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Review of ontology-based recommender systems in e-learning

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ABSTRACT

In recent years there has been an enormous increase in learning resources available online through massive open online courses and learning management systems. In this context, personalized resource recommendation has become an even more significant challenge, thereby increasing research in that direction. Recommender systems use ontology, artificial intelligence, among other techniques to provide personalized recommendations. Ontology is a way to model learners and learning resources, among others, which helps to retrieve details. This, in turn, generates more relevant materials to learners. Ontologies have benefits of reusability, reasoning ability, and supports inference mechanisms, which helps to provide enhanced recommendations. The comprehensive survey in this paper gives an overview of the research in progress using ontology to achieve personalization in recommender systems in the e-learning domain.

1. Introduction

Learning has seen a drastic shift from the traditional classroom to the e-learning platform.

E-learning is defined as learning that takes place utilizing electronic media, principally using the Internet. Other educational environments which are also gaining popularity include learning management system, adaptive hypermedia, and forums, among others. Mining data from the educational background is intended to predict student's performance and to group students according to their similarities. It also helps to detect undesirable behaviour in students and to recommend courses to them (Mohamad & Tasir, 2013; Romero & Ventura, 2010). Extracting such hidden data has become a massive need for the e-learning domain (Sanchez, 2011).

Educational data mining is an umbrella term under which recommender systems are used. Mining hugely available academics related data for i) analysis and ii) for recommending courses is known as Educational Data Mining (EDM). Learning Analytics (LA) gathers academics related data from different sources. Furthermore, meaningful information is extracted from the collected data. EDM and LA complement the working of a recommender system. Fig. 1 shows the relation between i) mining educational data, ii) applying learning analytics by academicians to discover knowledge, and iii) generating recommendations to learners (Sanchez, 2011). The big data available from the educational institutions are mined. Consequently, the mined data is used by administrators or decision-makers to get figurative feedback about several courses. The decision-makers can then pass on the required changes needed in the course to the pedagogues who are in charge of projecting and maintaining the course. The big data available from the educational institutions are also mined to generate recommendations for the students. Fig. 2 gives statistics on the popularity earned from the educational data mining field (Baker & Inventado, 2014). All educational research continues to revolve around analytics and data mining, which in turn leads to recommendations given by recommender systems.

The benefits of e-learning are mainly flexibility in time, takes into consideration the interest of the learner and the availability of quality resources that are free. However, the biggest problem faced by e-learning systems is the information overload on the Internet.

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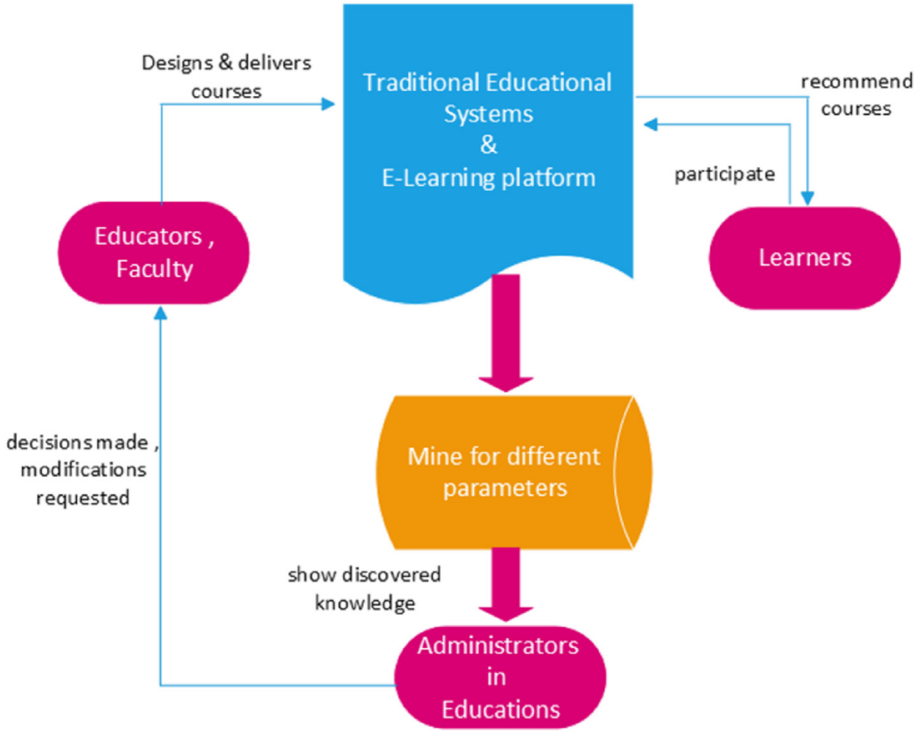


Fig. 1. Cycle of educational data mining.

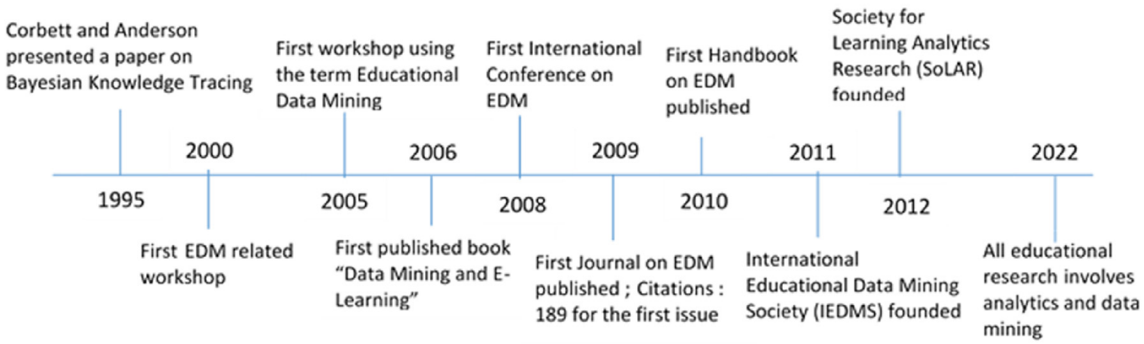


Fig. 2. Statistics on educational data mining.

The task of a recommender system in e-learning is to recommend relevant learning materials to the learners and help them in decision making (Aguilar, Valdiviezo-Díaz, & Riofrio, 2017). Recommender systems in e-learning is a branch of information retrieval where learning resources are filtered and presented to the learners (Chughtai, Selamat, Ghani, & Jung, 2014). Artificial intelligence is seen more in the forefront of research in retrieving and filtering of information. Recommender systems are a good example of using the artificial intelligence approach (Nilashi, Ibrahim, & Bagherifard, 2018). Recommender systems have a high success rate in the e-commerce domain. Recommender systems are seen across many other domains like movies, E-learning (Dascalu, Bodea, Mihailescu, Tanase, & Ordoñez de Pablos, 2016), E-business, E-government, E-library, E-tourism (Lu, Wu, Mao, Wang, & Zhang, 2015), and management science (Murthi & Sarkar, 2003). The interest in recommender systems is high, mainly due to the problem-rich research area, including the need for personalized recommendations (Adomavicius & Tuzhilin, 2005). Unfortunately, the algorithms underlying conventional recommender systems in other domains are not directly transferable to the area of e-learning. When comparing learning content to movies or books, the cognitive state of the learner and the learning content may change over time and context (Núñez-Valdéz et al., 2012).

Some common problems occur with traditional, non-personalized recommendations. A new user or new item can lead to a commonly referred problem known as cold-start. Cold-start occurs when it is not possible to make reliable recommendations due to an initial lack of ratings (Celdrán, Pérez, Clemente, & Pérez, 2016). This leads to no overlapping of ratings, which could have otherwise been used to suggest courses for the target learner (Shishehchi, Banihashem, Zin, Noah, & Malaysia, 2012). Rating sparsity is another problem where the number of users is high compared to the number of ratings. Hence to make recommendations for that item, with a very low number of ratings, becomes difficult. Scalability is yet another issue that occurs with the number of users, items mushrooming over the Internet (Paradarami, Bastian, & Wightman, 2017; Xiao, Wang, Jiang, & Li, 2018).

Resnick and Varian (1997) observed other issues in recommender systems like that of incentive problem and privacy. There are two incentive problems in recommender systems. Firstly, users who have established their profiles of interests may tend to get recommendations with the help of huge ratings that are available, i.e., the chance of free riding to occur is highly likely. So to avoid the phenomenon of free riding, the system offers an incentive that first the user should provide a recommendation as a pre-requisite to receiving recommendations, or the user provides a recommendation so that the user can get some incentive in monetary form. The second incentive problem occurring in recommender systems is if anyone can give recommendations, as stated above, content owners may generate a huge amount of positive recommendations for their content. Besides, they may try to generate negative ones against their competitors. Privacy is yet another concern where the users may not want their entire views, interests to be made available to the public.

Lack of proper student-support during the learning process, lack of appropriate content, and lack of personalization often lead the learner who is initially enthusiastic, to have less motivation, and thereby loses interest. Accordingly, Latham, Crockett, McLean, and Edmonds (2012), designed an intelligent tutoring system that predicts learner's learning style and suggests tutoring materials accordingly. The intelligent tutoring system helps a student to have a more positive learning experience. Having a personalized recommender system leads to more effective and efficient use of the wealth of information available over the Internet. When a learner browses for an online course with criteria like course name, many course suggestions are given. Therefore, this leads to the learner not being able to make a more informed choice. The low ratio of, students registering for the courses when compared to students completing those courses, is evidence for the same. Hence, personalized learning is meant to incorporate a learner's varied attributes, including learning style, knowledge level on a subject, preferences, and learner's prior knowledge. Learning style (Bernard, Chang, Popescu, & Graf, 2017; Fatahi, Moradi, & Kashani-Vahid, 2016; Hung, Chang, & Lin, 2016; Thalmann, 2014; Truong, 2016), learner profile, learner history, learner background knowledge are some of the factors that help for an adaptive, personalized recommender system in e-learning. In fact, there is a relationship between the learner's personality and his learning style; learner's performance and his learning style.

At the same time, one must keep in mind the different phases that exist in the e-learning cycle, which includes design, publication, use, and the auditing phase while designing courses. This assists in attracting learners and helping them finish the course they registered for (Santos & Boticario, 2015). Having adaptability in e-learning is beneficial to the learner. Several indicators show the effectiveness of adaptability that is possible in massive open online courses as noted by Leris, Sein-Echaluce, Hernandez, and Bueno (2017). The authors propose indicators like having the course content accessible according to the learner's choice; allowing the learner to study according to the learner's pace.

Table 1 highlights some of the papers in which user interests and ratings are used in recommender systems. An interesting finding is as the diversity in user's choices are included, the accuracy of the recommender system seems to improve (Hu, Zeng, & Shang, 2016). Knowledge of users' interests, preferences helps in personalization and thereby in getting better recommendations (Bennett, Collins-Thompson, Kelly, White, & Zhang, 2015).

Particularly, when it comes to e-learning, there is no single model for the learner profile or the structured content, which makes the need for ontology even more essential. Ontology is especially essential when interoperability of models is required. As defined by Gruber (1993), an ontology is "an explicit specification of a conceptualization." Another definition of ontology given by Agarwal (2005) is that "ontology is the manifestation of shared understanding of a domain that is agreed between a number of agents." Ontology is thought to be very important and useful for the development of Semantic Web (Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011; Martinez-Cruz, Blanco, & Vila, 2012; Ramakrishnan & Vijayan, 2014). Some of the limitations while using ontology in e-learning are i) creating ontology is time-consuming, ii) evaluating ontology-based recommender systems becomes difficult with no standard dataset available on e-learning, and iii) using ontology requires skills in knowledge engineering.

The purpose of the current study is to highlight the main research findings in recommender systems in the domain of e-learning. Mainly with the information overload existing on the Internet, the present study contributes to focus on those research papers that achieve personalization by using ontology. The main contribution of the paper is as follows:

1) Research findings in the area of recommender systems in the e-learning domain mainly during the period of 2010–2019. The distribution of journal papers covering exclusively on the topic of ontology and journal papers on the topic of ontology with E-learning has also been illustrated graphically.
2) The paper gives an overview of recommender systems in e-learning based on ontology and based on hybridization.
3) The paper also covers literature that discusses several techniques to calculate user similarity based on user interests.

Table 1
Highlight on papers covering user interests, ratings in recommender systems.

Reference	User Interests	Ratings
Cantador et al. (2008), Fraihat and Shambour (2015), Hawalah and Fasli (2014), Karpus et al. (2016), Tarus et al. (2017)	✓	✓
Harrathi et al. (2017), Margaris et al. (2018), Makwana et al. (2017), Obeid et al. (2018)	✓	
Nilashi et al. (2018)		✓

The categorization of this paper is as follows. Section 2 deals with the related work relevant to recommender systems. Section 3 introduces ontology-based recommender systems. Section 4 gives an overview of hybrid recommender systems in the e-learning domain. Section 5 presents recommender systems built using techniques other than ontology and other than hybridization. Finally, Section 6 concludes with direction for future work.

2. Related work

In this section, we give a summary of the research papers that were considered for the literature review and the methodology utilized for performing the review.

Tibaná-Herrera, Fernández-Bajón, and De Moya-Anegón (2018) conducted a study on the database indexed by SCOPUS using 64 descriptors related to e-learning. It concluded that the research trend over e-learning is shifting from technical to the educational context. However, with recommender systems extensively used in more domains, new research leads to new open problems, which lead to more research. Recommender systems are used in other areas successfully, but their adaptation to the e-learning becomes more complex (Montuschi, Lamberti, Gatteschi, & Demartini, 2015). Different technologies are used in the research area of recommender systems. Machine learning algorithms show to give high accuracy in the field of recommender systems. Detailed review which was done by Portugal, Alencar, and Cowan (2018) show that when machine learning algorithms are used to develop recommender systems, a majority of the papers reviewed use neighborhood-based collaborative filtering with supervised machine learning algorithms. Also, a quarter of the findings show a tendency towards collaborative filtering with clustering. Affective recommender systems are yet another trending area in recommender systems. These systems factor into account human emotions, moods, and other physiological parameters while suggesting recommendations. These recommender systems work using several algorithms like data mining, content-based filtering, collaborative filtering, and sentiment analysis, among others (Katarya & Verma, 2016).

The goal of this survey paper is to give a detailed understanding of the recommender system in the domain of e-learning developed in the last decade. For the purpose of the literature review done in this paper, journal articles across top-level electronic databases, including Springer, Elsevier, IEEE, ACM Digital Library, and Google Scholar were searched and downloaded. Comprehensive searches using keywords like "recommender system", "e-learning", "hybrid recommender system", "ontology", "ontology-based recommender system", "learning management system", "knowledge", "machine learning" were used to filter the searches. The papers were selected based on their relevance to the area under review. The inclusion criteria included: i) recommender system; ii) application domain area of e-learning; iii) published in leading journals and conferences. Considering the inclusion criteria resulted in 108 papers, of which 91 were from journal papers, 10 were from conference papers, and 5 were from books. Fig. 3(a) and (b) show the popularity of research in ontology and popularity of research on ontology and e-learning during 2010–2018, respectively.

Papers that do not integrate ontology has been included in this review paper for two reasons. Firstly, it is to highlight the other possible ways to design a recommender system. Secondly, the non-ontology based recommender systems have been included to make clear the issues those systems cannot address which ontology-based recommender systems can address.

3. Recommender systems in E-learning using techniques not involving ontology

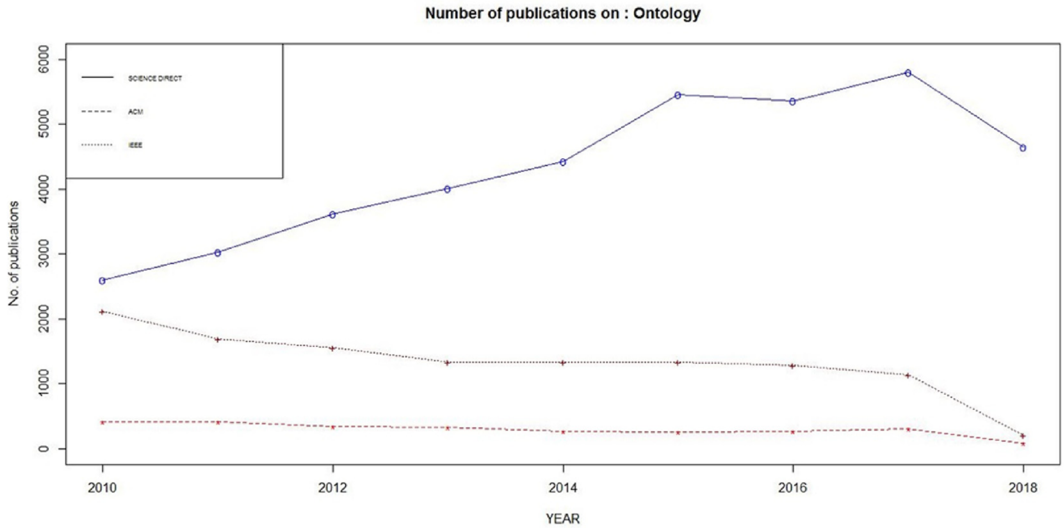
There are several works covering recommender systems in e-learning which use neither the concept of ontology nor hybridization. This section gives an overview of such papers. Christudas, Kirubakaran, and Thangaiah (2018) developed a way to deliver personalized e-learning content. For that reason, the authors integrate compatible genetic algorithm (CGA) over the learning objects and factor in the learning style, knowledge level, and interactivity level of the learner. Bousbahi and Chorfi (2015) proposed an architecture for personalizing the massive open online course based on Case-Based Reasoning (CBR) recommender system.

3.1. Matrix factorization based recommender system

Koren, Bell, and Volinsky (2009) described in detail the merits of using collaborative filtering, notably matrix factorization. The paper concludes that the matrix factorization model is more scalable, accurate, and flexible with an ability to accept varying levels of confidence. In yet another paper to integrate reliability when matrix factorizations are applied, a method using non-negative matrix factorization was employed using the known ratings. Next, an estimate of unknown ratings is predicted (Zhu, Ortega, Bobadilla, & Gutiérrez, 2018). The cross-validation technique was implemented to check the error of the proposed model with the reliability calculated as the inverse of the predicted errors.

3.2. Machine learning-based recommender systems

Imran, Belghis-Zadeh, Chang, and Graf (2016) worked out a system recommending personalized learning objects and generating recommendations by calculating Euclidean distance followed by association rule mining. Hussain, Zhu, Zhang, Abidi, and Ali (2019) developed a system using machine learning algorithms like Support Vector Machine, Logistic Regression, Naïve Bayes Classifier, and Artificial Neural Networks. This was done to predict students' difficulty while undergoing courses taken online, thereby giving indications to teachers who are using the Technology Enabled Learning (TEL) system. Colchester, Hagras, Alghazzawi, and Aldabbagh (2017) made an in-depth survey of the different artificial intelligence techniques like fuzzy logic, Bayesian networks, and



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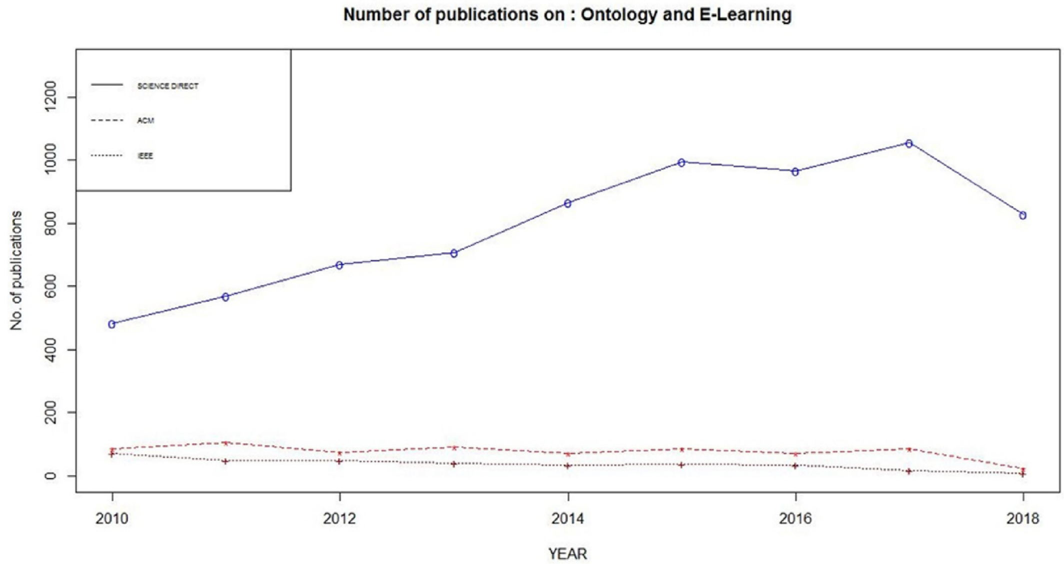

b

Fig. 3. (a) Number of publication using word ontology, Fig. 3b Number of publication using words ontology and e-learning.

genetic algorithms among others that could be employed in an adaptive, personalized e-learning system. Li et al. (2019) calculated the user-item category preferred ratio. The authors then clustered user's data that are based on the canopy algorithm and k-means algorithm. The similarity between the objective user and top-N users in that cluster are then calculated to generate prediction scores.

Q-learning, a reinforcement learning algorithm, is used in the web recommender system to overcome the information overload problem (Taghipour & Kardan, 2008, pp. 1164–1168). Since the Q-function cannot be used over large, continuous state-action and since the Q - function is derived from a finite set of tuples, a fitted Q-iteration is proposed. The fitted Q-iteration is used with functional networks (Gaeta, Orciuoli, Raritì, & Tomasiello, 2017). Functional networks (FN) are a type of artificial neural networks with additional features. An interesting approach to providing personalized recommendations was mining weblog and cache data, as seen in the works by Wang and Li (2006). Aguilar et al. (2017) created an intelligent recommender system (IRS) utilizing Fuzzy Cognitive Maps (FCM) to model the knowledge of learning resources. The IRS gives explanations for the recommendations by implementing knowledge acquisition, knowledge modeling, reasoning mechanism, and criticality mechanism.

3.3. User-based recommender systems

Recommender Systems often do not have enough information about a user to quantify the user's knowledge about a particular subject. Some recommended tools extract user knowledge from the user actions (Balabanovic, Shoham, & Yun, 1996; Wang & Li, 2006). Nt, Tomaz, De Souza, and Xexéo (2013) applies knowledge vector (which measures a user's knowledge about a subject) into the recommender system. Based on the user's knowledge, an item gets evaluated. The user's evaluation gets weighted based on the similarity between a user's knowledge vector and the item's term vector. Accordingly, the item gets recommended. A limitation observed by the authors is that of cold-start.

Ha and Lee (2017) designed a different collaborative filtering system that initially constructs a network for the user that is based on the user's history of used items. The betweenness centrality is calculated to understand the important items to the user. The closeness and degree centrality calculates the preference score for those items and ranks them to generate the recommended list of items. Bagher, Hassanpour, and Mashayekhi (2017) employed Table-based Similarity Dependent Chinese Restaurant Process in order to construct a trend vector which factors in the user profile and the user's evolving interests. Wang, Shao, Zhou, Wan, and Bouguettaya (2016) designed a framework to get personalized recommendations based on user's preferences using incomplete Conditional Preferences-networks (CP-net). In a further attempt to personalize learning resources to e-learners, Benhamdi, Babouri, and Chiky (2017), developed a new model, New multi-Personalized Recommender System for e-Learning (NPR-eL). The model takes into consideration a student's preference, level of study, and memory capacity while recommending.

3.4. Tag-based recommender system

Some of the benefits identified in the tag-based recommender system in the e-learning domain are enriched peer interactions, increased peer awareness around the learning content. Other benefits include allowing the learner to summarize his ideas, providing insight for the educators about the learners' comprehension and activity (Bateman, Brooks, Mccalla, & Brusilovsky, 2007; Doush, Alkhateeb, Maghayreh, Alsmadi, & Samarah, 2012). Tags help in the improvement of search and data mining of educational resources. Tag-based recommendation using ranking with tensor factorization helps to decrease running time for generating the recommendations and also to generate more personalized recommendations based on the learner's opinions or tags (Klašnja-Milićević, Ivanović, Vesin, & Budimac, 2018). Klašnja-Milićević, Ivanović, and Nanopoulos (2015) observed that collaborative tagging is employed as an approach for automatic analysis of user preference and recommendation.

3.5. Group-based recommender system

Recent trends have been focussing on recommending learning materials to a group of learners based on their common interests, preferences. In technical terms, recommendations here are based on score aggregation, preference aggregation (Amer-Yahia, Roy, Chawlat, Das, & Yu, 2009). Karataev and Zadorozhny (2017) proposed a framework to implement self-adaptive learning through teaching (SALT) framework based on the concept of crowdsourcing to a group of learners. Crowdsourcing technique occurs when the content consumers can become content contributors, depending on the control given by the respective web page.

Dwivedi and Bharadwaj (2015) proposed a unified learner profile (ULP) by integrating learning style, knowledge level into the profile merging scheme (PMS). This method aims at generating a common resource list to the group. Al-Rahmi and Zeki (2017) aimed at understanding the different factors that lead to better learning on the social media platform. Constructivism Theory and Technology Acceptance Model is used for the proposed model.

From the papers reviewed in this section, it becomes clear that there are a variety of ways that the recommender system can be designed other than the conventional techniques. Very novel approaches using functional networks, tag-based systems, genetic algorithm, and machine learning has been observed. However, when some approaches tackle the cold-start issue, those approaches may not be able to handle the lack of personalization issue, rating sparsity issue, and vice-versa. Hence, the next section reviews papers related to ontology in recommender system that can help solve some of the issues found in recommender systems.

4. Ontology-based recommender systems

The main aim of this section is to gain an overview of current research done in the field of e-learning, particularly applying ontologies. Ontology-based recommender systems are considered in this review paper, keeping in mind the benefits of ontology. Ontology can take different forms depending on the context. Ontology can represent a model using Web Ontology Language (OWL) among other languages; ontology can represent an XML schema in the context of a database (Falquet, Métral, Teller, & Tweed, 2011; Roussey, Pinet, Kang, & Corcho, 2011). The guidelines followed here for the systematic literature review (SLR) is based on the works of Xiao and Watson (2019).

Fig. 4 shows the different types of recommender systems (Aggarwal, 2016, pp. 1–28). Fig. 5 (Khanzode, 2015) shows the evolution of recommender systems from the basic collaborative based filtering, content-based filtering to the most used hybrid based filtering. Item hierarchy implies initially a user who buys a printer would next think of buying a cartridge. The attribute-based recommender system is used to consider a movie's genre and an actor from it. Based on those similar attributes, recommendations would be made. Collaborative filtering then came into the picture with two main types under it – based on similar items the user bought earlier and based on similar tastes users have. The next step of evolution occurred with ontology-based recommender systems being used to overcome the cold-start problem and to bring in a personalization angle. Social network-based recommender system was introduced later, which is based on the trust factor that exists between a user and his friends on a social networking site. The most recent and the trending recommender system is based on hybridizing existing techniques mentioned above to overcome limitations of individual techniques and hence come out stronger together.

Al-Yahya, George, and Alfaries (2015) conducted a literature review of ontology being applied in the e-learning domain. The

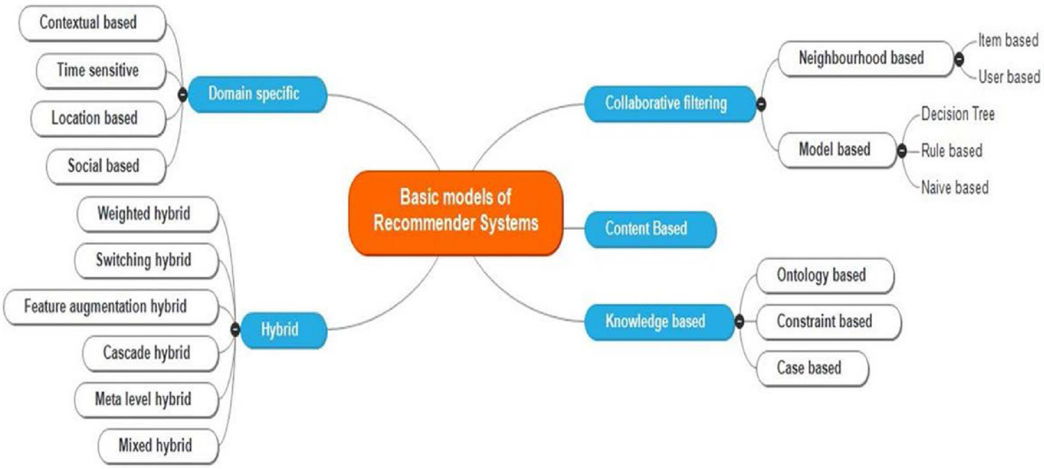

Fig. 4. Types of recommender systems.

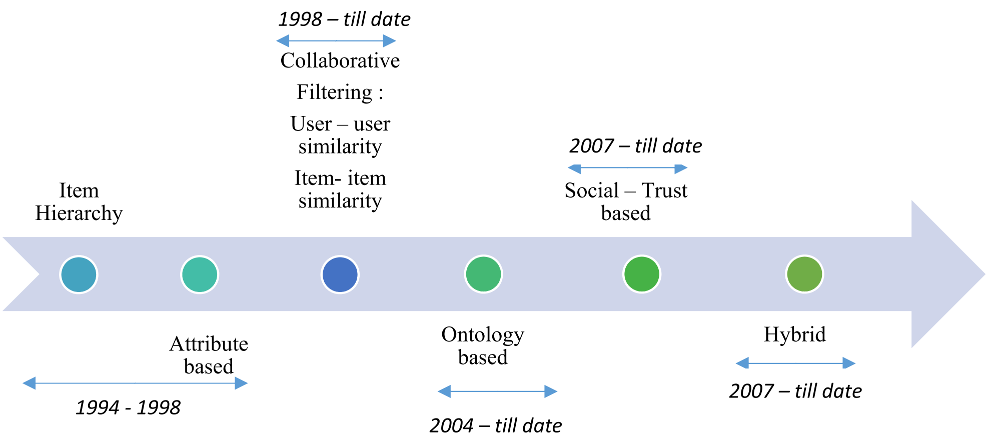

Fig. 5. Evolution of recommender systems.

authors' focus was mainly on curriculum modeling, describing learning domain, learner data, and the different standards in E-learning. Cakula and Sedleniece (2013) brought out the similarities of the concept of Knowledge Management (KM) and E-learning. The authors did this to improve knowledge transferring from the course content using ontology and other metadata standards. Cantador, Bellogín, and Castells (2008) designed a multi-layer hybrid form of recommendation by processing the ontology-based query and matching the query with the items.

Cerón-Figueroa et al. (2017) delved into the concept of ontology matching to check if two entities of different ontologies are the same. The proposal aims to share learning content among various search engines and learning management systems. The idea of ontology matching is mainly to discover meaning from heterogeneous data (Halpin & McNeill, 2013). Fraihat and Shambour (2015) designed a framework to store learning objects, to classify the learning objects, and to generate semantic recommendations based on ontology. Harrathi, Touzani, and Braham (2017, pp. 49–54) proposed a system that recommends learning activities. The authors use the ontology to represent the learner profile, domain model, and learning activities.

Hawalah and Fasli (2014) created a contextual-aware personalized system (CAPS). The interesting concepts within a context entity are weighted and then passed to the contextual, personalized ontological profile (CPOP). Karpus, Vagliano, Goczyła, and Morisio (2016) designed a context-aware recommender system that uses two ontologies, namely Recommender System Context Ontology (RSCtx) and the Contextual Ontological User Preferences ontology (COUP). The generated recommendations are based on the context that fits into the user profile. Labib, Canós, and Penadés (2017) designed an ontology to extract relationships between different learning style dimensions. Consequently, the ontology is used to relate the learning style to learner's characteristics. Lv, Hu, and Chen (2016) created a framework to integrate relational data by using ontology. A genetic algorithm is then implemented to perform the recommendation.

Martinez-Cruz, Porcel, Bernabé-Moreno, and Herrera-Viedma (2015) designed a recommender system using ontology and fuzzy linguistic modeling. The ontology is used to display the degree of satisfaction of the users. When the degree of satisfaction is not explicitly stated, the trust factor gets computed using linguistic modeling. Montuschi et al. (2015) described a semantics-based recommender system for adaptive learning. Ontology is used with a focus on the learning outcome. Nilashi et al. (2018) proposed a recommender system framework by integrating collaborative filtering and dimensionality reduction. An ontology is used in order to describe the semantic relations between the concepts.

Obeid, Lahoud, El Khoury, and Champin (2018) generated personalized recommendations by creating ontologies for the higher educational institutions, students, and employees. Machine learning techniques are then implemented to cluster similar graduate students. Next, the clustered students' data are sent to the hybrid recommendation engine.

Ouf, Ellatif, Salama, and Helmy (2017) developed a framework for personalizing e-learning resources by suggesting four ontologies to represent the learner, learner object, learning activities, and teaching method. Furthermore, the personalization dimension is added by using rules over the ontologies. Pukkhem (2013) designed multiple agents-based learning object recommendation system by utilizing ontologies for the agents. Rani, Nayak, and Vyas (2015) created an ontology for the learning style based on the Felder-Silverman learning style model. The multi-agents concept is used for personalization of the recommender system. Saleena and Srivatsa (2015) designed an adaptive learning system by utilizing a fuzzy domain ontology and domain expert's ontology. Shishehchi et al. (2012) used ontologies to understand more about the learners and learning resources like extracting the prerequisites for the topics searched, background knowledge, and learning styles of the learners. Suguna, Sundaravadivelu, and Gomathi (2016) proposed a semantic web search mechanism by evaluating different ontology-based text mining techniques.

Tarus, Niu, and Yousif (2017) performed a hybrid method of providing a recommendation. The authors implement ontology over the learners, learning resources. The sequential pattern mining is integrated to identify the learner's historical sequential pattern from weblogs. Tarus, Niu, and Mustafa (2018) presented an in-detailed review of several ontology-based recommender systems during the period 2005 to 2014. The authors' main finding is that the majority of the ontology-based recommender systems reviewed apply domain ontology and web ontology language for modeling. Werner, Cruz, and Nicolle (2013) used the idea that text can help in ontology learning, ontology population. Consequently, the ontology can help for annotating the text, thereby giving users a set of reviews that are customized according to the user profile.

Makwana, Patel, and Shah (2017) personalizes a user's web search in three phases. In the first phase, a weblog file is generated using the user's clicks. The weblog file is then analyzed to generate a knowledge base. The knowledge base is created in the form of ontology. Next, ontology mapping is done between items using item-item collaborative filtering. Weng and Chang (2008) proposed a recommender system by utilizing ontology and spreading activation. The ontology helps in creating a user profile. The spreading activation is applied to understand other influential users in the learner's network. Dascalu et al. (2016) proposed a recommender system to help learners within professional communities. The user's details are extracted when the user logs into Protégé through the LinkedIn profile. Furthermore, the details are added as instances in an ontology.

Hong, Suh, Kim, & Kim (2009) implemented a framework to provide personalized services based on user's information which are stored in ontologies. As a result, the user's information is used to infer contextual information. Association rules are inferred to generate recommendations based on user preferences. Huang, Liu, Tang, and Lu (2011) designed a way to integrate personalization in e-learning by using three ontologies that look into the learner, course, and learning objects. The effectiveness is checked by matching the learner's characteristics and learning object ontology. Bouihi and Bahaj (2017) designed a semantic layer to be integrated into the current e-learning platforms. The semantic layer has three ontologies to incorporate the learner's learning context, learning object, and learning content.

Yanes, Sassi, and Ghezala (2017) proposed an ontology-based recommender system for software engineering that uses Commercial-Off-The-Shelf (COTS) components. An ontology is used to represent the COTS components while a user model is designed to represent the user's interests. Di Noia, Magarelli, Maurino, Palmonari, and Rula (2018) considered different Resource Description Framework (RDF) properties as features. Different feature selection techniques like information gain, principal component analysis were applied. The features obtained from the feature selection techniques are given as input to the content-based recommendation algorithm. The Jaccard index is used to compute the similarity between the items. The authors then compare the output with ABSTAT. ABSTAT is a schema summarization tool which performs ontology-based summarization over linked data. The linked data is a knowledge graph which is seen as an important source of information to feed into a recommendation engine.

Table 2 gives categorization of recommender systems that use ontology.

4.1. Cold-start issue

Cold-start is an issue faced by traditional recommender systems which occur due to lack of the initial ratings for a new product or a new user. Further, it becomes difficult to recommend new products or make recommendations for new users. Cakula and Sedleniece (2013) attempt to solve the cold-start problem by using ontologies. The ontologies are used to query multiple repositories in order to realize associations which are not directly visible between the learning objects. Fraihat and Shambour (2015) solve the cold-start problem by utilizing the semantic relation between learning objects and learning activities. Their recommendation is not based only on ratings. Harrathi et al. (2017, pp. 49–54) solve the cold-start problem by using the hybridized approach. The authors suggest learning activities which have been modeled in the proposed ontology and do not rely only on ratings. Lv et al. (2016) solve the cold-start problem by grouping new items based on evaluation marks of 5, 10, 15, and 20. The author's proposed algorithm has lower MAE in case of cold-start. Tarus et al. (2017) overcome the cold start problem since the proposed system uses ontological domain knowledge. Hence, even when the initial data is not available in usual scenarios, the ontology is able to generate hidden information.

Table 2
Categorization by the ontology methodology.

Ontology	Ontology Language/ Tool	Methodology Applied	Proposed System Recommended	Merits	Further work required
Domain Ontology (Cerón-Figueroa, S. et al., 2017)	- OWL - RDF	- Feature Extraction - Pattern Classification using Ontology matching - Ontology merging	- Learning material	- Improves finding variety of similar e-learning resources - User can access different educative material stored in a semantic representation	- Need to experiment over other data repositories - Need to implement other similarity computing methods - Need to perform cost analysis over larger ontologies
Domain Ontology (Harrathi, M. et al., 2017)	- OWL	- Ontology representation - Categorization of Learning activities - Rules creation - Recommendation generation	- Learning Activities	- Able to factor in learner's characteristics like knowledge level, learning style - Maintains learner's motivation	- Needs implementing and evaluating - Need to evaluate effectiveness of proposed system over MOOCs
Reference Ontology (Hawalah, A. et al., 2014)	- Open Directory Project ontology	- Creating contextual personalized ontological profile - Pre-filtering contextualization contextual modeling - Personalization through spreading activation	- Contextualised services	- User preferences are extracted more accurately since proposed system is context based - Proposed system able to consider two different domains mainly computer and movies	- Need to evaluate integration of the proposed system with collaborative filtering - Need to evaluate the proposed system with domains other than movies, computer - Need to factor in other contextual dimensions
Formal Ontology (Labib,A. E. et al., 2017)	- OWL - Protégé	- Ontology Representation by performing feasibility study, learner's characteristics extraction, refinement, formalization	- Learning Objects	- Able to get flexibility to reuse personalized learning materials across different formats - Provides an authoring guide to author	- Need to integrate different learning styles - Need to integrate learner characteristics other than learning style
Formal Ontology (Ouf, S. et al., 2017)	- OWL - Protégé	- Ontology Representation - Semantic Web Rule Language applied for personalization	- Learning Material	- Ontology makes the learning environment rich - Ontology suitable for personalizing learning objects	- Need to apply ontology instances and ontology reasoning while creating ontology
-Linguistic Ontology -Domain Ontology (Yanes, N. et al., 2017)	- WordNet - OWL	- COTS components extracting - User query processed and COTS components filtered - Recommendation generated	- Commercial-of-the-shelf components for developers	- Allows users/developers to focus on domains of their interest - Allows the users to expand query - User profile updated as the user's interests evolve	- Need to check the working in areas other than software developing - Need to evaluate working of proposed system under ratings sparsity scenario in e-learning

4.2. Rating sparsity issue

The rating sparsity issue occurs when the number of ratings is smaller compared to the number of items. Hawalah and Fasli (2014) solve the rating sparsity problem by generating recommendations based on learner's contextual information and user interests. Karpus et al. (2016) consider not only the user's ratings of an item but also takes into consideration contextual information and user preferences. The contextual information and user preferences are stored in two ontologies that are used in the recommendation process. Harrathi et al. (2017, pp. 49–54) solve the rating sparsity problem by considering the learner profile, learning activities (which are stored in a learner ontology) and applying rules. Ratings are not considered here by the authors. Nilashi et al. (2018) solve rating sparsity issue by applying a hybridized approach. Clustering of ratings using expectation maximisation is done followed by singular value decomposition over each of the clusters. Similarity matrices over users and items are generated, which is compared with ontological metadata, which in turn helps to find semantic similarity between items. Tarus et al. (2017) overcome rating sparsity issue by using the learner's sequential patterns in accessing learning resources.

4.3. Lack of personalization issue

Cantador et al. (2008) provide personalization by building ontologies that describe user preferences and item features. Hawalah and Fasli (2014) offer an ontological user profile to provide personalization. Al-Yahya et al. (2015) describe ontologies in terms of learner and subjects, which helps to achieve personalization. Fraihat and Shambour (2015) use the semantic relation between learning objects and learner's needs by utilizing the metadata where the respective attributes are stored in an ontology. This serves to solve the lack of personalization. Harrathi et al. (2017, pp. 49–54) store the learner profile, learner's characteristics, learning style, and preferences in an ontology. Tarus et al. (2017) bring in the personalization by incorporating ontology for the learner and learning resource. Learner's learning style, knowledge level is used by the authors to help overcome the lack of personalization issue.

4.4. Information overload with a simple keyword search

Cakula and Sedleniece (2013) employ a concept tree that performs a semantic search which gets to search faster and effective than a simple keyword search. Rather than relying only on keywords while searching, which can lead to information overload, Al-Yahya et al. (2015) discuss how ontologies help in extracting relevant information when the information is retrieved based on the semantics of the learning objects. Fraihat and Shambour (2015) form a semantic query by extending learner's simple keyword query. Cerón-Figueroa et al. (2017) perform instance-based ontology matching by trying to find the similarity among several repositories using metadata. Obeid et al. (2018) proposed a system to filter the several options available to students for higher education. The authors made use of ontology and machine learning techniques to identify the user's interests. Thereby, the proposed system generates recommendations which help to overcome the information overload problem. Makwana et al. (2017) performs item-item collaborative filtering over a user search query and re-ranks the results to be shown to the user, which in turn helps to overcome the information overload problem.

Table 3 tabulates those papers that use ontology to overcome limitations faced by conventional recommender systems.

Thus, in this section, it could be summarized that ontology is used for modeling purpose. Reasoning the ontology helps to come towards certain inferences which are useful in the recommendation process. Also, it is observed that the use of ontology as part of the recommender systems framework helps to solve many of the issues traditionally seen in recommender systems.

5. Hybrid recommender system

Hybrid recommender system factors in the strengths of the techniques integrated to generate valid recommendations. This section aims to give an overview of the possible methods which can be employed while designing a hybrid recommender system.

Wan and Niu (2019) proposed applying Learner Influence Model (LIM), Self-Organizing based (SOB) approach and the sequential pattern mining (SPM) in the hybrid system for recommending personalized learning objects. The LIM helps to gather information related to the learner. The SOB helps to analyze the influence between active learners with the target learner. The SPM is applied lastly to decide on the learning objects to be recommended. Chen, Niu, Zhao, and Li (2014) utilize a hybrid approach with item-based collaborative filtering and sequential pattern mining to generate recommendations. Klašnja-Milićević et al. (2011) proposed a tutoring system, Protus, which clusters learners based on the learning styles. Further, learner's sequential pattern is mined. Finally, the recommendations are generated by applying collaborative filtering. Margaris, Vassilakis, and Georgiadis (2018) performed a query personalization. The user's preferences and that of the user's influencers on social media was considered. Thus, recommendations are based on collaborative filtering and social network influencing.

Salehi, Kamalabadi, and Ghoushchi (2014) modeled the learners and the learning materials to perform attribute-based collaborative filtering with sequential pattern recommendation. In light of trying to optimize the performance of a recommender system, a hybrid recommender system using new recommendation technique, i.e., context awareness, with traditional recommendation technique, i.e., collaborative filtering (CF), was suggested by Tarus, Niu, and Kalui (2018). The learner's sequential access pattern is determined by applying the generalized sequential pattern (GSP) algorithm on the result from the previous step. Bourkoukou, El Bachari, and El Adnani (2017) presented a recommender model for E-learning by incorporating collaborative filtering and association pattern analysis. Lastly, sequential pattern mining is applied to generate recommendations.

Bhaskaran and Santhi (2017) clustered the learners based on their learning style using a hybrid strategy of the firefly and the k-

Table 3
Ontology related papers addressing conventional recommender system issues.

Issues addressed	Technique Applied	Limitations/Further Work
Lack of personalization, Cold-start, Information overload with simple keyword search	• Personalization is achieved by considering students' skills, interests, preferences • Ontology is designed to model the higher education institution, student and employment while machine learning is applied to learn the profile of students • Cold-start issue is solved with the system requiring new users to complete their profiles with related personal information • The hybrid system filters possible options thereby solving the information overload issue (Obeid et al., 2018)	• The proposed framework needs to be implemented and evaluated
Lack of personalization Cold-start, Rating Sparsity	• Applying ontology domain knowledge about learner and learning resource along with applying sequential pattern mining of learner's historical data access helps to personalize recommendations • Cold-start issue is addressed by the use of ontology in the recommendation process • Rating sparsity issue is addressed by using the learner's sequential accessing pattern of data (Tarus et al., 2017)	• Learning style parameter of learner extracted through questionnaire method
Lack of personalization Cold-start	• Ontology is used to model a learner's knowledge level, learning style, preferences, learner characteristics • Based on Bloom's taxonomy, an ontology is created to represent the learning activities attributes • The ontology helps to solve lack of personalization and cold-start issues (Harrathi et al., 2017)	• Need to implement the proposed framework • Details of learner got through aid of questionnaire
Ratings sparsity	• Clustering is applied using expectation maximisation. Singular Value Decomposition (SVD) is applied to perform dimensionality reduction on each cluster. • Semantic similarity within cluster is achieved using ontology. Ontology helps to solve sparsity issue. • Dimensionality reduction, particularly the SVD used here, helps to address scalability issue (Nilashi et al., 2018)	• Other clustering and dimensionality techniques need to be applied and evaluated
Cold-start, Sparsity	• Sessions of customers on an E-commerce website is translated into an ontology and all relations between products are found • Genetic algorithm is applied to understand the weights needed to be given to different products' attributes • Cold-start and ratings sparsity issues are solved since the products' attributes and their relations are calculated rather than relying on ratings (.Lv et al., 2016)	• Need to check feasibility for the system in the E-learning domain in which each learner characteristics vary
Rating sparsity, Scalability	• Contextual pre-filtering using two ontologies • One ontology focusses on generalization of contextual dimension based on a user and the user situation • The second ontology focusses on identifying a matching context instance to the given context in order to understand user preferences • Sparsity issue is not encountered since the system depends on explicit and implicit ratings, contextual information and social networking data (Karpus et al., 2016)	• Descriptive ratings considered in the paper leads to large values of the Mean Average Error (MAE)
Lack of personalization, Cold-start, Information overload with simple keyword search	• Semantic indexing based on ontology classifies LOs according to concept. Semantic query framed is better than simple keyword query • Intra and extra semantic relationship between LOs helps in achieving personalization, overcomes cold-start (Fraihat & Shambour, 2015)	• Based on ratings • Need to implement the framework
Lack of personalization, Rating sparsity	• Builds ontology to describe user interests and contextual information • Spreading Activation technique helps to infer hidden user interests and thereby suggest relevant personalized recommendations (Hawalah & Fasli, 2014) • Learner's interests and contextual information is considered and not ratings thereby does not get affected by rating sparsity issue	• Expensive in terms of time and effort needed in order to build the initial reference ontology and contextual taxonomy
Lack of personalization, Information overload with simple keyword search	• Concept tree of learning objects (LOs) created • Detects learner's previous knowledge, technologies used • Ontology-based metadata extracts semantic relationship thereby achieving personalization (Cakula & Sedleniece, 2013)	• Need to implement the framework

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Table 3 (*continued*)

Issues addressed	Technique Applied	Limitations/Further Work
Lack of personalization, Cold-start, Sparsity	• Concept tree performs semantic searches thereby tackling the information overload occurring with simple keyword search • Builds ontology to describe user preferences & items features • Constrained Spreading Activation used to detect indirect relations between users • Semantic relationships between concepts and instances extracted. Thereby solves cold-start, lack of personalization issue, data sparsity issue (Cantador et al., 2008)	• Need for a more scalable clustering strategy

means algorithm. The preferences of learners which appear in the frequent sequences are mined using the AprioriAll algorithm. Also, using the trust-based weighted mean, the recommendations are customized. Paradarami et al. (2017) proposed a hybrid recommender system using artificial neural networks (ANN) with collaborative filtering and content-based features. ANN are known to show improvement over the recommendation process. E-learning personalization can also be done by applying artificial intelligence planning and case-based planning to achieve a more personalized e-learning route for students (Garrido, Morales, & Serina, 2016). Ghauth and Abdullah (2010) recommended the content by applying the vector space model to understand the similarity between items (learning materials) and good learner's rating.

Celdrán, Pérez, Clemente, and Pérez (2016) designed a hybrid recommender system by combining collaborative filtering, content-based filtering, and context-aware filtering. Ontology is used to model the location, preferences, tracking the user, and the recommendation modules of the proposed system. Najafabadi, Mahrin, Chuprat, and Sarkan (2017) clustered songs in an endeavor to reduce the data dimensionality. Association rule mining is employed over the clusters, thereby predicting the list of user's preferences. Similarity calculation between similar songs and user's predicted list is done. Xiao et al. (2018) designed a personalized recommender system by integrating a combinational algorithm using association rules, content-based filtering, and collaborative filtering. The user resource rating matrix is formed over which data sparsity is calculated. Based on the sparsity value, either a content-based or evaluation prediction algorithm gets chosen to calculate similarity. Thereby, the model generates top-k recommendations.

Ren and Wang (2018) designed a support vector machine (SVM) based collaborative filtering recommender system. The proposed system aims at correctly ranking the Web services than being used to predict ratings. Chen, Wang, and Yan (2018) proposed an evolutionary clustering algorithm for heterogeneous individuals (users and items). Constructed adjacent matrix is utilized to build the cluster. Next, the similarity between the individuals in the cluster is calculated using collaborative filtering. El Lakkah, Alimam, and Seghiouer (2017) proposed a hybrid system using ontology and artificial agents. The authors employed the ant colony optimization to get the learning objects adaptively for a more efficient learning path. Others, including Cantador et al. (2008), Tarus et al. (2017), Hawalah and Fasli (2014), Karpus et al. (2016), Lv et al. (2016), Martinez-Cruz et al. (2015), Nilashi et al. (2018), Obeid et al. (2018), Makwana et al. (2017) and Dascalu et al. (2016) have also proposed hybrid recommender systems, particularly integrating ontology.

From this section, it can be understood that hybridizing helps to overcome the limitations of individual methods. Collaborative filtering is one of the most widely and effectively used techniques found in these hybrid recommender systems. While other techniques like clustering, rules-based system, neural networks complement the collaborative filtering technique, the use of ontology with collaborative filtering is seen very promising. Table 4 gives a categorization based on the hybridization of different techniques in recommender systems. Fig. 6 summarizes the types of recommender systems with their advantages and disadvantages.

6. Limitations

Though ontology has several benefits like reusability, ability to share domain knowledge and ability to provide personalization (Shishehchi et al., 2012), the use of ontology has certain limitations. While ontology has the vantage of being reused by any person on the Web, the names given to the different classes, properties, and individuals of the ontology model are a challenge. Another challenge while designing ontologies is the incorrect use of classes and individuals. This leads to the requirement that ontology designing and maintenance requires knowledge engineering (Allemang & Hendler, 2011; Tarus, Niu, & Kalui, 2018).

There are different ways to hybridize, mainly by mixing, cascading, switching, applying weights to different techniques. However, there are limitations in these hybrid systems. The input for different techniques used in a hybridization has to be processed according to the required format. Pre-processing for hybrid systems can be time-consuming. With the different ways to hybridize and with the various algorithms available for hybridization, the right choice for the efficient functioning of a recommender system in e-learning is a challenge.

Table 4
Categorization by the hybridization strategy.

Ontology	Hybridization Method	Merits	Further work required
No Ontology (Bourkoukou et al., 2017)	- Sequential Pattern Mining - Collaborative Filtering	- Improved performance - New score function defined to weight the learning objects thereby considering learner preferences	- Need to integrate other learner characteristics - Need to deal with issues like cold start, data sparsity
No ontology (Bhaskaran and Santhi, 2017)	- Hybrid Firefly algorithm - K-means algorithm - AprioriAll algorithm - Trust-based weighted mean	- Shows improvement in performance in terms of accuracy and speed - Shows improvement in performance in terms of less error	- Need to apply other hybrid optimization algorithm to increase accuracy - Need to include tags concept for getting other students' interests and knowledge level
Domain Ontology (Cantador et al., 2008)	- Ontology - Clustering - Semantic Spreading Mechanism	- Explores different multimedia sources - Overcomes overspecialisation, cold-start problem - Reduces gray sheep problem	- Need to implement more efficient clustering technique - Need to implement context related concepts
Formal Ontology (Celdrán et al., 2016)	- Ontology creation - Collaborative Filtering - Content-Based Filtering - Context-Aware Filtering	- Provides more accurate recommendations based on user's location - Provides user's implicit ratings based on location and generated recommendations	- Need to consider other factors to calculate users' similarity - Need to implement in real world and evaluate user's satisfaction - Need to provide privacy for the recommenders and the users
No Ontology (Chen et al., 2018)	- Evolutionary Heterogeneous Clustering - Collaborative Filtering	- Mean Average Error is lesser than the compared algorithms of Collaborative Filtering (CF)only and K means-CF - Running time is lesser than the compared algorithms	- Need to evaluate the performance of the system over real-time online courses - Need to apply other similarity finding techniques other than collaborative filtering - Need to evaluate the scenarios with cold start, data sparsity
Domain Ontology (Karpus et al., 2016)	- Recommender System Context Ontology (RSCtx) - Contextual Ontological User Profile (COUP) - Pre-filtering - Recommendation using ItemKNN, UserAverage, SVD++, Random Guess	- Improves the accuracy of prediction - Represents context by combining different dimensions - Represents different granularity for each dimension	- Need to adapt user preferences for domain other than music - Need to integrate ranking of user preferences - Need to check recommendation diversity
Domain Ontology (Lv et al., 2016)	- Ontology - Clustering - Genetic Algorithm	- Performs with higher precision - Recommends with diversity - Performs better in cold-start situation - Execution time lesser	- Need to implement for user-based recommendations also - Need to apply item-based recommendation to other domains - Need to optimize recommendations by referring to relations between hierarchies
Domain Ontology (Martinez-Cruz, C. et al., 2015)	- Ontology created to show degree of trust between users - Ontology created to show membership degree - Fuzzy Linguistic Approach	- Reliability between users is considered - More relevant recommendations generated based on users trust and not based on similarities - Accuracy of hybrid system shows improvement	- Fuzzy ontologies can lead to vagueness - Large number of users would not explicitly state their trust level thereby estimate of trust factor is considered - Possible inclusion of social media network information for calculation of user trust level
No Ontology (Najafabadi et al., 2017)	- Association Rule Mining - Clustering	- Able to provide recommendations even in data sparsity condition - Able to reduce the data size by clustering - Efficiently creates user profile based on user's activities and tags associated with the items	- Need to implement the proposed framework over domains other than the music domain over which the experiment was done - Need to evaluate effectiveness of the proposed system using datasets other than the used Million Songs dataset
Domain Ontology (Nilashi et al., 2018)	- Ontology - Clustering using Expectation Maximisation - Dimensionality reduction using Singular Value Decomposition (SVD)	- Improved predictive accuracy - Improvement over the Scalability issue	- Need to apply incremental SVD - Need to evaluate performance over domains other than Movies - Need to implement clustering ensemble methods
Formal Ontology (Obeid et al., 2018)	- Explicit and Implicit data collection - Ontology - Machine Learning	- Generates recommendations based on skills, interests - Improves accuracy	- Need to integrate other machine learning techniques like k-mode, hierarchical clustering methods
No ontology (Paradarami et al., 2017)	- Artificial Neural Networks learning model - Collaborative Filtering using reviews, votes	- Records higher accuracy - Allows to build effective recommendations since multi-class prediction is performed	- Applying geo-spatial context can further improve performance

(*continued on next page*)

Table 4 (*continued*)

Ontology	Hybridization Method	Merits	Further work required
	- Content-based testing for users, business	- Allows flexibility to interpret due to the multi-categorical classification	- Applying Natural Language Processing over the reviews can help to understand the reviews better - Need to evaluate the performance of the system against other publicly available datasets
Formal Ontology (Tarus et al., 2017)	- Ontology - Collaborative Filtering (CF) - Generalized Sequential Pattern (GSP)	- Overcomes cold start, ratings sparsity problem - Performs better than only CF/CF with ontology	- Need to integrate tools from data mining, machine learning - Need to improve performance, accuracy
No ontology (Tarus et al., 2018)	- Contextual pre-filtering - Contextual Similarity Calculation - Generalized Sequential Pattern mining	- Accuracy improves as the number of neighbours reach optimal value - Lower mean average error for different levels of sparsity - Improved performance in terms of F1 measure	- Need to hybridize context awareness with other semantic web technologies - Personalization to be achieved on dimensions other than context, sequential patterns
No Ontology (Xiao et al., 2018)	- Association Rule Mining - Content-based filtering - Collaborative-based filtering	- Improves user's experience of viewing course - Saves time in searching for course	- More accurate user interest model to be built factoring in the dynamic changes of users' interests. - Cloud computing techniques can be integrated to evaluate performance

The gaps identified from the review done here are that there while ample research is done over recommender systems in e-learning, there is scope for more research in this area by integrating deep learning, advanced machine learning, genetic algorithm among other methodologies. The ratio of learners registering for a course to learners completing an enrolled course is low. Lack of personalization over the huge number of online resources available is one of the reasons for the low ratio. However, when it comes to e-learning, each learner's characteristics are complex and dynamic that there is a limit to the personalization that can be delivered. There is an extremely low number of publicly available datasets needed for implementation in recommender systems for e-learning. The available datasets may not possess the necessary attributes for different research problems in this field.

This literature review was focussed on peer-reviewed journal articles and not considerably from conference proceedings. There could be a possibility of related discussions in conference proceedings, but it has not found much scope in this review paper. However, with the stringent review process to publish articles in journals, the quality of content reviewed is high. Another limitation related to the scope of the review is the period of publications, 2010–2018. E-learning is growing exponentially. Hence, there is still further research being carried out till date, which needs to be explored. This review paper is limited to mainly ontology-based recommender systems. Many techniques need to be reviewed in-depth.

7. Practical implications

With massive educational resources available online, it becomes difficult for learners to choose a personalized course. From the extensive review done in this paper, it is clear there exists a huge gap between courses registered for and courses actually being completed. This shows the need for personalization while generating recommendations in the e-learning domain. Many issues exist in conventional recommender systems. Ontology-based recommender system helps to tackle most of these issues. The practical implications of using ontology-based recommender systems is in the long run to give personalized recommendations to learners. The recommendations suggested to the learner becomes more accurate based on the learner's interests, goals, and learning style. Thereby, the learner is motivated to complete what he starts.

8. Conclusion

Having a good turnover of students to the online learning platform, recommender systems in the e-learning domain is a trending research area. The conventional recommender systems working in e-commerce and other domains cannot be applied as it is in the e-learning domain. With the many techniques available to generate recommendations on e-learning, the papers reviewed here show more promising results when an ontology is used in the framework. Unlike the basic models of the recommender system, the ontology-based recommender system allows to factor in more details of the learner and learning objects.

Ontology, like any technique, has its pros and cons. Ontology designing requires knowledge engineering and is time-consuming. However, personalization is thought to be achieved to a greater extent when an ontology is applied. Ontologies help to overcome limitations seen in the traditional recommender systems.

Hybrid systems help to offset the limitations of one technique by combining several techniques. While hybridization has certain limitations, most research performs hybridization either with the input sources or with the algorithms. Using other strategies along with ontology to create a hybrid recommender system shows better performance.

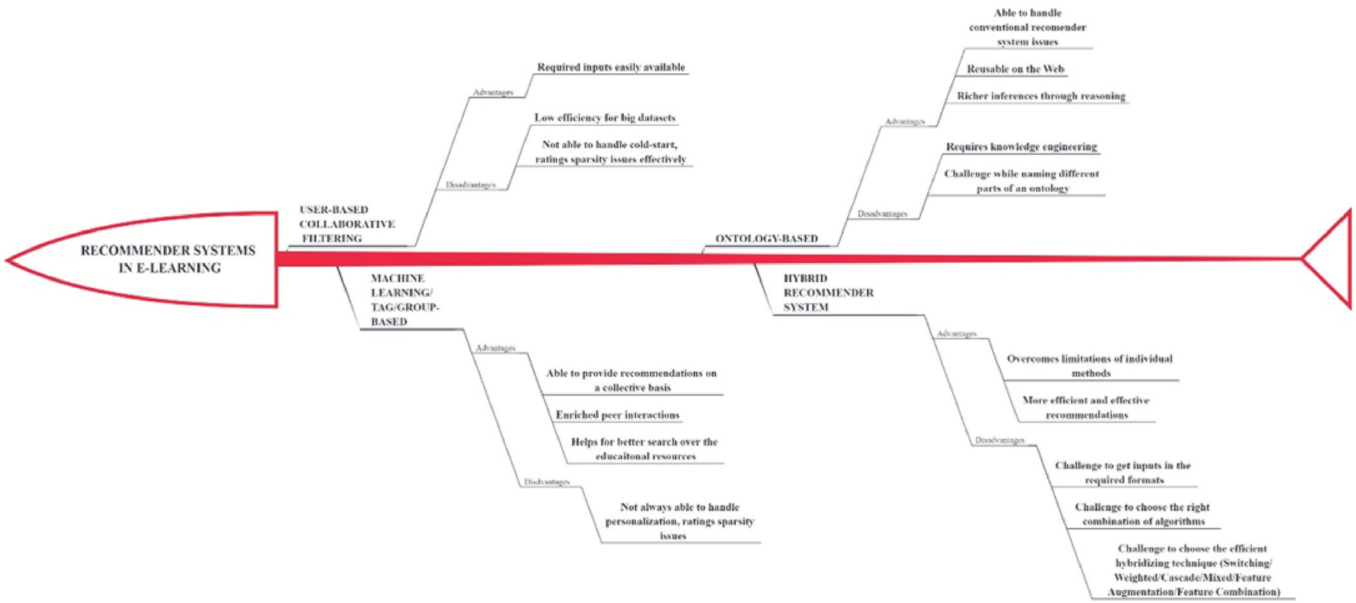

Fig. 6. Types of Recommender systems summarized– Merits and Demerits.

In this paper, a detailed review was done covering papers from 2010 to 2018. The review was directed to understand the different research work in two main areas: i) recommender systems in e-learning without using ontology, and ii) hybrid recommender systems in e-learning using ontology. The different papers surveyed were categorized i) according to the ontology method used, ii) according to how ontology-based systems solve issues faced by conventional recommender systems, and iii) according to the different hybridization techniques.

Future works include integrating the ontology, which is designed to cover different e-learning dimensions along with other semantic web techniques, ontology mining, and machine learning. With the advancement of ontology languages and ontology tools, the umpteen possibilities of working on an ontology need to be explored even more. It is seen that hybrid recommender systems perform more effectively than any particular technique. Extensive work can be done on finding the right combinations of the different techniques and evaluate its performance. Further, more options of which hybridizing technique to adopt with the chosen methods need to be explored.

Conflicts of interest

The authors declare that they have no conflict of interest.

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