European institution (60%). Seven works (28%) were developed by an author who belonged to an American institution including North, South and Central America. The three remainder proposals (12%) were performed by a person affiliated in an Asian institution.

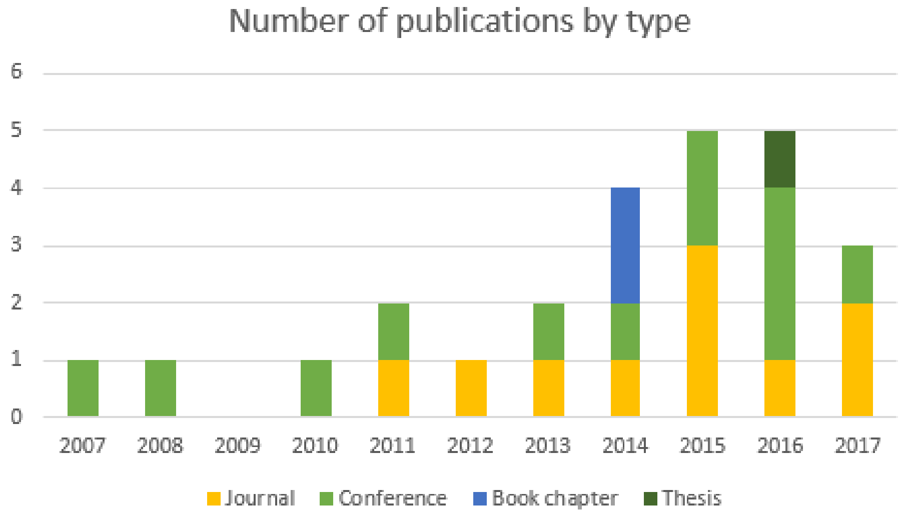

Figure 1. Number of publications grouped by type.

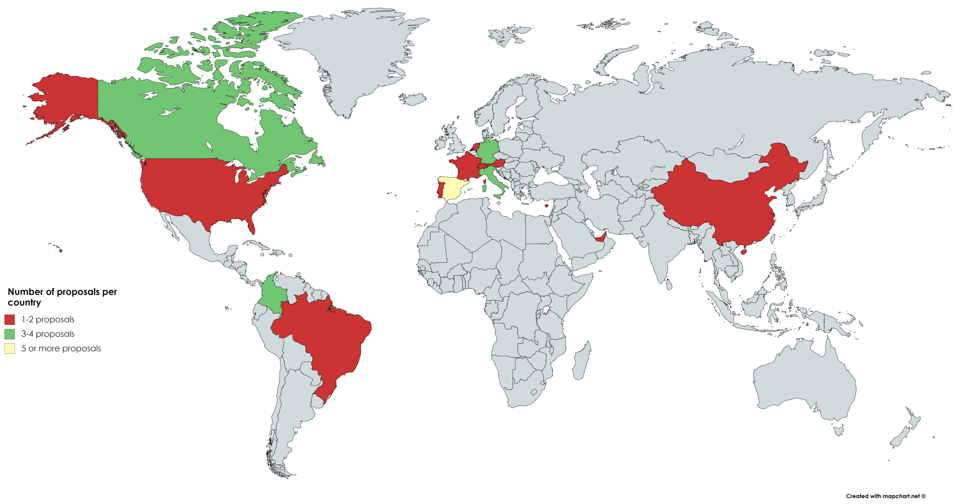

Figure 2. Number of proposals per country.

After contextualising the identified proposals, we pay attention on the first and second previously raised question. Accordingly, next subsections describe the involved elements and present the results in a textual and graphical way.

5.1. *RQ1: What criteria allow the recommender systems analysis and how these criteria can be assessed?*

Along this SLR, many different proposals of recommender systems are found. However, only a few works attempt to analyse the common characteristics of these works. Through these characteristics, a recommender system can be more easily assessed or compared with others. Among the most relevant works regarding criteria analysis, Dascalu et al.'s proposal is one of the most complete (Dascalu et al. 2016). In this proposal, 14 criteria were selected to assess a recommender system. A short description of the different criteria is detailed as follows:

(1) *coverage* - quantity of information needed to obtain acceptable recommendations. It is closely related to the *cold start* problem.
(2) *risk* - amount of flexibility to recommend items different from the most logical in the decision-making process. In low risk systems, new elements are hardly recommended but recommendations are often suitable.
(3) *robustness* - system's reliability under problematic situations such as the introduction of fake information or large requests.
(4) *adaptivity* - system capacity to modify the recommendations in accordance with produced changes.
(5) *scalability* - ability to provide the users with recommendations in a reasonable period of time when the amount of available information increments substantially.
(6) *implementation type* - system's degree of application (theory, prototype, implemented).
(7) *stand-alone or embedded* - indicates whether the application is integrated in a bigger system or not.
(8) *general or domain specific* - system's ability to work in different domains.
(9) *user feedback* - system's capability to learn about former recommendations by taking into account the user's opinion.
(10) *type* - content-based, collaborative filtering, knowledge-based, utility-based or hybrid.
(11) *access type* - the recommender system is in a desktop application or in a web-based one.
(12) *goal* - the aim of the recommender system. It includes the quantity of information provided (one element, a sequence of items) and the recommendation category (material, activities, users, etc.).
(13) *satisfaction* - user's opinion regarding the recommender system task.
(14) *teacher versus student directed* - indicates the target user, i.e, the person or people who receive the recommendation.

In addition to the criteria proposed by Dascalu et al., we consider that the domain model is also a relevant feature since it is the basis of most of the recommender systems. This model establishes the system's capability to offer more or less comprehensive recommendations with a significant impact on the system scalability and response speed. Thus, an analysis of the works found in the SLR is carried out.

5.1.1. *Set of criteria 1: Type, Domain model and Application domain*

Generally, it is a good practice to start with the most general features and end with the most specific. Thus, we begin this analysis with the *type* property. As described in Section 3, the recommender systems can be classified into content-based (CB), demographic-based (DB), collaborative filtering (CF), knowledge-based (KB), utility-based (UB) or hybrid (H).

- CB recommender systems are very common since they are easy to develop. In this survey we have identified five pure CB proposals (Serrano, Romero, and Olivas 2013; Koch and Landes 2014; Valentin et al. 2015; Torre and Torsani 2016; Guan et al. 2017).
- CF recommender systems are frequently employed in learning area as the learners/apprentices acquire analogous competences, find similar resources and make similar mistakes. A total of 4 out of 25 recommender systems are pure CF (Aimeur, Onana, and Saleman 2007; Santos and Boticario 2008; Capuano et al. 2014; Bakhshinategh et al. 2017).
- KB recommender systems are also suitable for learning due the adaptation of these systems to a particular situation. In this SLR, five proposals employed this recommendation technique, i.e., (Florian and Fabregat 2011; Mao et al. 2015; Paquette 2016; Emmenegger et al. 2016; Baneres and Conesa 2017).
- UB recommender systems are uncommon in all areas and in this survey, only one proposal was found (Sielis et al. 2011).
- Hybrid recommender systems represents the bulk of the identified proposals since they take advantage of two or three recommendation techniques, concretely:
  - six proposals combine CB and CF techniques (Isaias, Casaca, and Pifano 2010; Cazella et al. 2014; Montuschi et al. 2015; Damiani et al. 2015; Wang 2016; Duran et al. 2016).
  - two proposals use the combination of CB and KB (Colomo-Palacios et al. 2012; Khobreh et al. 2013).
  - one proposal is based on CF and KB (Chavarriaga, Florian-Gaviria, and Solarte 2014).
  - one proposal combines the three techniques CB, CF and KB (Rodríguez, Ovalle, and Duque 2015).

Another general feature is the domain model. It depends on the amount and type of required data (source and/or inferred) for recommendations. In this respect, those proposals which developed a simple recommender system, employed different datasets (Damiani et al. 2015; Guan et al. 2017; Bakhshinategh et al. 2017). Other proposals employed databases as model by requiring a greater amount of data (Aimeur, Onana, and Saleman 2007; Santos and Boticario 2008; Isaias, Casaca, and Pifano 2010; Manouselis et al. 2013; Serrano, Romero, and Olivas 2013; Chavarriaga, Florian-Gaviria, and Solarte 2014; Koch and Landes 2014; Cazella et al. 2014; Mao et al. 2015). A recent proposal included a data store as a repository for managing information (Baneres and Conesa 2017). The remainder of the analysed recommender systems used ontologies. An ontology is a formal, explicit specification of a shared conceptualization (Gruber 1993). The ontologies support the representation of abstract concepts and properties and allow reusability and reasoning by means of rules (Clemente, Ramírez and de Antonio 2011).

Figure 3 depicts the relation between the recommender system type and the domain model. The most popular combination of recommender systems are hybrid with an ontological domain. This blend facilitates the recommendation of multiple items since it is based on the more complete type and the more flexible domain model.

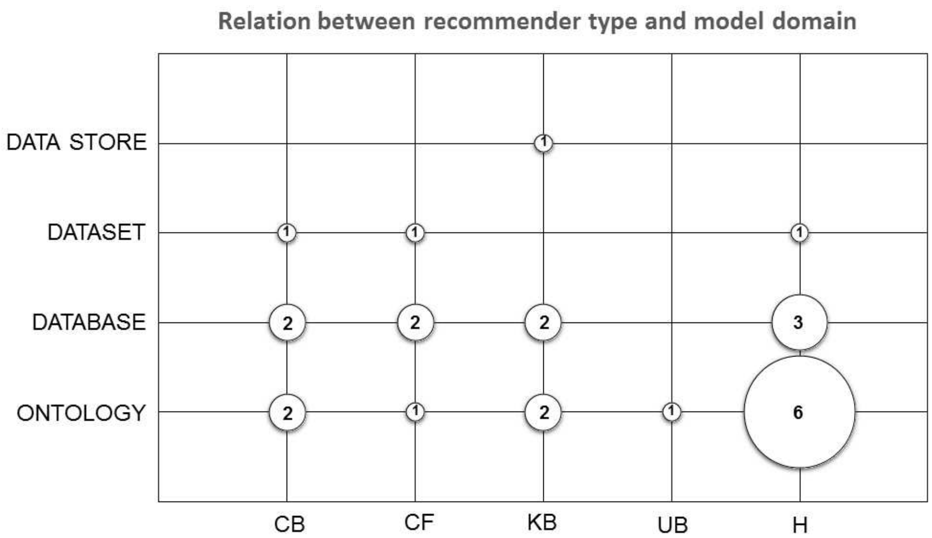

Figure 3. Relation between recommender type and model domain.

In addition to the above two assessment criteria, the application domain also represents a general criterion. By means of this property, we intent to identify whether the recommender system can be applied to any domain (general) or a specific domain. Moreover, if the recommender system admits only a concrete domain, we are interested in knowing which this domain is. In this survey, specific domains are classified into (1) health, (2) language & music, (3) social media & television and (4) employment & teamwork. Recommender systems in health area are hugely popular (Grer et al. 2016; Ali et al. 2017). However, we can only find one recommender system work based on competences applied to this area (Khobreh et al. 2013). In relation to language and music, recommender systems facilitate the resource's choice. In this sense, Mao et al. (2015) proposed a competence-based song recommendation system, Guan et al. (2017) provided a Karaoke recommender system and Torre and Torsani (2016) provided users with a step-by-step recommendation for computer-assisted language learning. As far as social media and television is concerned, Di Valentin et al. (2015) presented a recommender system prototype for recommending social media contents and Duran et al. (2016) proposed a system for recommending TV programs. Concerning the employment and teamwork area, four proposal were located. Isaias and Casaca (2010) developed a recommender system to assign tasks in accordance with the human resources. Later, Damiani et al. (2015) studied the impact of recommender systems on team processes. Also, Wang (2016) implemented a recommender system by exploiting diverse collaborative traces in a collaborative workspace. Finally, Bañeres and Conesa (2017) proposed a system to promote employability by recommending knowledge and skills improvements. The rest of the proposals (60%) implemented a general domain recommender system. Consequently, their implementation is not limited to one specific area. A pie diagram to illustrate the frequency of each domain is shown in Figure 4.

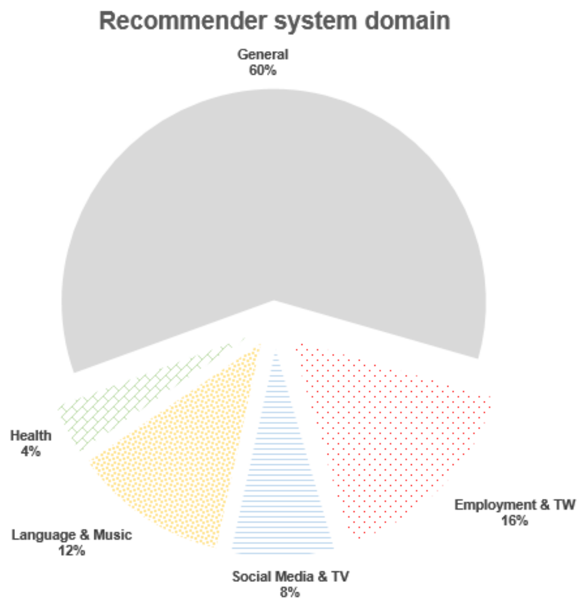

Figure 4. Recommender system domain.

5.1.2. *Set of criteria 2: Target user, Implementation and Goal*

One of the main features of any recommender system is its target user. In learning environments, most of the proposals are addressed either (i) to the person who receives the learning (e.g., learner, student, apprentice) or (ii) the person who transmits the learning (e.g., instructor, professor, teacher, lecturer). The major advantage of a student-directed recommender system is the direct interaction between the system and the person who benefits from the learning process. Whereas its main disadvantage is the loss of control of the provided recommendations. The teacher-directed approach facilitates that all the learners benefit from the recommendations. Nevertheless, instructors from massive courses may not manage properly so many recommendations. There is another alternative which consists of providing learners and instructors with recommendations. Both target users receive recommendations in two of the analysed works (Santos and Boticario 2008; Valentin et al. 2015). The authors of four proposals analysed in the SLR decided to provide the recommendation only to the tutor (Isaias, Casaca, and Pifano 2010; Colomo-Palacios et al. 2012; Koch and Landes 2014; Torre and Torsani 2016). The rest of the proposals are directed to the learner.

With regard to the implementation, three features are scrutinised. The first one represents the implementation's degree of the recommender system: fully implemented, prototype or implemented theory. In this survey, 60% of the works were identified as a prototype and 40% were totally implemented. With respect to the integration level, there are stand-alone systems (64%), recommender systems embedded in other systems (32%) and others that allow both integration levels (4%). This last case is the proposal from Duran et al. (2016) whose recommendations may be embedded in the television or accessible through a Web application. Concerning the access type, we distinguish three possibilities: web-based application, desktop application or both. As expected, all the analysed proposals included a web-based application as it facilitates the communication between the recommender system and the users. In addition to the online access, two proposals included a desktop program (Mao et al. 2015; Duran et al. 2016). A column chart to summarize the information about the implementation is shown in Figure 5.

Additionally to previous criteria, one of the most attractive features of any recommender system is its *goal*. This criterion describes the system recommendation and how it is shown (e.g., individually or through a list). In this SLR, we grouped the information into six categories according to the recommendation's item. First cluster meets the proposals that recommend, among others,

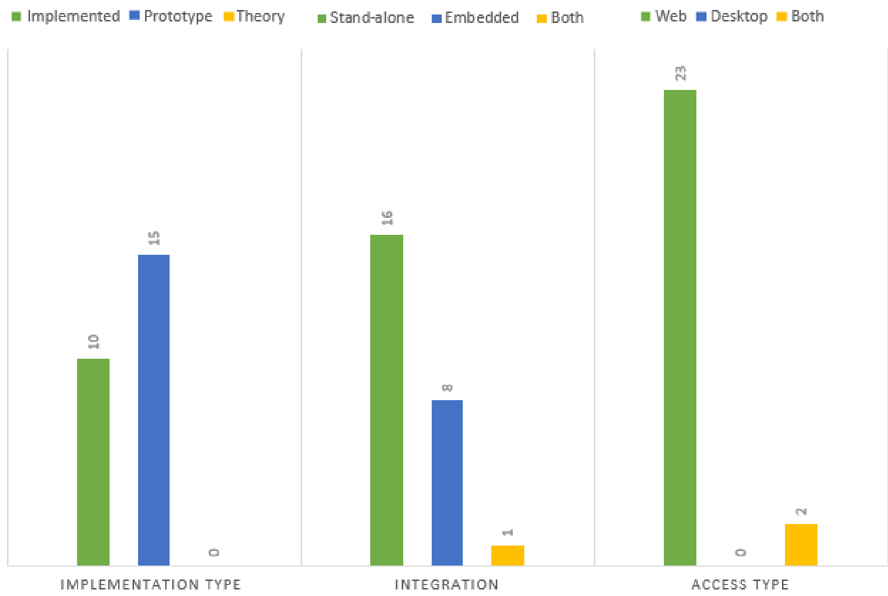

Figure 5. Implementation of recommender systems.

an expert user (Aimeur, Onana, and Saleman 2007; Sielis et al. 2011; Emmenegger et al. 2016). Second category contains the works that recommend any kind of resource. In this latter group, there are proposals recommending learning objects (Rodríguez, Ovalle, and Duque 2015), learning materials (Khobreh et al. 2013), general resources (Paquette 2016; Sielis et al. 2011; Valentin et al. 2015) or others (Torre and Torsani 2016; Guan et al. 2017). The third cluster includes the course recommendation's system from student's information, mainly, profile and competences (Koch and Landes 2014; Montuschi et al. 2015; Baneres and Conesa 2017; Bakhshinategh et al. 2017). The following category is related to the task distribution recommendation by taking into account previous traces (events, experience), profile and competences (Isaias, Casaca, and Pifano 2010; Florian and Fabregat 2011; Colomo-Palacios et al. 2012; Damiani et al. 2015; Wang 2016). Fifth cluster incorporates the works which recommend competences, learning goals or learning outcomes. This recommendation is based on the learning profile (Aimeur, Onana, and Saleman 2007) or competency state (Cazella et al. 2014). The last cluster comprises the recommendation of activities or actions. Recommender systems from this group use mainly competences and profile information to perform the recommendation (Santos and Boticario 2008; Isaias, Casaca, and Pifano 2010; Torre and Torsani 2016). All previous information is represented in Figure 6, in which the relation between the final recommendation and factors (user's profile, competences, previous traces and others) obtained from the analysed works in this SLR is outlined.

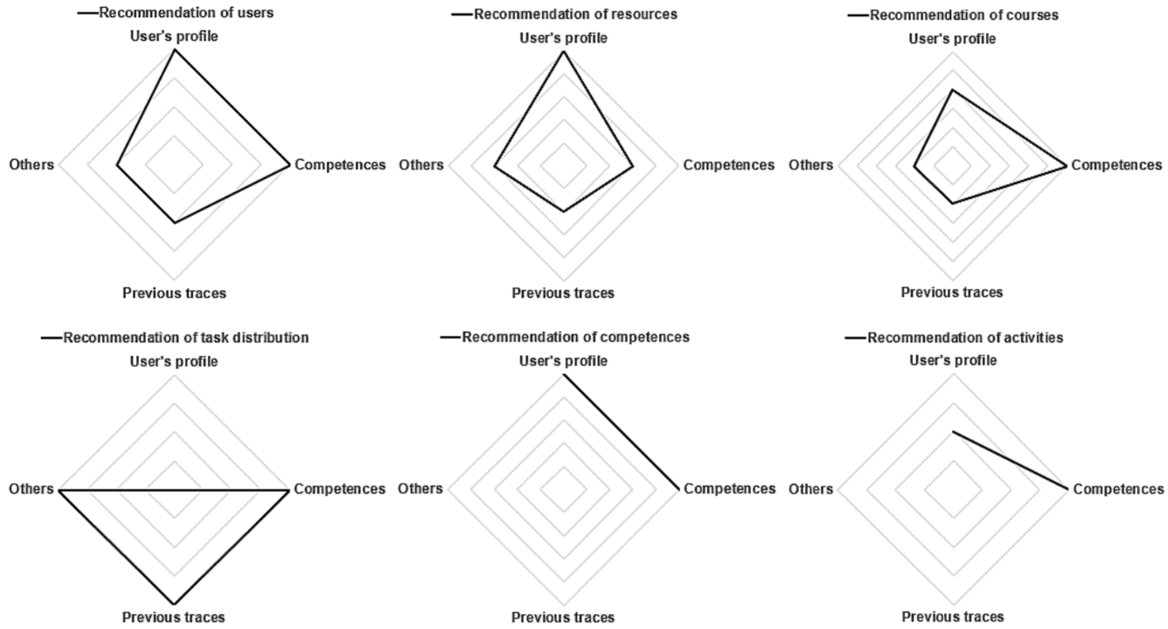

Figure 6. Recommender by features.

5.1.3. Set of criteria 3: Feedback, Coverage, Risk, Robustness, Adaptivity and Scalability

Two criteria closely related to the user include *feedback* and *satisfaction*. The first one studies whether the final user provides the system with information about its recommendations. In this sense, only 5 out of 25 proposals included this functionality to enhance future recommendations (Aimeur, Onana, and Saleman 2007; Santos and Boticario 2008; Cazella et al. 2014; Wang 2016; Duran et al. 2016). The second one evaluated the user's satisfaction with the recommender system. Most of the analysed proposals did not provide information about the user's opinion. However, five works considered this criterion. Sielis et al. (2011) asked the participants to fill two questionnaires which included six 7-level likert scale items obtaining promising results. Bañeres and Conesa (2017) carried out an opinion survey including five 5-level likert scale items. The results of this study are above average. Capuano et al. (2014) applied a 13 questions' questionnaire based on a 5-point likert's scale to evaluate its recommender system obtaining an average of 60.78 out of 100. The authors considered this mark a good score since the recommender system was only a prototype. Florian and Fabregat (2011) performed an opinion survey composed of five questions and 4-level likert items. The satisfaction with the recommendations in this survey was 55%. Santos and Boticario (2008) analysed the user's experience taking into account different features. A total of 90% of their users considered the recommender system very useful. Furthermore, they preferred (1) not to receive recommendations, (2) to receive recommendations from learning styles or (3) receiving them regarding the accessibility.

Finally, the last set of criteria related to the first research question assesses the *coverage*, *risk*, *robustness*, *adaptivity* and *scalability* parameters. These are evaluated into low level (-), high level (+) or if a parameter is not clear in the study, it will be identified as an interrogation symbol (?). The value of all these parameters in all the proposals is shown in Table 4.

Table 4. Common features in the analysed recommender systems.

RS	**Coverage**	**Risk**	**Robustness**	**Adaptivity**	**Scalability**
Sielis et al. (2011)	+	-	?	+	+
Bakhshinategh et al. (2017)	+	?	-	+	-
Baneres and Conesa (2017)	-	-	-	+	+
Chavarriaga, Florian-Gaviria, and Solarte (2014)	+	+	+	-	+
Montuschi et al. (2015)	+	-	-	-	-
Duran et al. (2016)	-	+	?	+	-
Rodríguez, Ovalle, and Duque (2015)	+	-	+	+	+
Torre and Torsani (2016)	?	-	?	+	+
Koch and Landes (2014)	-	-	+	-	+
Valentin et al. (2015)	+	-	?	+	+
Khobreh et al. (2013)	?	-	?	+	+
Damiani et al. (2015)	+	?	?	-	+
Mao et al. (2015)	-	-	-	?	+
Paquette (2016)	+	-	?	+	+
Cazella et al. (2014)	?	+	+	+	?
Guan et al. (2017)	-	-	+	?	+
Capuano et al. (2014)	-	+	-	+	+
Aimeur, Onana, and Saleman (2007)	+	-	?	+	?
Serrano, Romero, and Olivas (2013)	+	-	+	-	-
Isaias, Casaca, and Pifano (2010)	+	+	?	+	+
Colomo-Palacios et al. (2012)	?	-	+	+	-
Wang (2016)	?	+	+	+	-
Florian and Fabregat (2011)	?	-	+	+	?
Santos and Boticario (2008)	?	-	+	+	+
Emmenegger et al. (2016)	?	-	+	+	?

5.2. *RQ2: What is the nature of competences in the current competence-based recommender systems?*

Despite the fact that all the examined proposals are competence-based recommender systems, each proposal includes competences characterised in a different way. Therefore, we evaluate the nature of competences through the following questions:

(1) Does the recommender system take into account the more widespread taxonomies of competences in the literature at cognitive, affective, psycho-motor, social or productive meta-domains?

Nowadays, there are multiple classifications of competences. One of the most popular considers meta-domains. Concerning this classification, some of the analysed proposals embrace only a fragment of a meta-domain without considering any taxonomy (Koch and Landes 2014; Mao et al. 2015; Guan et al. 2017). Others support diverse domains (Colomo-Palacios et al. 2012; Cazella et al. 2014; Torre and Torsani 2016) by means of IPMA[4] or CEFR standards[5]. Most of the proposals left allow the definition of competences in almost all meta-domains. For instance, the EQF admits the definition of any competence and it is employed in the works of Montuschi et al. (2015), Florian and Fabregat (2011), Chavarriaga et al. (2014) and Emmenegger et al. (2016). Paquette (2016) and Wang (2016) proposals use the Paquette skill's taxonomy which lets us define competences in cognitive, affective, psychomotor and social meta-domains. The RDCEO is the standard chosen by Duran et al. (2016) to model the competences of all domains. Other proposals were not based on extensive competence's taxonomies but admit competences from different meta-domains such as the ones by Khobreh et al. (2013), Serrano et al. (2013), Valentin et al. (2015) and Baneres and Conesa (2017). The rest of the proposals do not provide enough information to know the meta-domains included on them.

(2) When are the competence states valid indicators of the achievement level reached by the learner?

The evolution of state of the competences allows us to detect anomalies or disorders which may arise during the learning process. However, it is often not possible to check it as the needed information is only available at the end of the process, i.e., a track of the state of the competence progress is not kept (Colomo-Palacios et al. 2012; Serrano, Romero, and Olivas 2013; Koch and Landes 2014; Cazella et al. 2014; Montuschi et al. 2015; Damiani et al. 2015; Bakhshinategh et al. 2017). In spite of the difficulties to manage information during the learning process, some proposals facilitate intermediate recommendations (Santos and Boticario 2008; Sielis et al. 2011; Khobreh et al. 2013; Capuano et al. 2014; Chavarriaga, Florian-Gaviria, and Solarte 2014; Rodríguez, Ovalle, and Duque 2015; Paquette 2016; Torre and Torsani 2016; Wang 2016; Emmenegger et al. 2016; Duran et al. 2016). Finally, the rest of the proposals do not offer information concerning the state of the competences or do not provide enough information.

[4] `http://www.ipma-usa.org/`
[5] `https://www.coe.int/en/web/common-european-framework-reference-languages/`

(3) Does the recommender system take into account the information regarding the state of the competences to guide the student about what competences require more attention to be achieved?

As illustrated in this paper, many recommender systems are based on competences. Nevertheless, only a few of them consider that not all the competences are equally important. For example, Paquette (2016) implements a methodology to first value the competence's level and second, compare the expected level and current student's level of a competence. This idea is also implemented by Wang (2016). In addition to these works, Serrano et al. (2013) and Colomo-Palacios et al. (2012) proposals are ready to contemplate the competence levels and in turn, detect the most important competences for a student in a specific learning activity.

(4) Do the instructors evaluate the competences in depth (desired level, context, complexity, scope, etc.)?

Each competence can be reached or not in different ways. For example, driving a vehicle can be considered a general skill, but it is not the same when driving at night, on a snowy road or in the city. For this reason, it is a good practice that instructors describe accurately the criteria needed to achieve a competence including the number of attempts, level of assistance allowed, the need to overcome the competence partially or totally, etc. Only few proposals provide information regarding these features. The most outstanding work concerning this idea is Paquette's proposal which identifies the scope, frequency, complexity, autonomy and context as performance indicators for each skill (Paquette 2016). Montuschi et al. (2015) considered that learning outcomes can be achieved with different level of performance. Shou et al. (2015) measured properties from the indicators to evaluate it. For instance, the value of pitch is obtained from the combination of semitone scale and intensity. Colomo-Palacios et al. (2012) classified competences according to the level of need (essential, desirable, not desirable).

(5) How does the state of competences of a student is initially set?

The most common problem related to recommender systems is its initial state. As far as competences are concerned, the initial state of competences is sometimes obtained by means of a questionnaire (Colomo-Palacios et al. 2012; Cazella et al. 2014; Damiani et al. 2015; Mao et al. 2015; Guan et al. 2017). Other recommender systems require students to fill out the data before providing any recommendation (Aimeur, Onana, and Saleman 2007; Paquette

2016; Montuschi et al. 2015; Wang 2016; Baneres and Conesa 2017). Finally, the rest of the works use previous information to provide recommendations. If there is no previous data, these proposals start with an empty system until information is added.

(6) Does the recommender system take into account the active participation of learners regarding competences in the recommendation process?

Learners are usually the final users in recommender systems, and even when recommendations are not addressed to them directly, they are targeted to improve their learning. Thus, many systems consider the active participation of learners in the recommendation process. In these cases, it is possible the related data input by the user. For example, competences are manually introduced by the user in Sielis et al. (2011) proposal. Baneres and Conesa (2017) implement a system that enables the introduction of skills. Competency gaps are detected in Montuschi et al. (2015) work by analysing the summaries entered by the learners. Paquette's recommender system requests the students to enter their current performance level in the set of competences related to the learning activity. Strongly related to last proposal, Capuano et al. (2014) developed a system in which the students can express their formative needs to keep control about their learning. Other works contemplate the possibility that students assess the information. For example, in Bakhshinategh et al. (2017) proposal, learners must rate their improvement in the graduating attributes (qualities, skills, etc.). Criteria related to cognitive, social, affective and productive competences of experts are assessed by the users in the HELP system (Aimeur, Onana, and Saleman 2007). Recommendations of Wang's proposal are produced according to the assessment of the resources performed by users (Wang 2016). Finally, students can evaluate their performance level in different learning experiences to obtain their level in the distinct learning outcomes (Florian and Fabregat 2011).

(7) Does the system provide the user with recommendations of different granularity levels?

The level of detail provided by recommendations is many cases as significant as actual recommendations themselves. Whilst learners frequently need general advices, sometimes they also require more specific recommendations. To handle this problem, some authors include recommendations of diverse granularity levels. Chavarriaga et al. (2014) recommended the execution of activities regarding the student's competences at different levels. In this proposal, recommendations can be more general such as "read chapter three", or more specific such as "read pages 15-18". Montuschi et al. (2015) analysed the required learning outcomes and the availability from the job seeker to offer more general courses such as "introduction to cooking" or more specific such as "bartender". In spite of ReSySTER recommends finally team formations, competences can be defined to different granularity levels (Colomo-Palacios et al. 2012). Therefore, the detail level influences the final recommendation. Santos and Boticario (2008) implemented one of the most granular recommender system. In this system, the users can receive recommendations to, for instance, read a resource, a comment, a file, a message or a FAQ, general advices as "work on objective" or specific recommendations like "see a user model".

Table 5 shows in a synthesized way all the competence's features previosuly analysed.

Table 5. Competence features in the analysed recommender systems.

Recommender System	**Meta-domains**						**Rec. during the learning**	**Rec. after the learning**	**State of competences**	**Competences evaluation**	**Initial state**	**Active participation**	**Granularity levels**
	C	A	Ps	S	Pr	E							
Sielis et al. (2011)	?	?	?	?	?	?	✓	✓	×	×	×	✓	×
Bakhshinategh et al. (2017)	?	?	?	?	?	?	×	✓	×	×	×	✓	×
Baneres and Conesa (2017)	✓	✓	✓	✓	✓	✓	?	?	×	×	M	✓	×
Chavarriaga, Florian-Gaviria, and Solarte (2014)	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓
Montuschi et al. (2015)	✓	✓	✓	✓	✓	✓	×	✓	×	✓	M	✓	✓
Duran et al. (2016)	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	×
Rodríguez, Ovalle, and Duque (2015)	?	?	?	?	?	?	✓	✓	×	×	×	×	×
Torre and Torsani (2016)	✓	×	×	✓	×	×	✓	✓	×	×	×	×	×
Koch and Landes (2014)	✓	×	×	×	×	×	×	✓	×	×	×	×	×
Valentin et al. (2015)	✓	✓	✓	✓	✓	✓	?	?	×	×	×	×	×
Khobreh et al. (2013)	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	×
Damiani et al. (2015)	?	?	?	?	?	?	×	✓	×	×	Q	×	×
Mao et al. (2015)	×	×	✓	×	×	×	?	?	×	✓	Q	×	×
Paquette (2016)	✓	✓	✓	✓	×	×	✓	✓	✓	✓	M	✓	×
Cazella et al. (2014)	×	×	×	✓	✓	×	×	✓	×	×	Q	×	×
Guan et al. (2017)	×	×	✓	×	×	×	?	?	×	×	Q	×	×
Capuano et al. (2014)	?	?	?	?	?	?	✓	✓	×	×	×	✓	×
Aimeur, Onana, and Saleman (2007)	?	?	?	?	?	?	?	?	×	×	M	✓	×
Serrano, Romero, and Olivas (2013)	✓	✓	✓	✓	✓	✓	×	✓	✓	×	×	×	×
Isaias, Casaca, and Pifano (2010)	?	?	?	?	?	?	?	?	×	×	×	×	×
Colomo-Palacios et al. (2012)	✓	✓	✓	✓	✓	✓	×	✓	✓	✓	Q	×	✓
Wang (2016)	✓	✓	✓	✓	×	×	✓	✓	✓	×	M	✓	×
Florian and Fabregat (2011)	?	?	?	?	?	?	?	?	×	×	×	✓	×
Santos and Boticario (2008)	?	?	?	?	?	?	✓	✓	×	×	×	×	✓
Emmenegger et al. (2016)	✓	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	×

(C) Cognitive (A) Affective (PS) Psychomotor (S) Social (Pr) Productive (E) Ethical, (Q) Questionnaires (M) Manually

6. Discussion

After studying the selected works, a critical analysis was carried out to check the strengths and weakness of the revised proposals (see Section 6.1). This analysis focused on the three research questions, i.e, the criteria assessment, the nature of competences and the emerging challenges. Additionally, Section 6.2 includes the strengths and limitations of the proposed work.

6.1. *Principal findings*

Regarding the criteria assessment, proposals address the common recommender system pitfalls (e.g., cold start, overspecialisation or black sheep). In this line, the domain model acquires special relevance. The more significant information concerning the learner the system has, the larger the number of recommendations it can provide. We consider that ontologies are the best instrument to record the learner's information because: (1) ontologies can be easily extended if new student's data must be incorporated; (2) ontologies are based on registered information that easily enables reasoning by means of rules as well as lot of tools for its management; (3) ontologies include the same advantages than other modelling techniques such as databases or datasets. Most of the authors agree with this idea and, therefore, many of the proposals are based on ontologies. However, the scope of the ontologies largely varies among the different studies and proposals.

The recommender system type is also a determining factor so that, for example, content-based systems frequently suffer from the *cold start* and *overspecialisation* problems. The *cold start* problem is usually solved by providing previously the needed data (Serrano, Romero, and Olivas 2013) and *overspecialisation* can be solved by taking into account easily fickle information such as student's profile. However, collaborative filtering recommender systems may suffer from *cold start*, *sparsity*, *black and grey sheep* problems. As a result, the *coverage* and *scalability* are often the most affected properties. The analysed systems confirm this supposition since the proposal's weaknesses are related to these pitfalls. Knowledge-based systems require an initial effort to get a quality recommendation set of items, for instance, a very specific query may provide an empty set of elements and, moreover, they must address the overspecialisation problem. As we identified in the survey, the most affected properties in KB systems are *coverage*, *robustness* and *scalability*. Finally, the main problem of hybrid recommender systems is related to the *scalability*. These systems combine two or more techniques and the information processing is slower than in the rest of techniques. Therefore, they usually suffer if the amount of data to process is high. Most of the analysed hybrid approaches use ontology data models because the information registered on it can be automatically inferred and accordingly, *scalability* is improved.

We next emphasize the nature of competences in recommender systems. In this regard, competences can be reached in formal or informal learning activities and they comprise any meta-domain. For example, "is able to make good decisions" is a productive competence related to leadership that can be properly achieved in a business experience and "is able to apply the Pythagoras' theorem to find missing lengths of a triangle" is a cognitive competence to be often achieved during the maths problem resolution. For this reason, a complete recommender system based on competences should provide the ability to incorporate objectives, outcomes or competences into any possible meta-domain. In this context, the use of standards such as IMS RDCEO or EQF to model competences facilitates the understanding and extensibility of the recommender systems.

This paper also discusses the relevance of assessment process in competence-based recommender systems. It is worth noting that diagnostic assessment reduces the *cold start* problem, but recommendations are less reliable since the available information is rather limited. Although an adequate formative assessment requires a monitoring or a competences state progress trace for each student and this can entails the additional complexity to infer the objective state for each student and register the trace of these states in the data model, it is appropriately significant if recommender system is adaptable to different learning environments such as IVETs (Clemente, Ramírez and de Antonio 2014). Finally, summative assessments help to detect the causes of the problems but only when the learning activities are already finished. Accordingly, the combination of the proper combination of the three kinds of assessments can be beneficial for the learning process.

It is also worth mentioning that the formative assessment is frequently carried out by the means of rubrics[6]. Furthermore, the assessment may be obtained by analysing the state of the objectives of a student at the beginning, during and at the end of a learning experience. By considering this complementary last assessment, more specific information about the student's knowledge state can be obtained, but this entails the additional complexity to infer the objective' state for each student and register the trace of these states in the data model. The combination of both, rubric and objective' state assessment is a real challenge for competence-based recommender system and its application would provide different granularity levels in the recommendations.

After studying the selected proposals, common challenges related to recommender systems and emerging challenges regarding the competence-based recommendations should be analysed to pro-

[6]Rubrics are objective scoring instruments which specify the assessment criteria and their performance levels in an activity.

vide recommender systems with better quality. As previously mentioned, the first challenge involves the recommendation of elements according different granularity levels. In this regard, the flexibility of recommender systems should provide feedback at early stages to tutor/student to address the difficulties, problems, conflicts or deviations that may arise during the learning process.

Further challenges refer to the assessment of competence achievement levels of a learner throughout the whole learning process. Users can demonstrate different performance levels concerning a knowledge or a skill depending on the context, complexity or learner's knowledge state. For instance, at any given time a learner can be absent-minded and performs wrongly an action related to a skill which he/she domains, or can be nervous and forgets a knowledge or can work hard and achieves the competence for himself/herself. Consequently, three emerging challenges arise from the competences assessment. The first emerging challenge consists of analysing how a competence can be assessed, i.e., the parameters that influence in the competence's evaluation (Paquette 2016). The second one faces how the competence achievement level for each student throughout the learning process is a crucial source of information to provide recommendations. Finally, the third emerging challenge focuses on how competence states require to be properly measured through the learning process just like validate such valuation.

6.2. *Strenghts and limitations of the proposed work*

One of the major strengths of this analysis is that we apply an extensive SLR methodology to review recommender systems from the point of view of an approach that has never been analysed to the extend of our knowledge. This approach, competence-based, is increasingly being applied in many learning institutions. Consequently, this research may be used as support for the development of new competence-based recommender systems. Another strength of this work is related to the inclusion and exclusion criteria. We did not limit the SLR with a particular type of recommender system, user target or model domain.

As far as weaknesses are concerned, the search of this work is limited to research articles, conference proceedings, book chapters or Ph.D thesis found in most popular digital libraries and search engines. We are aware that there are other competence-based recommender systems that (i) are not documented in a research paper yet, (ii) are published in a different digital library or search engine and/or (iii) are not included in the results of the search query defined in our proposal. Despite this fact, we consider that our research represents a comprehensive study of the current state of the art since we also take into account works identified in previous recommender system SLRs. A second limitation of our work is that more specific criteria of competence-based recommender systems can be taken into account. For instance, whether the analysed proposals can be applied to different learning environments, such as IVETs. In this regard, a second criteria can be, using a student model, the specific source information represented on this model to analyse the extent of recommendation flexibility. For example, this information can allow the inclusion of hints or instruction suggestions provided by the tutor or instructor in a virtual environment, etc. Finally, the proposed search query can be considered as a limitation factor of our work because other authors may use other terms like *learning objective* or *learning outcome* instead of *competence* or *competency*. Regarding this limitation, we did not include these keywords in the search query because we cannot consider that a recommender system is competence-based if the competence (or competency) keyword is not included in paper.

Comparing this SLR with previous ones we highlight our contributions as follows:

(1) The main contribution of this paper is that, despite the fact that there are many SLR about recommender systems, we did not find any about *competence-based* recommender systems. Consequently, to the extend of our knowledge, we provide the first literature review in an increasingly popular research area.
(2) A second contribution is that we propose seven criteria related to competences to compare the competence-based recommender system proposals.
(3) Another contribution of this research is related to the analysis of recommender systems. We extend the 14 criteria defined by Dascalu et al. to analyse the recommender systems with a new criterion, the *domain model*. We consider these criteria as essential indicators of the flexibility and completeness of recommendations.

7. Conclusions and future work

In this paper, we conducted a survey related to competence-based recommender systems in order to analyse the current state and emerging challenges in this context.

Competence-based learning is increasingly being deployed in many institutions and as a result, there are many proposals linked to competences during the last years. Among these proposals we focused on the competence-based recommender systems since they advise the students and instructors in the learning progress. On the one hand, students usually receive recommendations concerning resources or activities according to their profile, traces or similarities with other students. On the other hand, more effectively strategies such as *scaffolding*[7] or *self-regulation*[8] can be more easily applied during the learning process since the instructor can be provided with more information regarding the student's knowledge acquisition process.

Regarding the emerging challenges to be faced by the new competence-based recommender systems, overcoming the set of typical and smaller challenges should be considered. In this regard, we highlighted features such as flexibility, reusability, adaptivity, maintainability, robustness, security or scalability that currently should be taken into account in the development of any educational software. In addition to enumerated features, competence-based recommender systems should contemplate factors related to the sources, for instance, the choice of a suitable representation formalism, the extend of the employed taxonomies or competence standardization. Moreover, they should address the typical pitfalls of recommender systems, i.e., *cold start*, *black sheep*, *sparsity* or *overspecialisation* problems. Although previous features, factors and problems have been treated to a certain extent in many systems, the major challenge is to develop recommender systems that face all these challenges at the same time.

Overcoming the challenges stated above would provide a key support and encourage developers to face bigger and newer challenges as future work. These include: (1) to apply the recommender system to different environments, for instance, IVET where procedural learning is specially relevant, (2) to provide different granularity levels by means of coarse-grained recommendations based on performance criteria and competence; and fine-grained recommendations based on learner's competence achievement level throughout the learning process, (3) to establish, from a pedagogic point of view, how a competence must be assessed demonstrating the validity of the measurement and (4) to develop a common strategy for validating assessment models.

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[7]Tutoring strategy in which, the instructor gives the student only the necessary support in an attempt to transform the student in a more independent person regarding the learning.
[8]Tutoring strategy in which, the students decide what and how to learn.

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