A COMPREHENSIVE REVIEW OF COURSE RECOMMENDER SYSTEMS IN E-LEARNING

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ABSTRACT

The amount of information available online for higher education could be overwhelming to students in deciding the appropriate and relevant courses they should take. This issue has led to the need for automated and intelligent adaptive mechanisms to assist students in finding resources that match their individual goals, interests, and current knowledge. Although various course recommendation approaches have been introduced in recent years, they suffer from complexity, efficiency, and trust issues. This paper aims to categorize various course recommendation approaches put forward by researchers in recent years and to review the strengths and limitations of them.

Keywords: collaborative filtering (CF), content-based (CB), knowledge-based (KB), course recommendation system (CRS), online learning

INTRODUCTION

The significance of online learning in higher education in the modern era is of vital interest to students. The exponential growth of online courses makes it difficult for students to choose the best course that meets their course requirements and preferences. Random course selection is a significant problem because universities usually provide students with a pool of elective courses and ask them to register in some of the courses to complete their studies. This decision may not be a trivial one for learners, who usually do not have the information needed to choose and get overwhelmed by the number of available options. Chen, Lee, and Chen (2005) have highlighted that the complex hyperlink structure in web-based learning is another significant problem because it places a burden on learners of sorting through a massive amount of information and making it complicated for learners to understand and easily navigate through all the courses. Such problems can discourage learners from using and later promoting online education. These challenges support the need to build more sophisticated tools and techniques to help learners select a personalized course according to their own criteria.

In this article, we will be using frequent terms such as learners, students, users, and course recommendations and need to define these terms. A learner is a person who is acquiring practical skills, while a student is a person engaged in the study of academic subjects and the acquisition of knowledge, so we use these terms interchangeably. A user is a generic term to describe a person interacting with a recommendation system. Due to the growth of online courses and learners, there has been an increase in researchers' attention in designing optimized strategies to identify intelligently and autonomously the relevant online courses for learners, which is known as course recommendation. Course recommendation techniques help students save time and effort in exploring the courses from a large pool of resources, and it involves considering multiple attributes, such as social influence, prior knowledge, area of interest and skills, and so on. Therefore, course recommendation is a complex system that requires a researcher's attention to assist learners by playing a role in promoting online education.

The objective of this research is twofold. The first is to investigate state-of-the-art methods that exist for course recommendation, and the second is to explore what the existing research has identified as the significant challenges for course recommendations in e-learning. The article will explore the course recommendation systems in detail and discuss their weaknesses and strength.

BACKGROUND

Recommendation Systems (RSs) are information filtering systems that assist users in finding content, products, or services (such as web sites, books, digital products, movies, songs, travel destination, and e-learning materials) by implicitly or explicitly collecting preferences from other users (Farzan & Brusilovsky, 2006) or by analyzing their behaviors (Tai et al., 2008). Computing this depends on finding explicit user preferences (e.g., the user gives a product a score) or implicit preferences that are inferred by the system based on user behavior (e.g., choices of browsing on an online shopping site). For simplicity, this phenomenon has been presented in Figure 1.

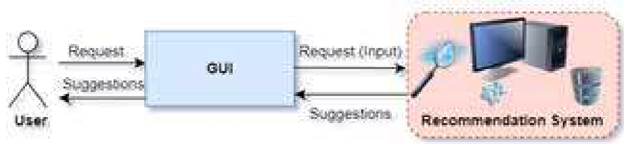

Figure 1. Recommendation Process

We can categorize the recommendation systems in four major categories, as follows:

- *Content-based (CB):* Content-based methods typically propose items to a targeted user based on the similarity between item's profile and the user's profile while ignoring data from other users (Al-Badarenah & Alsakran, 2016; Neamah & El-Ameer, 2018).
- *Collaborative Filtering (CF):* In collaborative recommendation methods, items are recommended to a target user based on their resemblance to other users' preferences (e.g., user ratings) while ignoring the items' attributes.
- *Knowledge-based (KB):* Knowledge-based recommendation methods combine artificial intelligence and deep learning techniques to gain extensive knowledge of users and the learning domain to construct a match between a user and an item (Al-Badarenah & Alsakran, 2016).
- *Hybrid Recommender Systems:* Hybrid approaches are used to combine other recommendation methods to overcome deficiencies associated with using a single recommender system (Al-Badarenah & Alsakran, 2016).

Figure 2 presents the generic framework of the course recommendation process. We have considered courses as items that are to be recommended to students according to their preferences and personalized features.

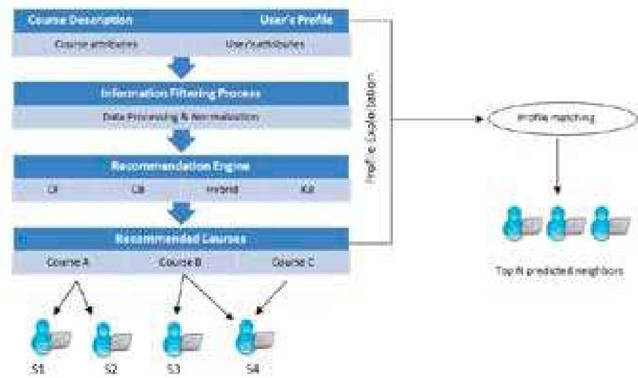

Figure 2. General Framework of Course Recommendation Process

RELATED WORK

In this section, we present a comprehensive review of the existing methods and techniques of course recommendation. We have organized the literature into various categories to portray a clear picture of the existing approaches.

Hybrid Data Mining Techniques in Recommendations

Data mining approaches have been proven to be very useful in almost every field. Integrating machine learning techniques in a recommender system certainly improves the accuracy of the recommendations. Counselors play an essential role in advising students in selecting the right courses for them. A hybrid recommender system composed of association rules and neural network techniques can help the advisors learn and understand the relationship between learners and courses to help learners when selecting online courses (Kongsakun & Fung, 2012).

Chu, Chang, and Hsia (2003) proposed a combined approach using data mining and graph theory for course recommendation. They examined two years of academic data to validate their proposed method and recommended for a future direction of research course development predicting dynamic changes according to a learner's interest. Chen et al. (2005) proposed a personalized e-learning system based on Item Response Theory (PEL-IRT) and considered course difficulty and learner ability factors to suggest personalized learning paths for learners. Apaza, Cervantes, and Quispe (2014) applied a different technique on student's previous grades for course recommendation using probabilistic topic models to infer topics from the course syllabus. They consulted MOOC syllabi to get another set of topics for comparison purposes. These sets, along with grading information, were compared using a content-based recommendation system to recommend appropriate online courses to students. They used Latent Dirichlet Allocation (LDA) to discover the semantic structure of both sets of syllabi discussed in the article. Ng and Linn (2017) gathered student priorities and preferences through surveys and applied a hybrid technique of combining topic analysis, tag analysis, and sentiment analysis to recommend courses to college students.

Rule-based Methods

Aher (2014) tested the performance of combined data mining algorithms for course recommendations by choosing the clustering and a priori association algorithm and compared the results with a single a priori algorithm. The results favored a combined approach by generating optimized results. A distributed a priori algorithm was analyzed by considering three data sets to improve the efficiency of the basic apriori algorithm. The experimental results revealed that the performance of the association rules algorithm is far better than the Hadoop-based association rule mining algorithm. However, Aher (2014) did not discuss any mechanism for dealing with contextual information of learners for personalization (Zhang et al., 2017).

Aher and Lobo (2013) presented an e-learning course recommendation system based on machine learning techniques that identify the student's behavior and match it to their interested courses. Various combinations of data mining algorithms were compared, such as the classification and association rule algorithm, the association rule mining of classified and clustered data, and the clustering and association rule algorithm. The results proved that the combination of the clustering and classification and association rule algorithm is the best one. These approaches consider course enrolment behavior in the recommendation process, but in the absence of historical information, these rule-based methods may not perform well for new students (Schein et al., 2002).

Dahdouh, Oughdir, Dakkak, and Ibriz (2018) used the FP-growth algorithm to analyze the historical data of course registration to match appropriate courses according to the learner's behavior and choices. Experimental results proved the efficiency and consistency of the proposed system in enhancing the excellence of student's decisions and provided the best courses to meet the needs of the learners.

Association rules are used to infer rules from previous students' experiences to aid in the recommendation process. Bendakir and Esma (2006) used a rating of the current user, along with former student experience, and developed a recommendation system. However, this system has some limitations when providing its recommendations. One obvious flaw is that it depends upon student registration data, which is not usually accessible. Another study discussed the combination of association rules and collaborative filtering methods. Collaborative methods can be successfully used to find similar users based on interest, and the association rule mining algorithm is used to extract courses by association rules. This method recommends courses while calculating the students' respective grades, as achieving good grades is the goal of students (Al-Badarenah & Alsakran, 2016).

Role of Learner Modeling in Recommendations

Learner modeling plays a fundamental part in course recommendation systems, and there are different techniques available for this, including data mining. Tai, Wu, and Li (2008) used self-organizing and data mining techniques in designing a recommender system. They used demographic features, applied neural network and association rules to find out the cluster of learners, and studied learners' behavioral patterns to recommend prospective courses. However, this study did not take into account learners' career goals and job interest.

Aher and Lobo (2013) proposed many studies in this domain using a combination of different algorithms in course recommendation. One study suggested using k-means clustering and the a priori association rule algorithm. In another study, a course recommender system was proposed based on learner's profiles. Moodle has been used to collect learner's information while creating their profiles through a k-means algorithm. However, this study has neglected various other important factors discussed in the literature, such as course availability and student potential (Rawat & Dwivedi, 2017).

Piao and Breslin (2016) presented three different user modeling methods based on a LinkedIn data set. The results revealed that the skill-based user modeling method outperforms other methods. Another study discussed the content-based approach using K-nearest neighbors (KNN) and Naïve Bayes algorithms of data mining for learner modeling in course recommendations (Neamah & El-Ameer, 2018). Jing and Tang (2017) proposed a collaborative filtering learner modeling approach based on their access behavior, demographics, and course prerequisite in solving the cold-start problem. Dahdouh et al. (2019) analyzed the historical data of course enrolments to explore many items sets to establish existing facts in the operational database. These policies have been used to uncover more appropriate courses according to learner's behaviors and preferences.

Real-time Systems for Course Recommendations

There are a few course recommender systems deployed in some educational institutes. Personal Assistant Recommendation Engine (PARE) is a course recommender system developed for Stanford University students that uses the vector-space model and hybrid method (Koutrika et al., 2009). Another recommender system at the University of Pittsburgh is CourseAgent, which was evaluated based on long-term evaluation experiments with students using the same methodology (Farzan & Brusilovsky, 2011).

For the university enrolment process, CF-based methods have been used to advise the students in elective course selection according to their interests. There are few institutions in which these systems are functioning to support students, e.g., the University College Dublin at which a memory-based collaborative method has been using for online enrolment of the students (O'Mahony & Smyth, 2007).

"Guess you like" is a course recommender framework deployed onto the XuetangX Chinese MOOC platform. Students' behavior was systematically studied while considering their demographic profile, interest, and course prerequisite relation using collaborative filtering in the recommendation process. The new feature has recorded +24.6% click rates, making it reliable and efficient in recommending a course (Jing & Tang, 2017). Li and Li (2017) have highlighted some limitations to the recommendation strategies of the existing MOOCs platform. These platforms use the learner profile and historical learning record but ignores the learner's browsing behavior. Moreover, these platforms consider the single interest of the learner and ignore multiple or dynamic changes of interest in the recommendation process.

Performance Efficiency in Recommendation

Li, Wang, Wang, and Tang (2018) proposed a formal interactive course recommendation model and an algorithm to reduce the performance-cost score. A variety of experiments on real MOOC registration data sets showed the proposed strategy to be very useful and the proposed algorithm outperformed conventional methods by 30.25% in terms of the performance-cost.

With the massive increase of learners in online education, it is computationally heavy to explore similar learner's preferences in the recommendation system. Garg and Tiwari (2016) addressed this problem by proposing a hybrid collaborative filtering approach that considers a small fraction of a similar learner database instead of investigating the learner's entire record.

A Case-Based Reasoning (CBR) approach has been used to recommend courses best suited to a learner's profile, need, and knowledge. In contrast to other recommender systems, CBR recommender systems do not use massive item ratings or learner data. As future work, more search features such as learning outcomes, course outline, and course prerequisites are needed (Bousbahi & Chorfi, 2015).

Hou, Zhou, Xu, and Wu (2018) paid attention to course sequencing, which is a lesser issue for course recommendation. The course sequence can help significantly improve the recommendation process. An experimental result on a real-world data set proved that the proposed algorithm notably outperforms traditional algorithms. Future work was mentioned to design and develop algorithms that can deal with dynamically increasing course data sets. In the same context, another approach studied prerequisite requirements and course availability attributes with a forward-search backward-algorithm to facilitate students in choosing the right sequence of courses and thereby decreasing the overall effort and time invested in this tedious work. Using real-world student data from a California university, promising results have been presented when compared with other algorithms that do not take into account the student's contextual information when making course sequence recommendations (Xu et al., 2016).

Shah, Shah, and Banerjee (2017) used the online matrix factorization method by considering student's grades and their previous school results as experiment parameters to improve computational time and course prediction accuracy. However, this study lacked the benefit of adding other essential features for the recommendation. Traditional CF-based algorithms cannot efficiently deal with sparse data and learner's multidimensional attributes, which result in an inefficiency of resource recommendation. As a solution, this study proposed a personalized recommendation system based on a dynamic Bayesian network (DBN) in the MOOC environment that exploits the high performance of DBN in prediction classification. The experimental results on a real MOOC platform revealed that dynamic Bayesian network collaborative filtering (DBNCF) were more efficient than the traditional filtering method (Zhang et al., 2017).

Effect of Social Influence in Recommendation

Bydžovská (2016) proposed a data mining approach that considers the student's profile and social influence to suggest elective courses and to warn students about challenging courses. Social interactions and their effects are determined through statistical data presented by sociograms. The feedback of previous students is an essential factor in the course recommendation process. Farzan and Brusilovsky (2006) have studied feedback and categorized it as implicit and explicit feedback to be incorporated into a user's experience in the form of clicking links or rating an item.

Upendran, Chatterjee, Sindhumol, and Bijlani (2016) considered the previous student's skills and capabilities as a trained data set and used these attributes to recommend courses to similar new students having the same abilities. Another study considered professor ratings as a controlled filter to eliminate courses from the recommendation list that have professors with lower ratings. They used a two-tier collaborative-filtering method and an immune system model to build the course recommendations (Chang et al., 2016).

Grades Prediction Strategy for Course Recommendation

Some researchers worked on the prediction of grades, as students tend to select the courses in which there are greater chances for them to score a higher grade. Sobecki and Tomczak (2010) suggested that ant colony optimization (ACO) can be used effectively in predicting grades for the students.

Student potential and course complexity can also be used to determine student grades. Vialardi et al. (2011) used CRISP-DM methodology with CF to suggest courses to the students in which there are more chances for them to score higher grades. They considered various features such as course name, attempt number, cumulative average course credits, number of credits, and a final class grade in this process. These features have been categorized under student potential and course complexity. Experimental results show that the bagging ensemble technique outperforms the C4.5 algorithm. Additional features could be measured, such as the course difficulty assessment, student support and interest, or secondary school grades, among others, or the time devoted to study, etc.

CF has been used successfully to predict grades earlier in the learning phase, which are used in the recommendation process to suggest courses for students. Item-based and user-based collaborative approaches are used and applied to real-time data for recommendations (Ray & Sharma, 2011).

Hybrid Collaborative Filtering Methods

An integer linear programming model with a combination of collaborative methods has been used to suggest schedules and courses to students of Boğaziçi University. Target learner preferences were matched with the other learners who enrolled in the same courses (Uslu et al., 2017). Bozyiğit et al. (2018) proposed using collaborative methods with Ordered Weighted Averaging (OWA) operators to recommend courses. Existing approaches consider only recent grades in the recommendation process, but this approach studied the effect of the number of times the course is taken and how students have performed in them. This study lacks, however, other important factors used in existing research, such as the social influence of students towards their friends and classmates.

Another interesting approach has been suggested that considers more recent assessments in the recommendation process. This time aware method is based on the graduating attributes of students, i.e., their skills, qualities, and personality traits. The algorithm relies on recent assessments provided by the students. This work contains many avenues for further experimentation and improvement, including the consideration of productive factors and matrix factorization method (Bakhshinategh et al., 2017).

Another recommendation method that has been suggested to study is examining the similarity between the course templates of students. Bhumichitr, Channarukul, Saejiem, Jiamthapthaksin, and Nongpong (2017) used collaborative filtering with Pearson correlation and alternating least square (ALS) methods and compared their performance on some academic data sets. For accuracy, the ALS based approach was found to be superior to the Pearson based method. However, this study only considered student similarity based on their enrolment records, which might not be adequate.

Researchers have used a hybrid approach by combining CF and CB filtering methods that consider student preference, previous results, scores of each subject, and overall percentages from the entire database, job interest, and feedback. A clustering or association rules mining algorithm has been used to extract the relationship between the courses. This study gave practicable predictions for course selection based on student's marks and job interest (Grewal & Kaur, 2016).

Semantic-based Course Recommendation Systems

The semantic web is an extension of the current web, in which information is given a defined meaning that enables machines and users to cooperate (Huanget al., 2013). Jhaveri, Pareek, and Jha (2013) developed a prototype based on students' requirements and interests, while considering university constraints, to recommend a degree program to students. However, this study lacked other significant attributes, such as course prerequisites and completion requirements. This research also shed light on integrating a natural language processing (NLP) based query dialogue system for students interacting with the system for suggested courses.

Huang, Chen, and Chen (2013) calculated the percentage of completed courses for the student and then generated a list of courses the student should take. Domain experts were responsible for constructing curriculum program ontology using a protégé tool. The research suggested making an effort in the future to define and check the demand of courses by automatically generating relations among related courses.

The combination of an ontology-based recommender system with machine learning techniques is a promising approach for improving recommendation accuracy. In the context of e-learning, a successful system must deal with many factors of learners, including their learning style. Unfortunately, many methods have been proposed that do not incorporate the learning style of the learners. Because students progressively learn material, it is challenging to guide them. Vaishali, Archana, Monika, Vidya, and Sanap (2016) addressed this problem by introducing a hybrid recommender system that includes collaborative filtering with domain ontology. Future directions would utilize contextual information while designing the recommender system to improve its performance and learner satisfaction.

Gulzar and Leema (2017) considered learner's requirements and interests to propose an ontology-based, natural language dialogue-based system to process student's queries regarding course recommendation. The framework of the recommender system has been proposed and tested under four significant domains of computer science. Researchers found this system very useful, but they faced vague query limitations early in their work. Later on, query classification and expansion with word net were adopted to address this problem. Finally, they introduced finding similar learners based on their learning profiles so that students can trust the recommender system. The evaluation shows that the semantics-based methods of the recommender system improved the recommendations' accuracy. However, this study does not consider many other factors, as stated in the previous research, such as feedback, learning style, job requirement, etc. For future work, sound directions have been proposed to design and evaluate perfect ontology in general (Gulzar et al., 2018).

Rabahallah, Mahdaoui, and Azouaou (2018) proposed an ontology-based hybrid recommender system for MOOC platforms. The proposed hybrid recommendation algorithm enriches ontological knowledge about the learner and MOOCs into the recommendation process while collaborative filtering predicts ratings to produce recommendations. According to the researchers, there is no previous study that discusses the relationship and usage of ontology with the MOOC platform, which opens an exciting direction for new researcher. Further experiments can be performed while integrating other machine learning algorithms such as support vector machine (SVM) for diverse, interesting results.

Ibrahim, Yang, Ndzi, Yang, and Almaliki (2018) have proposed a novel hybrid ontology-based approach to achieve learners' satisfaction and deal with the cold start problem. The proposed work has combined CF and CB methods for recommendations. Moreover, this approach improves the cold-start problem in the collaborative method by integrating ontology similarity into the proposed method. Dynamic ontology mapping has been used to link courses and student profiles with job profiles. It has been suggested as a way to make the system more comprehensive and intelligent while using heterogeneous data sources and incorporating additional user contexts into the recommendation process, e.g., available student behavior, learning style, and learning interests.

Lotfy and Salama (2014) extended the Hermes framework with subject recommendation functionality. They used a combined method of term frequency-inverse document frequency (TF-IDF) extraction with cosine similarity in the knowledge-based system. Experimental results prove that semantic recommender systems perform better in general than traditional recommender systems. We have summarized the abovementioned extensive literature in Table 1 by identifying their parameters and techniques.

DISCUSSION

In this section, we will discuss and compare the extensive literature presented above to uncover the challenges that exist in the course recommendation. All these approaches intend to work on the course recommendation problem by considering different sets of features and performance parameters. Though CF, CB, and KB approaches are predominant across various kinds of applications, hybrid RS are more popular to reduce the existing drawbacks of single RS.

In some methods, the researchers worked to improve performance by using a formal interactive model and the learner's implicit rating (Garg & Tiwari, 2016; Li et al., 2018). We have not found any other study that considers these performance parameters to reduce performance cost. A priori algorithm has been used to improve performance in one study, but it did not discuss any mechanism to deal with contextual information of learners for personalization (Huang et al., 2017).

Less work has been devoted to course sequence problems to improve the accuracy of the system (Hou et al., 2018; Xu et al., 2016). Most data mining techniques rely on previous course enrolment behavior. Therefore, in the absence of historical information, these rule-based methods may not perform well for new learners (Aher, 2014; Aher & Lobo, 2012; Aher & Lobo, 2013; Bendakir & Esma, 2006; Huang et al., 2017; Kongsakun & Fung, 2012; Tai et al., 2008). We have not found any systematic approach to deal with the increasing course data sets (Hou et al., 2018). One suggestion has been to use a smaller database size for the learner's rating to improve computational cost, but this factor has not been widely studied in the research (Bousbahi & Chorfi, 2015).

CF methods have been used in recommendation by calculating a student's grades using the item- and user-based techniques (Ray & Sharma, 2011), ACO (Sobecki & Tomczak, 2010), CRISP-DM (Vialardi et al., 2011), and item response based theory (Chen et al., 2005). However, it has been found that fewer researchers have paid attention to considering the number of times the student enrolls in the course, which could be a vital recommendation feature of the process (Bozyiğit et al., 2018).

Although ontologies have been proven to be beneficial, still, this is an undiscovered area in course recommendation. The experimental evaluation, in

Table 1. Parameters and Techniques of Existing Work

Parameters	Techniques	References
Learner modeling (demographic features of learners)	Self-organizing technique	(Tai et al., 2008)
Learner profile	A priori algorithm, clustering methods	(Rawat & Dwivedi, 2017)
Learner modeling	Skill-based methods	(Piao & Breslin, 2016)
Learner modeling	CB based system with KNN and Naïve Bayes algorithms	(Neamah & El-Ameer, 2018)
Learner modeling (access behavior, demographics, and course prerequisite)	CF method	(Jing & Tang, 2017)
Course historical information	Rule-based Methods (classification and association rule algorithm)	(Aher & Lobo, 2013)
Learner profile and social influence	Data mining approach	(Bydžovská, 2016)
Grades, marks, and their previous school results	Matrix factorization method	(Shah et al., 2017)
Historical data of course registration	FP growth algorithm	(Dahdouh et al., 2018)
Former learner data and rating of current students	Association Rules	(Bendakir & Esma, 2006)
Performance cost score	Formal interactive course recommendation model	(Li et al., 2018)
Learner previous grades	Probabilistic topic models	(Apaza et al., 2014)
Learner priorities and preferences	Topic analysis, tag analysis, and sentiment analysis	(Ng & Linn, 2017)
Prerequisite requirements and course availability	Forward-search backward-algorithm	(Xu et al., 2016)
Learner preference, previous results, scores for each subject, and overall percentages from the entire database, job interest, and feedback	Hybrid methods (CF & CB), clustering methods	(Grewal & Kaur, 2016)
Professor ratings	Two-tier CF-based method	(Chang et al., 2016)
Learner potential course complexity	CRISP-DM methodology with a collaborative filtering	(Vialardi et al., 2011)
Course difficulty and learner ability factors	Item Response based theory	(Chen et al., 2005)
Learner profile	Item-based and user-based collaborative approaches	(Ray & Sharma, 2011)
Learner's preferences	CF based Integer Linear Programming Model	(Uslu et al., 2017)
Learner's skills	CF based method	(Upendran et al., 2016)
Number of times the course is taken	CF based OWA operators	(Bozyiğit et al., 2018)
Learner's enrolment record	CF based ALS methods	(Bhumichitr et al., 2017)
Learner's requirement and interest and university constraints	Semantic-based method	(Jhaveri et al., 2013)
Percentage of completed courses	Semantic-based method	(Huang et al., 2013)
Learner profile	CF with domain ontology	(Vaishali et al., 2016)
Learner profile	Semantic-based method	(Gulzar et al., 2018)
Learner profile	Ontology-based hybrid recommender system	(Rabahallah et al., 2018)
Learners, course, and job profiles	Hybrid ontology-based approach	(Ibrahim et al., 2018)

general, shows that the semantics-based methods in the recommendation process improve the accuracy of the recommendations (Gulzar et al., 2018). However, despite the enormous benefits of ontologies in research, there is still a lack of promising and sound work in course recommendation. It would be highly beneficial to explore ontologies in this area to facilitate learners and for administrators to benefit from this. Ontologies can be enriched by designing NLP dialogue-based systems (Jhaveri et al., 2013) and combining machine learning algorithms such as SVM (Rabahallah et al., 2018). Researchers have been given sound directions for designing and evaluating perfect ontology (Gulzar et al., 2018) and studying heterogeneous data sources (Ibrahim et al., 2018).

We have found various factors that have been used in solving the course recommendation problems. Table 2 describes the taxonomy of those factors that appear in the existing literature for the course recommendation problem.

Table 2 shows that time-based assessments are not commonly taken into consideration in the recommendation process. This factor can be productive by combining a matrix factorization method for the same purpose (Bakhshinategh et al., 2017). Similarly, the social influence of students towards their friends and classmates is a less often considered factor (Bozyiğit et al., 2018). Also, there is less work on improving computational time and the parallel processing of data (Dahdouh et al., 2019). The dynamic changes in learner's interests and incorporating the browsing behavior of learners were found to be an essential direction for new research (Huang et al., 2018; Li & Li, 2017).

The importance of demographic information in the recommendation process can be seen in Table 2. Researchers have usually considered demographic attributes (Shah et al., 2017) while neglecting other essential features, including career goals and job interest (Tai et al., 2008), course availability or student potential (Rawat & Dwivedi, 2017), area of interest and predicting dynamic changes in their interests (Chu et al., 2003), and learning outcomes, course outline, and course prerequisites (Bousbahi & Chorfi, 2015). Some neglected factors for user

Table 2. Taxonomy of Factors in CRS

Factors	References
learning style	(Vaishali et al., 2016)
area of interest	(Aher & Lobo, 2013; Al-Badarenah & Alsakran, 2016; Dahdouh et al., 2018; Gulzar & Leema, 2017; Gulzar et al., 2018; Ibrahim et al., 2018; Jhaveri et al., 2013; Li et al., 2018; O'Mahony & Smyth, 2007)
fees affordable	(Jhaveri et al., 2013)
preferred university	(Jhaveri et al., 2013)
course availability	(Xu et al., 2016)
last degree obtained	(Jhaveri et al., 2013)
feedback of previous students	(Bendakir & Esma, 2006; Farzan & Brusilovsky, 2006; Grewal & Kaur, 2016; Koutrika et al., 2009)
rating of current students	(Bendakir & Esma, 2006)
student's previous results (marks or grades)	(Apaza et al., 2014; Grewal & Kaur, 2016; Shah et al., 2017)
previous students' skills and capabilities	(Upendran et al., 2016)
course historical data (log data)	(Dahdouh et al., 2019; Huang et al., 2018; Ibrahim et al., 2018)
student potential	(Bakhshinategh et al., 2017; Bydžovská, 2016; Chen et al., 2005; Sobecki & Tomczak, 2010; Vialardi et al., 2011)
course complexity	(Chen et al., 2005; Sobecki & Tomczak, 2010; Vialardi et al., 2011)
demographic profile	(Bakhshinategh et al., 2017; Bousbahi & Chorfi, 2015; Dahdouh et al., 2019; Garg & Tiwari, 2016; Huang et al., 2018; Ibrahim et al., 2018; Jing & Tang, 2017; Rawat & Dwivedi, 2017; Tai et al., 2008;Vaishali et al., 2016)
course prerequisite	(Jing & Tang, 2017; Xu et al., 2016)
course attempt number (repeating)	(Bozyiğit et al., 2018; Vialardi et al., 2011)
job interest	(Grewal & Kaur, 2016; Ibrahim et al., 2018)
professor rating	(Chang et al., 2016)
learner's knowledge	(Bousbahi & Chorfi, 2015; Bydžovská, 2016)
free time slots in their schedules	(Bydžovská, 2016)
social influence	(Bydžovská, 2016)
student preference	(Dahdouh et al., 2019; Grewal & Kaur, 2016; Uslu et al., 2017)
scores of each subject	(Grewal & Kaur, 2016)
an overall percentage from the entire database	(Grewal & Kaur, 2016; Vialardi et al., 2011)
recent assessment (time based)	(Bakhshinategh et al., 2017)

contextual information are be found in the research on feedback and learning style (Gulzar et al., 2018; Ibrahim et al., 2018), learning interests (Ibrahim et al., 2018), and available student behavior (Ibrahim et al., 2018). Only a few features have been used in research, including the area of interest and the user's profile, and only one researcher has considered the learning style factor in designing a recommender system (Vaishali et al., 2016). Some factors can play a significant role in achieving learners' satisfaction, such as recent assessments (Bakhshinategh et al., 2017), course availability (Xu et al., 2016), job interest (Grewal & Kaur, 2016; Ibrahim et al., 2018), social influence (Bydžovská, 2016), and learner's knowledge (Bousbahi & Chorfi, 2015; Bydžovská, 2016). These attributes can significantly help to improve a learner's trust in using a recommendation system.

CONCLUSIONS AND FUTURE WORK

Course recommendation methods help learners find suitable courses from an exponentially growing database of online courses. This study presents a comprehensive review of the state-of-the-art techniques that exist for course recommendation. We categorically discuss the existing methods by explaining their parameters, data sets, and procedures, and we identify some areas of improvement for the recommendation process.

The scarcity of benchmark data sets in e-learning specifically for course recommendation is a significant limitation to generalizing the experimental results. Also, some researchers have proposed only frameworks or evaluated their methods on smaller data sets. Thus, it would be worth suggesting that researchers use large and heterogeneous data sources in future work to produce more reliable results. Moreover, ontologies are not explored thoroughly for their inherent benefits in various aspects of course recommendation. We found relatively little research that combines machine learning and semantic-based techniques in course recommendation.

This study is a contribution towards critically analyzing the existing literature for course recommendation. We discuss the limitations and challenges that exist in the course recommendation to propose further research directions. This work will be a great help for researchers, learners, and developers to further investigate and improve the course recommendation problem for a better future of technology-enhanced learning.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

ACKNOWLEDGMENTS

I am grateful to my coauthors, who have helped me in organizing the concepts and proofreading this manuscript.

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