Hybrid Knowledge-based Recommendation Approach for E-Learning Resources

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电子学习资源的混合基于知识推荐方法

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摘要

近年来，万维网上的学习资源数量显著上升，越来越多的用户使用网络资源进行在线学习。然而，尽管在线学习资源的利用率大幅提升，信息过载问题让用户在检索相关的学习资源时遇到较大的困难。作为一种软件工具，推荐系统被广泛用于缓解信息过载问题。推荐系统在 e-learning 中扮演着重要的角色，它帮助学习者获取与他们学习需求相匹配的学习资源。

虽然传统的推荐方法，如基于内容的推荐、协同过滤推荐在许多领域取得巨大的成功，这些领域包括电子商务、音乐和电影等。但是在 e-learning 中，推荐系统在为用户进行准确和个性化的推荐时却遇到一些困难，这主要是由于学习者个体在特征、上下文和顺序存取模式上的差异性所导致的。学习者在背景知识、学习风格、技能和学习水平等诸多方面具有显著的差异，而这些因素对用户定义和个性化资源的推荐起着至关重要的作用。另外，学习者的知识水平、学习目标和学习经验会随时间和情境而变化，这些上下文信息的变化对学习者的资源偏好产生了较大的影响。而且，不同的学习者有不同的顺序存取模式，这在很大程度上决定了应该将什么样的资源推荐给用户。考虑到这些附加的学习者信息，即学习特征、学习情境和顺序存取模式对用户学习资源的偏好有一定的影响，因此在推荐过程中应该获取这些信息，将其纳入推荐的考虑因素中。在 e-learning 的上下文研究中，协同滤推荐方法将与目标用户的偏好相似的其他用户所喜欢的资源推荐给目标学习者。目标学习者和其他学习者的评分被用作衡量用户或学习资源的相似性。评分信息用于衡量资源对用户学习的重要性，通过评分信息计算用户之间以及资源之间的相似性。基于内容的推荐将与学习者之前喜欢的内容相似的学习资源推荐给用户。除了评分和资源内容之外，传统的推荐方法还没有利用其他学习者信息进行资源推荐，如学习者的特性，上下文和序列存取模式。此外，传统的推荐方法遇到了冷启动和数据稀疏问题，这使得它们在 e-learning 中的推荐效果受到限制。值得注意的是，由于没有考虑学习者的其他信息，目前的许多推荐方法在相似性计算上也遇到挑战。因此，在 e-learning 推荐中，大多数现有的推荐方法在推荐的准确度和用户个性化实现上遇到问题。为了克服这一问题，需要进一步研究考虑用户其他信息的推荐方法。

本文的主要目的是研究和开发基于知识的混合推荐算法，此算法考虑了更多学习者的信息，例如学习者的特征、学习者上下文信息和学习者的学习序列模式，以帮助提高推荐算法的个性化程度和准确性，同时能够缓解稀疏性和冷启动问题。本文的主要贡献如下：

首先，我们通过对 e-learning 推荐系统的期刊论文的系统性的文献综述，探讨了 e-learning 推荐系统中的挑战，并按照学习者相关和研究者相关对这些挑战进行了识别和分类。此外，我们列出了每种挑战对应的解决办法。

其次，提出了一种基于本体和序列模式挖掘算法的混合基于知识推荐的方法，为 e-learning 环境中的学习者推荐相关的学习资源。在提出的推荐方法中，采用本体论模型对学习者和学习资源进行建模。应用序列模式挖掘（SPM） 算法挖掘用户的 web 日志，获取用户的序列存取模式，并根据此模式进行学习资源的过滤。我们应用真实的数据集进行实验，结果表明了所提方法在准确度、精确度和召回率上有较大提高。此外，提出的办法在给出初始化评分数据之前使用了本体领域知识和学习者序列存取模式的方法，分别缓解了冷启动和数据稀疏度问题。

最后，我们提出了一种结合上下文感知、SPM 算法和协同过滤的混合推荐方法，为学习者推荐相关的学习资料。其中，上下文感知被用来整合学习者的相关上下文信息，如学习水平、知识水平和学习风格，而 SPM 则用来发现学习者的顺序存取模式。协同过滤在考虑上下文数据和学习者的顺序存取模式的前提下，被用于计算相似性、预测用户评分和产生推荐资源。实验结果表明，本文提出的混合推荐方法在推荐质量和和准确性上优于其他相关推荐方法。

关键词：推荐系统, e-learning, 协作过滤, 混合过滤, 基于知识的推荐, 本体,序列挖掘模式, 上下文信息, 学习者挑战, 研究员挑战

Abstract

Recent years has witnessed substantial increase of learning resources available on the World Wide Web. As a result, there has been a remarkable growth in the utilization of online learning resources by learners in e-learning environments. However, despite this growth in usage of e-learning resources, learners encounter difficulties of retrieval of relevant learning resources due to information overload. Recommender systems are software tools that have been largely accepted as useful solutions to alleviate the problem of information overload. They play a beneficial educational role in e-learning by assisting learners to access relevant learning resources that match their learning needs.

Although conventional recommendation methods such as collaborative filtering and content-based have demonstrated success in domains such as e-commerce, music and movies, there are still some challenges experienced in attempts to provide accurate and personalized recommendations of learning resources in e-learning arising from differences in learner characteristics, learner contexts and sequential access patterns among the learners. Learners possess characteristics such as learning style, background knowledge, skills and study level among others which are crucial in personalization of the learner profile and recommendations of learning resources in e-learning environments. In addition, learner's contextual information such as knowledge level and learning goals change with time and situations. These contextual changes have an impact on learner preferences for learning resources. Similarly, different learners have different sequential access patterns for learning resources that can equally influence the learning resources that should be recommended to the learner. These additional learner information namely learner characteristics, learner context and sequential access patterns have some influence in determining the learner preferences for a learning resource, hence they should be captured during recommendation. In the context of e-learning, collaborative filtering recommendation approach recommends learning items to the target learner similar to the ones liked by other learners with similar preferences. A rating is used to measure the degree of usefulness of an item to a user. Ratings of learning resources by the learners are used to measure similarity of learners or learning resources. Content-based

recommendation approach recommends learning resources to the target learner that are similar in content features to those liked by the learner in the past. Conventional recommendation methods do not incorporate additional learner information such as learner characteristics, learner context and learner's sequential access patterns in generating recommendations for the learner. Besides, conventional recommendation approaches experience the cold-start and sparsity problems, making them unreliable in e-learning scenarios. Majority of the recommendation methods currently in use still face similar challenges due to lack of incorporation of additional learner information in their recommendation processes. As such, most of the existing recommendation methods are likely to generate recommendations with lower accuracy and poor personalization to learner preferences in e-learning environments. To overcome this problem, recommendation approaches that incorporate additional learner information into the recommendation process are required.

The main goal of this thesis is to develop hybrid knowledge-based recommendation algorithms that take into account additional learner information such as learner characteristics, learner context and learner's sequential access patterns in their recommendation processes to help improve personalization and accuracy of recommendations as well as alleviate sparsity and cold-start problems. Additionally, this thesis explores the learner and researcher related challenges of e-learning recommender systems. The major contributions of this thesis are described below.

First, we explored the challenges of e-learning recommender systems by carrying out a systematic literature review of journal papers on e-learning recommender systems with a view to identifying and categorizing the challenges as either learner or researcher related challenges. In addition, we discuss the solutions for addressing each of the challenges.

Secondly, we proposed a hybrid knowledge-based recommendation approach based on ontology and sequential pattern mining (SPM) algorithm for recommending relevant learning resources to learners in e-learning environments. In the proposed recommendation method, ontology was used to model as well as represent the knowledge about the learner and learning resources while SPM algorithm was used to mine the web logs and discover the learner's sequential access patterns for filtering the recommendations according to the learner's sequential access patterns. Experimental results over a real world dataset show improvement in performance in terms of accuracy, precision and recall metrics. Furthermore, the proposed recommendation method can alleviate the cold-start and data sparsity problems by using the ontological domain knowledge and learner's sequential access patterns respectively before the initial ratings to work on are available in the recommender system.

Lastly, we proposed a hybrid recommendation method combining context-awareness, SPM algorithm and collaborative filtering for recommending relevant learning resources to learners. In our method, context-awareness was used to incorporate the learner's context information such as knowledge level and learning goals while SPM was used to discover the learner's sequential access patterns. These sequential access patterns were incorporated as well into the recommendation process. Collaborative filtering was used to compute similarities, predict learner ratings and generate recommendations for the target learner taking into account contextualized data and learner's sequential access patterns. Experimental results show that the proposed hybrid recommendation method can outperform other related recommendation approaches in terms of quality and accuracy of recommendations.

Keywords: Recommender systems, e-learning, collaborative filtering, knowledge-based, hybrid filtering, ontology, sequential pattern mining, context awareness

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List of Abbreviations

CA	Context-Aware
CB	Content-Based
CF	Collaborative Filtering
DAML	DARPA Agent Markup Language
DB	Demographic-Based
FB	Fuzzy-Based
GB	Group-Based
GSP	Generalized Sequential Pattern
ICT	Information and Communication Technology
IDF	Inverse Document Frequency
KB	Knowledge-Based
kNN	k Nearest Neighbor
LMS	Learning Management System
MAE	Mean Absolute Error
OB	Ontology-Based
OIL	Ontology Inference Layer
Onto	Ontology
OWL	Web Ontology Language
PLE	Personal Learning Environment
RDF	Resource Description Framework
SB	Social-network Based
SPADE	Sequential PAttern Discovery using Equivalence classes
SPM	Sequential Pattern Mining
SWRL	Semantic Web Rule Language
TA	Trust-Aware
TD_IDF	Term Frequency-Inverse Document Frequency
TEL	Technology Enhanced Learning
TORMES	Tutor Oriented Recommendations Modeling for Education Systems
UB	Utility-Based
VSM	Vector Space Model
WWW	World Wide Web

Chapter 1

Introduction

1.1 Research Background

In recent years, the World Wide Web (WWW) has witnessed a massive growth in the amount of learning resources available online. This explosion in the number of learning resources available on the Internet has been precipitated by the huge demand for online learning resources by learners in e-learning environments. Furthermore, e-learning in institutions of higher learning has been acknowledged as an alternative and innovative approach to support teaching and learning using ICT technologies. Many learners prefer using e-learning approach to support their learning since they can take their learning anytime, anywhere and at any place [1]. It is for this reason that it is gaining acceptance in many educational institutions worldwide as an alternative approach to learning [2]. However, with the growth of WWW coupled with large volumes of learning resources available online, learners are experiencing some challenges in retrieval of relevant learning resources in a large space of possible options [3]–[5]. Tang and McCalla [6] point out that in e-learning environments, learners are overwhelmed by information overload which is difficult to handle. As a result, learners get confused in their attempt to choose the appropriate learning resources especially when the number of choices increases. To overcome this problem, recommender systems provide an effective solution that can assist the learners to find relevant learning resources that meet their learning needs in online environments. Recommender systems are software tools which suggest the most suitable items to a particular user by predicting the user's preference on the item [7]. Research on recommender systems was motivated by the challenges of retrieval of relevant information by users due to information overload on the WWW.

Among the areas where recommender systems have been successfully used include Amazon[1] for recommendation of books, Netflix[2] for recommendation of movies, Last.fm[3] for music recommendation, and Coursera[4] for recommendation of courses among others [8], [9]. The idea of search engines as well as recommendation systems have become popular solutions towards addressing the difficulties of information retrieval arising as a result of information overload [10]. However, unlike the search engines which retrieve information by returning results that match the user query, recommender systems suggest recommendations automatically that are personalized and tailored to the needs and preferences of the user. "*The Web, they say, is leaving the era of search and entering one of discovery. What's the difference? Search is what you do when you're looking for something. Discovery is when something wonderful that you didn't know existed, or didn't know how to ask for, finds you*" [11]. Currently, recommender systems are used widely in fields such as e-commerce for product recommendation as well as in e-learning for recommendation of learning resources [12]. Recommender systems in various domains such as e-commerce, movies and e-learning have been used widely to address the problem of information overload by filtering out irrelevant information and recommending relevant information to the users according to their personalized preferences [13], [14]. User preferences refer to relevant items that meet the needs and interests of the user.

E-learning recommendation systems play a beneficial role of supporting learners in e-learning environments by providing recommendations of relevant learning resources that are personalized to the learner's needs for better achievement of their learning goals [15], [16]. The main goal of recommender systems in e-learning is to recommend relevant and accurate learning resources to the learner by predicting the learner's preferences or ratings on learning resources not yet seen by the learner [17]. Research on recommender systems in the area of e-learning has attracted increased attention due to its importance as a tool of information retrieval for online learners [14]. They help the learners to access learning resources that they couldn't have known about without the aid of recommender systems. To provide accurate

[1] https://www.amazon.com/
[2] https://www.netflix.com/
[3] https://www.last.fm/
[4] https://www.coursera.org/

recommendations of relevant items, recommender systems should perform proper combination between the user's preferences and the items to be recommended [18].

Unlike product recommendation in e-commerce, requirements for recommendation of online learning resources in e-learning are different due to differences in learner characteristics, learner context and learner's sequential access patterns. Over the years, researchers have proposed different recommendation methods but with the same goal of filtering out irrelevant information from relevant information [19]. Conventional recommendation methods such as content-based (CB) and collaborative filtering (CF) have become popular in many recommendation domains such as e-commerce, movies and music. Collaborative filtering recommender systems [20], [21] recommend items to the target user[5] that other users with similar preferences liked in the past. The similarity between two users is measured based on their similarities in their ratings of items. On the other hand, CB recommender systems suggest items that are similar in content features to the items that the target user liked in the past [22], [23]. However, CF and CB recommender systems on their own cannot guarantee personalized and accurate recommendation of learning resources in e-learning environments since they do not consider in recommendation the differences in learner's context and learner characteristics such as knowledge level, skills, background knowledge and learning style among others. These learner characteristics play a role in determination of learner's preference for learning resources and personalization of recommendations. Similarly, learner's contextual information such as knowledge level and learning goals keep changing as situations change and these changes in learner context affect the learner's preference for a learning resource at that particular context. In addition, learner's sequential access patterns equally plays a role in prediction of what learning resource the learner is likely to access next. Learner's sequential access patterns refers to the learner's frequent web navigation patterns as the learner browses a sequence of web pages and accesses the learning resources over a period of time. Failure to incorporate this additional learner information namely learner characteristics, learner context and learner's sequential access patterns into the recommendation process can result in recommendations that are inaccurate with poor personalization to learner preferences. For

[5] Target user/learner is the user/learner for whom the recommender system will produce predictions and recommendations.

example, although two learners may have similar ratings for a given learning item, additional learner information such as learner characteristics, learner's context and sequential access patterns may differ. This additional learner information have some influence in learner's preference for a learning item as well as personalization of recommendations, hence they should be considered in providing recommendations to the learner. Conventional and most existing recommendation techniques do not consider the additional learner information in their recommendation processes, hence they cannot guarantee personalized and accurate recommendation of relevant learning resources to the learners. Such recommendation approaches on their own are not suitable for recommendation of learning resources in e-learning environments. Furthermore, previous studies point out that conventional recommender systems encounter cold-start [24]–[26] and sparsity [27], [28] problems. Cold-start problem occurs in CF recommender systems in scenarios where there is lack of sufficient ratings for new users who have not rated any items or new items that have been added to the recommender system but they have not been rated by any user [20], [24]. Cold-start problem makes recommendations to the user unreliable. Similarly, sparsity problem in recommender systems occurs in a case where the number of users in the recommender system who have rated the items are too few compared to the large number of items, hence there is no overlap in the ratings of the target user and other users [27]. Sparsity and cold-start problems are prevalent in CF.

To attain good personalization and accuracy of recommendations of learning resources, additional information about the learner should be incorporated into the recommender system alongside the ratings or content features. Additional learner information that include learner characteristics (learning style, study level, knowledge level, and skills); learner's contextual information (knowledge level and learning goals); and learner's sequential access patterns should be integrated into the recommender system to help improve personalization and accuracy of recommendations. In addition, incorporation of additional learner information into the recommendation process helps to address the issue of sparsity and cold-start problems.

1.2 The Recommendation Problem in E-Learning

Learners in e-learning environments experience information retrieval challenges in their search for useful learning resources due to information overload in scenarios where recommender systems are not used. Traditional search engines cannot distinguish between useful information from useless information on the web. In cases where recommender systems are used to address the problem of information overload, learners can still receive recommendations that are not well personalized to learner’s needs if the recommender system does not take into account additional learner information to help improve personalization of recommendations. E-learning recommender systems differ from recommender systems in other domains since learners have different characteristics, learner contexts and sequential access patterns. Additional learner information such as learner contexts, learner characteristics and learner’s sequential access patterns should be incorporated into the recommendation process [29]. The purpose of incorporation of additional information alongside the ratings into the recommendation process is to improve personalization as well as accuracy of recommendations. Even if any two learners have similar ratings, their preference for a learning resource is likely to be different if the learner characteristics, learner context and sequential access patterns are not the same. Klašnja-Milicevic et al. [30] pointed out that in e-learning recommendation, a recommender system should consider the learner's specific characteristics, requirements and demands. Taking into account additional learner information during recommendation process translates to better personalization and relevance of recommendations. Collaborative filtering and content-based recommender systems perform poorly in personalization of recommendations in e-learning environments since they do not incorporate additional learner information in their recommendation processes, instead, they recommend items to the users based solely on ratings and content features respectively. Verbert et al. [31] emphasized in their survey of CA recommender systems the importance of incorporating learner and teacher characteristics as well as their context into the recommendation process. Existing recommendation methods still experience drawbacks of poor personalization and low accuracy in their recommendations of learning resources in e-learning environments.

In e-learning recommendation, learner preferences differ from context to context. Adomavicius and Tuzhilin [32] and Zheng et al. [33] point out that CB and CF recommender systems deal with two types of entities in recommendation namely *users* and *items* and do not consider the user context when suggesting recommended items to users. Due to the uniqueness of the learning process, recommendation of learning items to online learners requires the consideration of not only the ratings and content features but also other additional characteristics and contextual information about the learner and learning items. Learner contexts such as knowledge level and learning goals among others should be taken into account to improve both accuracy of recommendations and personalization. Different learners under different contextual environments may reveal different patterns of learner preferences and behavior. For instance, a learner whose knowledge level at one instance is *beginner* can have different preferences for a learning item when the knowledge level of the same learner changes to *intermediate*. Moreover, learners have differences in sequential access patterns which equally influence the learning item that should be recommended to the learner. By incorporating contextual information, learner's sequential access patterns and other additional learner characteristics such as learning style, background knowledge, skills and prerequisites among others, the recommendation results will improve in terms of personalization and accuracy. The recommendation problem arising from differences in learner's characteristics, context and sequential access patterns in e-learning recommender systems can be addressed by integrating tools such as ontology, context awareness and SPM algorithm into the recommendation process. These recommendation tools enable the incorporation of additional learner information into the recommender system.

In this thesis, we address the problem of recommendation of online learning resources to learners by focusing on hybrid knowledge-based recommendation approaches that incorporate additional learner information such as learner characteristics, learner context and learner's sequential access patterns. Techniques such as ontology, context awareness and SPM algorithm are employed for incorporating additional learner information into the recommender system. The importance of incorporation of additional information into the recommendation process has been emphasized by [34]. How to improve personalization and accuracy of recommendations of learning resources as well as alleviate the sparsity and cold-start problems are among the goals of this thesis.

1.3 Research Goal and Objectives

The main goal of this thesis is to investigate the recommendation problem of online learning items in e-learning environments and propose practical recommendation solutions using hybrid recommendation approaches that take into account additional learner information in their recommendation process. Additional information includes learner characteristics (knowledge level and learning style), learner context and learner's sequential access patterns. This goal will be achieved through the following three specific objectives:

(i) To explore the learner and researcher related challenges facing e-learning recommender systems.

(ii) To develop a hybrid knowledge-based recommendation algorithm for recommending online learning resources based on ontology and sequential pattern mining.

(iii) To develop a hybrid recommendation algorithm for recommending learning materials by combining collaborative filtering, context awareness and sequential pattern mining.

1.4 Thesis Contributions

This thesis focuses on the design and use of hybrid knowledge-based recommendation algorithms in e-learning domain for recommending learning resources to online learners. The study makes significant contributions in the field of e-learning resource recommendation. The main contributions of this thesis are as follows:

(i) Review of learner and researcher related challenges of e-learning recommender systems.

A review is conducted on challenges of e-learning recommender systems and these challenges are categorized as either learner or researcher challenges. Possible solutions for alleviating the challenges are also discussed.

(ii) Integration of ontology and sequential pattern mining for recommendation of e-learning resources

A hybrid knowledge-based recommendation approach based on ontology and SPM for recommending useful learning resources to learners is proposed. In the proposed recommendation approach, ontology was used for modeling and representing knowledge about the learner and learning resources while SPM algorithm was used to mine the web logs and discover the learner's sequential access patterns. First, in recommending the learning resources to the learners, we take into account additional learner characteristics such as learning style and knowledge level by using ontology to model and represent knowledge about the learner and learning resources. Similarly, we use SPM algorithm to discover the learner's sequential access patterns for incorporation into the recommendation process. Aggregation of this additional information into the recommender system helps to improve personalization of recommendations to the learner. Secondly, in computing similarity of learners and learning items as well as generating predictions, ontology domain knowledge about the learner is taken into account alongside the ratings, hence resulting in improvement of accuracy of predictions of learner preference for a learning item. Thirdly, this knowledge-based recommendation method addresses the cold-start problem by using the ontology domain knowledge arising from integration of ontology into the recommendation process. Additionally, sparsity problem is also alleviated by using the learner's sequential access patterns to predict learner's preferred learning resources in cases where their ratings are sparse. Lastly, experimental results of the proposed ontology and SPM based recommendation algorithm tested over a real world dataset showed improved performance in comparison with other recommendation methods.

(iii) Incorporation of contextual information and sequential access patterns into a hybrid e-learning recommendation approach.

A hybrid recommendation approach for recommending learning resources based on context awareness and sequential pattern mining is proposed. The proposed approach combines CF, CA and GSP algorithms to improve personalization and accuracy of recommendations. Context awareness is used to incorporate learner's contextual information such as knowledge level and learning goals while GSP algorithm is used to mine the web logs and discover the learner's sequential access patterns for filtering the recommendations according to the learner's sequential access patterns as well as to help alleviate sparsity problem. The recommendation approach takes into consideration the learner's context information in computing both the ratings similarity and predictions for the target learner. Experimental results demonstrate that the proposed recommendation approach that combines CF, CA and SPM algorithm provides more accurate and personalized recommendations than the existing related recommendation methods.

1.5 Structure of the Thesis

This thesis contains five chapters. The entire thesis is structured as follows:

Chapter 1 is the introduction of this research thesis with focus on the research background on e-learning recommender systems and the recommendation problem in e-learning domain. In this chapter, we also present the research goals and objectives of this thesis. Furthermore, we highlight the main contributions of this thesis. The structure of this thesis is also presented in this chapter.

In Chapter 2, we review the literature related to this thesis. The chapter introduces the common recommendation techniques such as collaborative filtering, content-based, knowledge-based, hybrid filtering, ontology-based and context-aware based recommendation techniques among others. Ontology and sequential pattern mining is also discussed in this chapter with more emphasis on their usage in e-learning recommender systems. In addition, we discuss recommender systems for e-learning as well as context awareness in e-learning recommendation. The chapter further explores the learner and researcher related challenges of e-learning recommender systems. Possible solutions from different studies for addressing the challenges are also discussed. Lastly, the chapter presents the evaluation metrics for e-learning recommender systems such as Mean Absolute Error, Recall, Precision and F1 measure.

In Chapter 3, we present a hybrid knowledge-based recommendation approach for recommending online learning resources based on ontology and SPM algorithm. We describe how ontology and SPM algorithm is used to incorporate additional learner information into the recommendation process. The chapter further presents our recommendation model as well as the learner and learning resources ontologies. Experimental evaluation of the proposed recommendation method and comparison of results with other related approaches is also presented in this chapter.

Chapter 4 presents a hybrid recommendation approach for e-learning based on context awareness and sequential pattern mining. In this method, we explain how the learner’s context and sequential access patterns are incorporated into the recommendation process. The recommendation model of the proposed recommendation approach and the hybrid recommendation algorithm are also presented and described in this chapter. The experimental results of evaluation of the proposed recommendation approach are presented as well in this chapter.

Finally, Chapter 5 concludes this thesis. In this chapter, we also present the summary of the thesis and discuss possible future research directions of this research area.

Chapter 2

Literature Review

This section discusses the literature from previous studies relevant to this thesis with a focus on common recommendation techniques, e-learning recommender systems, ontology-based recommendation approach in e-learning, context awareness in e-learning recommender systems, sequential pattern mining and evaluation of e-learning recommender systems. The chapter further reviews the challenges of e-learning recommender systems.

2.1 Common Recommendation Techniques

Recommender systems are popular software tools of information retrieval and are widely used today as a solution towards addressing the common problem of information overload on the WWW. They are useful software tools that aid the users by suggesting appropriate items that meet the user's needs in areas such as e-commerce and e-learning [12]. Recommender systems are categorized according to the technique they use in making recommendations. In this sub-section, we introduce the different classifications of recommendation techniques. Burke [35], Adomavicius & Tuzhilin [24] and Jannach et al. [36] distinguish between the classes of common recommendation methods. These recommendation techniques include content-based (CB), collaborative filtering (CF), demographic-based (DB), utility-based (UB), knowledge-based (KB), and hybrid filtering. Other recent recommendation techniques include context-aware (CA) based [32], [37], trust-aware (TA) based, group-based (GB) [38], social-network based (SB) [39], fuzzy-based (FB) [40], and ontology-based (OB) recommendation techniques. Each recommendation technique has its strengths and drawbacks. Figure 2.1 illustrates the classification of recommendation techniques that are commonly used in recommender systems.

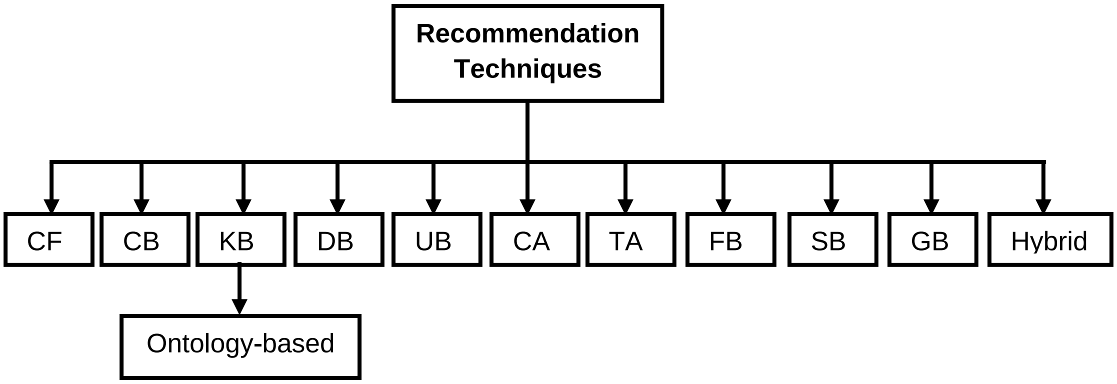

Figure 2.1: Classification of recommendation techniques

Collaborative filtering: CF recommender systems suggest items to the active[6] user that are similar in terms of ratings to those that other users with same preference liked in the past. This recommendation technique provides recommendations of items based on the opinions and preferences of other similar users [41], [42]. The principle behind CF recommendation technique is based on the assumption that if users had similar preferences of items in the past, then there is a likelihood that they will also have similar preferences for items in the future [36]. The similarity in preferences between two users in a CF recommender system is measured based on rating similarities in their rating history [20], [23]. In the context of recommender systems, a rating is defined as the degree of interest in an item by a given user. The key principle behind CF is measuring the similarity in ratings between users/items and predicting the ratings for the active user for unseen items. It involves looking for other users with similar ratings as the active user and then using their ratings to predict the ratings of the active user for unrated items; or looking for similar items which were liked by other users and using their ratings to compute predictions of ratings for the active user [23]. There are various measures of similarity for measuring similarity of ratings between users or items in a recommender system. The most common and widely used measures of similarity are correlation-based and cosine-based measures of similarity [43]. Chen et al. [5] pointed out Adjusted Cosine Similarity (eq.2.1) as among the widely used measures of similarity in item-item CF. Similarity among two items namely *i* and *j* can be measured using the Adjusted Cosine Similarity formula in eq. 2.1:

[6] Active user/learner is the user/learner for whom the recommender system will produce predictions and recommendations.

$$sim(i,j)=\frac{\sum(\mathrm{r}_{u,i}-\overline{r_u})(\mathrm{r}_{u,j}-\overline{r_u})}{\sqrt{\sum(\mathrm{r}_{u,i}-\overline{r_u})^2}\sqrt{\sum(\mathrm{r}_{u,j}-\overline{r_u})^2}} \tag{2.1}$$

where $\mathrm{r}_{u,i}$ is the rating given to an item *i* by a user *u*, $\mathrm{r}_{u,j}$ is the rating given to an item *j* by a user *u*, $\overline{r_u}$ represents the mean of all the ratings provided by *u* [36].

The commonly used algorithm for CF is the *k* Nearest Neighbor abbreviated as *k*NN [20], [24], [44]. Nearest neighbors refers to users in the recommender system with similar preferences as the active user in terms of similarity of ratings. In the case of user-based CF, *k*NN performs three main tasks to provide the recommendations for an active user: (1) find the *k* number of users called neighbors for the active user *u*; (2) execute an aggregation approach using ratings for the items in the neighborhood that have not been rated by *u*; and (3) extract the predictions of ratings in step 2 and then select the *top-N* list of recommendations [45]. Fig. 2.2 illustrates the process of recommendation in CF.

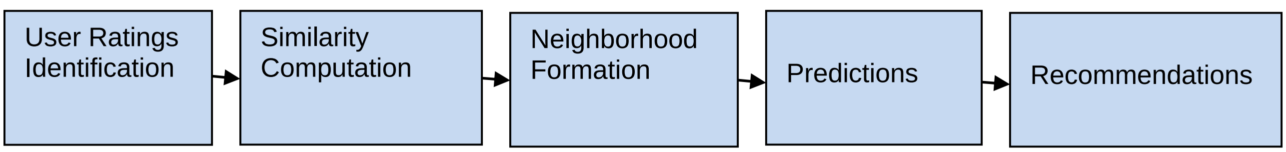

Figure 2.2: Recommendation process in collaborative filtering

Although CF is the widely used recommendation method [7], it faces some challenges such as data sparsity and cold-start problems. Cold-start problem occurs in situations where a recommender system cannot provide reliable recommendations due to lack of initial ratings by a new user or for a new item in the case of new user and new item problems [24] respectively. New user problem can occur in the event a new user has entered the system and has not rated any of the items, hence the recommender system cannot provide recommendations to the new user due to missing user preferences. A new item problem can arise in the event a new item which has not been rated by any user is added to the recommender system, hence the item cannot be recommended [20], [24]. Sparsity problem on the other hand occurs in scenarios where there are few users and many items in the recommender system and the few users in the system have not rated the same item with the active user, hence no overlap in ratings between the active user and other users [46].

Content-based: In CB recommendation technique, the recommender system recommends to the active user items that are similar in terms of content features to those that the active user liked previously. The similarity of items in CB recommendation approach is computed using the content features possessed by the compared items [22], [35]. Measurement of similarity among the items in the recommender system is the key principle behind CB recommendation technique. CB recommendation technique can be classified into case-based reasoning [24] and attribute-based technique [16]. Case based reasoning method recommends those items with the highest similarity to the ones the user liked in the past while attribute-based technique recommends items to the user by considering the matching of their attributes to the user profile [47].

Content-based recommendation technique uses simple information retrieval models like keyword matching or Vector Space Model which uses basic Term Frequency-Inverse Document Frequency (TF-IDF) for weighting. TF-IDF is a measure used to calculate the overall importance of keywords in a document (eq. 2.2) [48].

$$TF\_IDF(\mathrm{t}_k, d_j) = \underbrace{TF(t_k, d_j)}_{TF} \bullet \underbrace{\log\frac{N}{n_k}}_{IDF} \tag{2.2}$$

where d_j represents the document in *n*-dimensional vector space, t_k denotes the term in document d_j, N represents the documents in the corpus, and n_k represents the documents in the collection where the term t_k occurs at least once.

The benefits of CB recommender systems are transparency, user independence as well as new unrated item recommendation. However, the drawbacks associated with CB recommendation technique include overspecialization, limited content analysis, new user problem and serendipity [7]. Limited content analysis refers to cases in which there is difficulty by the recommender system in extraction of reliable and useful information from heterogeneous data formats like video, images and audio formats. If the recommender system fails to extract reliable and useful information for content features comparison, then the quality of the recommendation results will be affected. Overspecialization in CB recommendation occurs in cases where the active user receives recommendations of items which are so similar in content features to what they liked in the past, hence the users cannot receive recommendations of items that they do not know but are likely to be of interest to them due to lack of diversity in recommendations. On the contrary, serendipity refers to situations where discoveries of those items not seen by the user before are made by accident and the discovered items are totally different from those that the user liked or rated in the past [7].

Knowledge-based: KB recommendation technique suggests items to users by making use of the domain knowledge of the items that meet the user preferences [49]. Knowledge-based recommender systems need to employ three types of knowledge; knowledge about the items, knowledge about the users as well as knowledge about the matching between the item and user's need [24]. In the context of recommender systems for e-learning, KB approach incorporates knowledge about both the learners and the learning items, and this knowledge is applied into the recommendation process [50]. Unlike CF and CB recommender systems, KB recommender systems do not encounter the cold-start problem or sparsity problem [24], [46] since they don't rely on ratings in making recommendations but instead, they employ the domain knowledge. KB recommendation techniques are therefore widely used for hybridization with other recommendation methods. However, the main drawbacks facing KB recommendation technique is the requirement of skills in knowledge engineering [35].

Ontology-based: Ontology has been defined as an explicit formal specification of a shared conceptualization [51]. Ontologies are generally used to model and represent knowledge about the user, knowledge about the item, and the domain knowledge [52]. Ontology contains a set of concepts called entities, attributes and properties related to the domain alongside their definitions as well as relations among them [53]. Domain ontologies are created manually or automatically and they can be used with other technologies such as web mining tools [54]. Ontologies are created using ontology representation languages like Web Ontology Language (OWL) and Resource Description Framework (RDF). They are beneficial because they enable reuse of their domain knowledge. Moreover, reusing ontologies is beneficial in that it can save time and also ensures quality ontologies since such ontologies and their components have already been well tested during their previous use. In addition, ontologies can also be used together with other tools and techniques such as machine learning and data mining to give better results [55]. Due to the usefulness of ontology as an important tool for knowledge modeling and knowledge representation, it has been widely embraced by researchers in fields such as recommender systems and information retrieval.

In e-learning recommender systems, ontology can also be used for knowledge modeling and representation [50]. Ontology-based recommender systems are KB recommender systems that use ontology to represent knowledge about the users and items [56], [57]. In recommender systems for e-learning, ontology is used for modeling knowledge about both the learner and learning items. Like KB recommendation technique, OB recommender systems do not encounter most of the drawbacks associated with traditional recommender systems such as sparsity problem, cold-start problem [46] and overspecialization problem since OB recommender systems make use of domain knowledge. This advantage over conventional recommender systems makes OB recommender systems suitable for use in e-learning resources recommendation [58], [59]. However, creation of ontologies is both a difficult and expensive procedure. Besides, ontology construction is a time consuming exercise. To address these problems associated with creation of ontologies, modern tools of ontology creation have been proposed to facilitate automatic creation of ontologies [60].

Hybrid filtering: Hybrid filtering recommendation technique entails combining two or more existing recommendation techniques with the goal of improving performance [35], [61], [62]. The method combines the features of two or more recommendation techniques so as to use the strengths of both recommendation techniques to improve the performance of the recommender system [63]. In addition, hybridizing two or more recommendation methods helps address the limitations of an individual recommendation technique as well as provide good recommendation results [63], [64]. For example, Chen et al. [5] proposed a hybrid learning material recommendation approach which combines CF and sequential pattern mining for recommending learning items to the learners using e-learning. Similarly, Zhao et al. [27] proposed a hybrid recommendation method that combines matrix factorization and topic model in a two-step process for solving a recommendation problem. In both Chen et al. [5] and Zhao et al. [27] proposed recommendation methods, they recorded improvements in accuracy of recommendations. Different hybridization methods have been suggested by researchers in the area of recommender systems. For instance, Burke [35] presented seven techniques of hybridization of recommender systems namely: mixed, cascade, switching, meta-level, weighted, feature augmentation, and feature combination (Fig. 2.3).

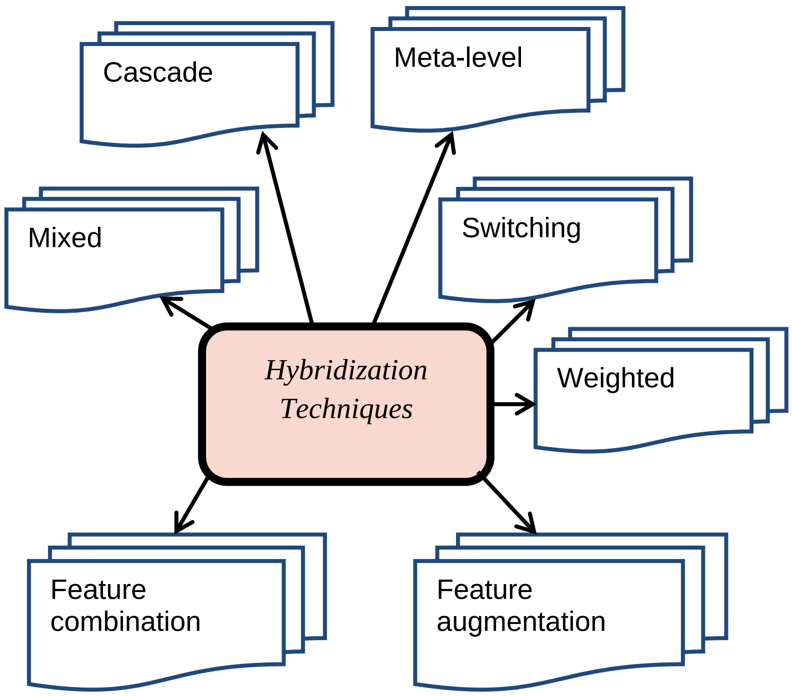

Figure 2.3: Hybridization techniques in recommender systems

Drawbacks associated with conventional recommendation techniques such as sparsity, cold-start and over specialization problems can possibly be alleviated through hybridization of recommendation methods [64].

Demographic-based and ***Utility-based:*** Demographic-based recommendation approach aims to classify the user based on their personal attributes and provide recommendations based on the demographic classes. The principle of demographic-based approach is users having the same personal attributes are also likely to have similarity of preferences for items. Utility-based recommender systems make suggestions for items based on the computation of each object's utility for the user [35], [65].

Context-aware based: Dey et al. [66] defines context as any information that may be used in characterizing the situation of an entity. In CA recommendation approach, contextual information of a user or an item are used to filter the dataset before application of a conventional recommendation algorithm [31], [32], [37].

Context-aware recommendation approach in e-learning domain entails recommendation of learning items to the target learner based on the current context of that learner [3], [32]. Incorporation of contextual information for the learner or learning resource into the recommendation process facilitates more personalized and accurate recommendations of learning items to the learners with similar contextualized preferences. The ability to aggregate additional learner's contextual information into the recommender system helps to personalize the recommendations according to the learner preferences and profile.

Trust-aware based: Trust in a person can be defined as a commitment to an action with the belief that the future actions of that particular person will result to a good outcome [67]. The objective of trust-aware based recommendation approach is to provide personalized recommendations to the user from known trust relationships and opinions. In areas such as e-learning and e-commerce recommender systems, trust is considered an important aspect in improving social network relationships among users [68].

Social-network based: In social-network based recommender systems, recommendations are provided based on information about the user's profiles and the relationships between users [39], [69]. Examples of web applications using social-network based recommendation technique include LinkedIn[7] and Facebook[8].

Fuzzy-based: Fuzzy-based recommender systems are recommender systems where recommendations of items to users are provided on the basis of vague or uncertain information. In many practical cases for instance, users can express their preferences for items in linguistic terms such as 'interested', 'very interested' or 'not interested' [40].

[7] https://www.linkedin.com/
[8] https://www.facebook.com/

Group-based: Group-based recommender systems provide recommendations of items to users in a group rather than an individual. Group recommendations are suitable in scenarios where a group of people participate in a single activity [38]. A practical example is where a recommender system selects television programmes for a group to view.

2.2 Recommender Systems for E-Learning

E-learning plays a beneficial role in supporting teaching and learning in educational institutions. Manouselis et al. [14] points out that e-learning is an application domain that covers technologies that support all forms of teaching and learning activities. Many learners today prefer e-learning as an alternative new approach to learning since they can take their learning anytime, anywhere and at any place [1], [70]. It is for this reason that it is gaining acceptance in many educational institutions as an innovative approach to teaching and learning supported by information and communication technologies (ICTs) [2]. However, with the explosion of the information available on the web, learners are experiencing difficulty in searching for relevant learning resources in a large space of possible options [3], [4]. Tang and McCalla [6] point out that learners using e-learning on online environments are overwhelmed by information overload which is difficult to handle. As a result, learners get confused in their attempt to choose the appropriate learning resources especially when the number of choices increases. To overcome this problem, recommender systems provide a very effective solution that can aid learners to find useful learning resources that meet their learning needs in e-learning environments. Recommender systems are useful software tools which recommend the most suitable items to particular user by predicting the preferences of the user on the item [7].

The main purpose of recommender systems in e-learning is to aid the learners to easily find relevant learning resources that are suitable for their learning requirements and needs. Whereas conventional recommendation techniques such as CF and CB recommend items to the target users based on similarity of ratings and content features respectively, recommender systems for e-learning domain require additional information about the learner for purposes of improving personalization of recommendations according to the learner preferences and learning needs. Besides the ratings and content features, learner characteristics such as knowledge level, learner experience, learning style, and study level among others should be incorporated into the recommendation process. Salehi et al. [71] underscores that personalization is among the main goals of recommender systems for e-learning.

Application of recommender systems to educational domain has attracted increased attention in recent years [14]. As such, several studies on recommender systems for e-learning have been undertaken in the last few years. Recommender systems for e-learning differ from general recommender systems in a number of ways. The notable trend in research on recommender systems for e-learning is the notion of combining different recommendation methods to improve the accuracy and performance of the recommendation systems. Garcia-Martinez and Hamou-Lhadj [72] points out that the context of recommendations in e-learning recommender systems is pedagogically related. Such pedagogical contexts include the learners learning style, instructional design and pre-requisites among others. The main benefit of recommender systems in e-learning is to help the learners reach their desired pedagogical goals through improving learner performance, social learning enhancement and increase of learner's motivation. Moreover, recommender systems help the learners to find useful and relevant learning resources for purposes of improving the achievement of learning goals and development of competences in less time [16], [73]. Tang et al. [74] notes that a good educational recommender system should make use of contextual information rather than relying purely on ratings in determining the preferences of learners. Hoic-Bozic et al. [75] proposed a recommender system for enhancing personalized online learning through incorporation of pedagogical approaches, problem-based learning and collaborative learning in their proposed recommendation model. Experimental results show that their proposed recommendation model assisted the students to achieve better course results. Klašnja-Milićević et al. [30] describe a recommender system that automatically adapts to the knowledge level and interests of the learners. Their system is used to recommend learning activities to online learners based on their preferences and knowledge. Jovanović et al. [76] used several kinds of learning related ontologies such as content structuring and user modeling ontologies in order to acquire the information specific context of learning objects, learning designs and personalization. In Tarus et al. [77], ontology was used to represent the knowledge about the learner's learning style and knowledge level in a recommender system for recommending learning resources to learners in an e-learning environment. The experimental results of their hybrid recommendation method showed improvement in accuracy and performance. Most personalized e-learning recommender systems use ontologies for semantic knowledge representation, domain conceptualization and knowledge acquisition [57], [78]. Personalization of learner profile by using ontology makes the recommendations more tailored to the target learner preferences. For instance, Lv et al. [79] presented a hybrid recommendation approach by combining both ontology and genetic algorithm. Their experimental results show that hybridizing ontology with genetic algorithm improved the effectiveness and accuracy of recommendations. Similarly, Zheng et al. [80] proposed a trust-based recommendation method that can mitigate the learning issues in the online communities of practice. Evaluation results of their hybrid recommendation method indicated that their proposed hybrid algorithm provided more accurate results than other related recommendation algorithms. Chen et al. [5] similarly proposed a hybrid e-learning recommendation method for learning resources and their experimental results showed significant improvement in predictions accuracy and performance of the recommender system. On the other hand, Pukkhem [81] proposed a learning object recommender (LORecommendNet) that uses ontology in representing knowledge as well as mapping the learner to the learning objects. Their recommender system can as well enable machines to interpret the learning objects in their recommender system. Furthermore, Mota et al. [82] proposed a KB recommendation approach that is capable of assisting in the design of teaching and learning activities by the educators. Ontology was used to model the knowledge about the educators and teaching activities.

Moreover, Cobos et al. [83] proposed a recommender system called "*Recommendation System for Pedagogical Patterns*". Their hybrid recommender system combines CF and CB recommendation techniques and uses ontology to represent pedagogical patterns. In addition, their recommender system can allow lecturers to state their best strategies for teaching and use those strategies within the context of a given class. Takano and Li [84] presented a hybrid e-learning recommender system that uses a hybrid method to monitor the feedback implicitly for the web browsing actions that are associated with the user's preferred contents and explicit feedback for the recommended contents. Alimam et al. [85] presented a recommender system for e-learning based on ontology that can recommend careers in the context of e-learning while

[86] proposed a semantic ontology-based recommendation framework that can provide personalized recommendations for assisting learners using e-learning to find and select relevant learning items in their field of interest. Their recommender system is based on the semantic relations and also reasoning means within the domain ontology. Similarly, Salehi and Kamalabadi [71] presented a hybrid e-learning recommendation system that uses the attributes and the sequential patterns of the accessed learning materials. Experimental results of their proposed recommendation approach showed good performance. Ting et al. [87] proposed a hybrid personalized recommendation method that is based on bipartite graph using weights and web log mining. Their experimental results over a real world dataset showed that combining web log mining with weighted bipartite graph is not only feasible but improves significantly the recommendation results.

Furthermore, Drachsler et al. [15] reviewed recommender systems for TEL from year 2000 – 2014 and classified 82 recommender systems into 7 clusters according to their characteristics and their overall contribution to recommender systems for TEL research. In their survey, the 16 papers that were analyzed under cluster 3 were relevant to e-learning and the tools used for knowledge representation and modeling in those recommender systems include ontologies, semantic relations and concept maps. Similarly, Tarus et al. [57] conducted a review of KB recommender systems for e-learning domain and found out that e-learning recommender systems that use ontology for knowledge representation reported an improvement in performance. Klašnja-Mili´cevi´c et al. [47] carried out a survey of recommender systems for e-learning with a focus on major requirements and also challenges encountered by designers of recommender systems for e-learning. In their work, they recommended possible extensions with tag-based recommendation and a model for tagging activities. Erdt et al. [17] conducted a survey of recommender systems for technology enhanced learning (TEL) by classifying papers according to the methodology used for evaluation methodology, evaluation subject, and also effects measured by the evaluation. Yang et al. [88] carried out a review of studies on social recommender systems based on CF and categorized the social recommender systems based on CF into two classes namely neighborhood based and matrix factorization based social recommendation approaches.

Other related studies in recommender systems for e-learning such as [89] employed recommender system technologies and social semantic web to incorporate teacher's personal learning competencies, learning environment, learner's interaction history and social web data for generating recommendations that are personalized for each of the learners. Wan and Niu [90] proposed a recommendation method that is learner oriented and based on immune algorithm and mixed concept mapping. Their proposed recommendation algorithm shows a high adaptability and also efficiency in recommendation of learning items. A learning goals recommender system that can suggest the learning goals to the learners using some adaptive learning system was proposed by [91]. Evaluation of this recommendation system provided good results. Limongelli et al. [92] proposed a recommender system that can help teachers in building their courses through the Moodle LMS and also help them to retrieve the relevant learning objects. Dascalu et al. [93] proposed a recommender system for e-learning based on ontology for use in lifelong learning. Evaluation of their educational recommendation system demonstrated that it can successfully support some new learning paradigms in an e-learning environment. Rodríguez et al. [94] proposed a hybrid e-learning recommender system for recommending learning resources by combining CB, CF and KB recommendation methods. Experimental tests of their recommender system on a database with real data provided improved performance. Salehi et al. [71] presented a hybrid recommender system for e-learning that can make automatic suggestions of learning items using genetic algorithm and also multidimensional information model. Their recommendation method outperformed other related recommendation approaches in terms of accuracy of predictions. Their proposed approach also helps alleviate sparsity problem and also cold-start problem. Martinez-Cruz et al. [95] developed an ontology-based recommender system that can characterize the trust in recommendations among the users by using fuzzy linguistic modeling. Their experimental results illustrated that recommender systems using ontology perform better than those recommendation approaches based on purely CF.

2.3 Ontology

Ontology is a formal explicit description of concepts in a domain consisting of objects, classes (concepts), properties, relationships, rules and constraints [96]. Knowledge about specific domains can be encoded using ontology representation languages such as OWL, RDF, Ontology Inference Layer (OIL) and DARPA Agent Markup Language (DAML) [96]. OWL and RDF are the widely used ontology formal representation languages for creating ontologies. Ruotsal [56] and Kalibatiene and Vasilecas [97] explained that ontology encoding languages are used to formally describe concepts and properties between them. These representation languages in most cases include predefined semantics and reasoning rules to support the processing of that knowledge. Semantic Web Rule Language (SWRL) is an example of the rule languages which are specifically used for introducing inference rules in the knowledge models represented in OWL [98]. A number of studies have used ontology representation languages as well as rule languages in recommender systems. Vesin et al. [99] for instance used OWL representation language to encode an ontology used in their proposed recommender system that uses Jess rules and SWRL for reasoning. Kontopoulos et al. [100] employed RDF representation language to encode their ontology in their proposed recommendation approach.

Ontologies can be classified based on their domain scope. The classifications according to domain scope include domain ontology, general ontology, application ontology, reference ontology, and top level/generic ontology [101]. Domain ontologies for instance represent knowledge regarding a particular part of the world. Application ontologies refer to specializations of domain ontologies which represents the particular model of a domain according to a single viewpoint of a developer or a user. Reference ontologies represent the knowledge about some particular part of the world in a way that is independent from specific objectives, through a theory of the domain that is represented [102]. General ontologies are not dedicated to any specific field or domain. They contain general knowledge of a huge area. Examples of general ontologies are DBpedia and CYC. CYC is a commonsense reasoning engine and general knowledge base whereas DBpedia represents a community effort for structuring information content from information in Wikipedia and making this information available on the web [103]. Top level ontology refers to generic ontologies that are applicable to diverse domains. They define basic notions like objects, relations, events, processes and so on [103]. In a recommendation approach described in [99], they employed two main types of ontologies namely task ontology and domain ontology while [83] used reference ontology in their recommender system.

Table 2.1 shows the summary of studies between year 2005 and 2014 on e-learning recommender systems that used ontology with focus on ontology type, ontology encoding language and type of learning resource recommended by the respective ontology-based recommender systems [57].

Table 2.1: Summary of previous studies on e-learning recommender systems that used ontology

References	**Ontology type**	**Ontology encoding language**	**Recommended learning resources**
Pukkhem [81]	Domain ontology	OWL	Learning materials
Capuano et al. [91]	Domain ontology		Learning goals
Ruiz-iniesta et al. [104]	Domain ontology	OWL	Educational resources
Rani et al. [105]	Domain ontology	OWL	Answers to questions
Fraihat and Shambour [86]	Domain ontology	OWL	Learning materials
Baseera [106]	Domain ontology		Course content
Nowakowski et al. [107]	Domain ontology		Learning materials
Cobos et al. [83]	Reference ontology	OWL & RDF	Learning patterns
Pukkhem [108]	Domain ontology	OWL	Learning materials
Cheng et al. [19]	Domain ontology	OWL	Learning materials
Zhang et al. [58]	Domain ontology		Nearest neighbors
Wang and Huang [109]	Domain ontology		Learning materials
Dwivedi and Bharadwaj [110]	Domain ontology		Learning materials
Shishehchi et al. [50]	Domain ontology	OWL	Learning materials
Vesin et al. [99]	Domain ontology	OWL	Java programming content
Ferreira-Satler et al. [111]	Domain ontology	OWL	Learning materials
Bahmani [112]	Generic & domain ontology		Courses and curricula
Vesin et al. [113]	Domain ontology & task ontology	OWL & RDF	Learning links and actions
Blanco-Fernández et al. [114]	Domain ontology		Digital TV content
Huang et al. [115]	Domain ontology		Learning paths & content
Shishehchi & Banihashem [116]	Domain ontology	OWL	Learning materials
Hsu et al. [117]	Domain ontology		Reading material
Zhuhadar and Nasraoui [118]	Domain ontology		Courses and lectures
Ciuciu and Tang [119]	Domain ontology	OWL	Learning materials
Yang [59]	Domain ontology		Information for scholars
Rey-lópez et al. [120]	Domain ontology	OWL	TV learning objects
Biletskiy et al. [121]	Domain ontology		Learning materials
Žitko et al. [122]	Domain ontology	OWL	Tests/questions
Neri and Colombetti [123]	Domain ontology	OWL-DL	Learning materials
Weng [124]	Domain ontology		Research document
Kontopoulos et al. [100]	Domain ontology	RDF & XML	Personalized curricula
Cantador et al. [125]	Domain ontology	OWL & RDF	Learning materials
Yu et al. [52]	Domain ontology	OWL	Learning materials
Wang et al. [126]	Domain ontology		Learning materials
Mao et al. [127]	Domain ontology		Course materials
Shen and Shen [128]	Domain ontology	OWL	Learning materials

From the summary of previous studies using ontology shown in Table 2.1, it can be observed that majority of the previous studies on ontology-based recommendation for e-learning made use of domain ontology type. A few studies such as [83] used reference ontology, [112] used both domain and generic ontologies while [99] used both task and domain ontologies in their e-learning recommender systems. Furthermore, Table 2.1 shows that most ontologies used in e-learning recommender systems were encoded using OWL encoding language with a few encoded with RDF representation language.

2.3.1 Using Ontologies in Recommender Systems for E-Learning

Ontologies are used in different application areas but with different goals. For example, recommender systems employ ontologies to establish relationships between the users and their preferences about the recommendation item. Furthermore, they use ontologies to complement other existing techniques for knowledge representation in a recommender system [95]. Knowledge-based recommendation approach in e-learning makes use of ontologies for knowledge representation of both the learners and learning resources. In such cases, the recommender system uses ontology to establish the relationship between the learners and their preferences for learning resources. Ontology-based recommender systems uses ontology for knowledge modeling and representation [56]. In Cheng et al. [19], ontology was used to achieve personalization of learner profile and recommendations whereas in Zhang et al. [58], ontology was employed in user modeling.

Ontology-based recommendation technique is a useful technique and has gained popularity in usage in e-learning recommender systems in recent years. Garcı´a et al. [129] points out that ontologies have demonstrated to be useful and convenient structures in representation of knowledge models. Whereas CF recommender systems make use of ratings for computing user or item similarity [46], OB recommender systems aggregate knowledge about the learner and learning items into their recommendation process. E-learning recommender systems should aggregate additional information about the learner into the recommender system to improve the quality of recommendations. Such additional information include background knowledge, learning goals, study level, knowledge level, skills, experience and learning style among others. This additional information is not only important for personalization but also for accuracy of predictions. Similarly, additional information about the learning item should be considered in e-learning recommendation. In learning resources with heterogeneous formats like images, text, video and audio, ontology can be used for aggregation of additional information into the recommendation process. In their work, Klašnja-Milicevic et al. [30] proposed a personalized e-learning recommendation system that can adapt to the interests, habits and also knowledge levels of the learners. Among the advantages of using ontologies in knowledge-based recommendation systems is the benefit of additional ontological knowledge about the learner in improving personalization and the quality of the recommendations provided to the learner [77]. What determines the effectiveness of OB recommendation approach is not only the completeness but also the accuracy of knowledge maintained in the ontology domain knowledge. More advantages associated with use of ontology for knowledge representation have been enumerated by [130].

A number of previous studies have employed ontology as a tool for knowledge representation in their recommender systems for e-learning and have reported improvement in quality of the recommendations. For instance, Sosnovsky et al. [131] proposed a recommendation approach where ontology was used for personalization and knowledge representation. Their recommendation method for suggesting supplementary reading materials was implemented in an adaptive system. Qiyan et al. [132] similarly proposed an OB recommendation framework for learning items and semantic content. Their recommender system contains three important components namely semantic rules, ontology and concept lattices. Ontology in their case was used for learning object knowledge representation and also for modeling the cognitive structure of the learner. Web Ontology Language was used in their recommendation model specifically to encode the ontology knowledge. Other studies such as [50], [81], [83], [99] also aggregated ontology as a suitable tool for representing knowledge in their recommendation approaches. Encoding of ontology in the work of [81] was based on OWL with SWRL for reasoning rules. Both OWL and RDF encoding languages were used to encode ontology knowledge in the work of [83]. Their reference ontology contained a total of 23 classes and 76 instances. Shishehchi et al. [50] also described an ontology used in their recommender system which was encoded using OWL and contained two main classes namely learning material class and learner class.

However, despite the success in usage of ontologies in e-learning recommender systems, there are still some drawbacks associated with usage of ontologies in the field of recommender systems. The major challenge is that construction of ontologies is quite difficult and also time consuming process. Besides, knowledge engineering skills are required in creating ontologies. As a result, to create ontology for e-learning related tasks, an expert in the field of education may be required. However, researchers of OB recommender systems for e-learning have proposed some tools to alleviate the difficulty in construction of ontologies. One such tool is a learner centered methodology called Tutor-Oriented Recommendations Modeling for Educational Systems (TORMES) which was proposed by [15], [60]. This tool can assist the educators to identify the recommendation opportunities in e-learning and other educational environments. In addition, this methodology can also be used in elicitation of knowledge that is required for ontology creation in an ontology-based recommender system.

Despite the challenges associated with construction of ontologies, usage of ontology in KB recommender systems in e-learning domain has attracted increased attention due to their benefit of improving personalization of learner profiles and enabling the incorporation of additional learner information into the recommender system such as knowledge level, study level, learning goals, prerequisites and learning style among others. In addition, incorporation of these additional learner information into the recommendation process can improve the accuracy and quality of recommendation results. In many previous studies, ontology was used in combination with other recommendation techniques in most cases [57]. Table 2.2 shows the summary of previous studies between year 2005 and 2014 that used ontology-based (OB) recommendation method alongside other recommendation techniques for recommending e-learning resources [57].

Table 2.2: Previous studies on e-learning recommender systems that used ontology-based recommendation method

Author(s) & recommender system	**Hybrid**	**CF**	**CB**	**KB/OB**	**CA**	**FB**	**TA**	**Others**
Pukkhem [81] – LORecommendNet	-	-	-	X	-	-	-	-
Capuano et al. [91] – IWT	X	X	-	X	-	-	-	-
Ruiz-iniesta et al. [104]	X	-	-	X	X	-	-	-
Rani et al. [105]	X	-	-	X	-	X	-	-
Fraihat and Shambour [86] - Semantic RS	X	-	-	X	-	-	-	X
Baseera [106] - E-Learning Modules RS	-	-	-	X	-	-	-	-
Nowakowski et al. [107] - OP4L	-	-	-	X	-	-	-	-
Cobos et al. [83] – RSPP	X	X	X	X	-	-	-	-
Pukkhem [108]	-	-	-	X	-	-	-	-
Cheng et al. [19]	X	-	X	X	-	-	-	-
Zhang et al. [58]	X	X	-	X	-	-	-	-
Wang and Huang [109] - E-material RS	-	X	-	X	-	-	-	-
Dwivedi & Bharadwaj [110]	X	X	-	X	-	-	X	X
Shishehchi et al. [50] - E-learning RS	-	-	-	X	-	-	-	-
Vesin et al. [99] - Protus 2.0	-	-	-	X	-	-	-	-
Ferreira-Satler et al. [111]	X	-	-	X	X	-	-	-
Bahmani [112] – PERCEPOLIS	X	-	-	X	X	-	-	-
Vesin et al. [113] – Protus	-	-	-	X	-	-	-	-
Blanco-Fernández et al. [114]	X	-	X	X	-	-	-	-
Huang et al. [115] - Semantic RS	-	-	-	X	-	-	-	-
Shishehchi and Banihashem [116]	-	-	-	X	-	-	-	-
Hsu et al. [117] - Reading RS	-	-	-	X	-	-	-	-
Zhuhadar and Nasraoui [118] (HyperManyMedia)	X	-	X	X	-	-	-	X
Ciuciu and Tang [119] - Virtual teacher	-	-	-	X	-	-	-	-
Yang [59]	-	-	-	X	-	-	-	-
Rey-lópez et al. [120] - T-Learning 2.0	X	-	-	X	-	-	-	X
Biletskiy et al. [121] – PSDLO	-	-	-	X	-	-	-	-
Žitko et al. [122] - Questions RS	-	-	-	X	-	-	-	-
Neri and Colombetti [123]	-	-	-	X	-	-	-	-
Weng [124]	-	-	-	X	-	-	-	-
Kontopoulos et al. [100] – PASER	-	-	-	X	-	-	-	-
Cantador et al. [125]	X	-	X	X	-	-	-	-
Yu et al. [52] - Content RS	-	-	-	X	-	-	-	-
Wang et al. [126] - (LORM)	X	-	-	X	-	-	-	X
Mao et al. [127] – DiLight	X	-	X	X	-	-	-	-
Shen and Shen [128]	-	-	-	X	-	-	-	-

It is evident that ontology is widely used in e-learning recommender systems as can be seen in Table 2.2. Ontology-based recommendation in most cases is used in combination with other recommendation techniques such as collaborative filtering, content-based, context-aware, fuzzy-based and trust-aware based among others.

2.3.2 Future Trends in Ontology-based Recommendation in E-Learning Domain

A number of studies on e-learning recommendation approaches have been undertaken in recent years. However, there are some challenges and areas of improvement that still needs to be researched further and addressed in order to improve the effectiveness of ontology-based recommendation systems in e-learning domain. In this sub-section, we discuss the possible future research direction towards the improvement of ontology-based recommendation approach for e-learning.

Hybridization of recommendation methods: Recent studies have revealed a trend of hybridization of recommendation methods such as ontology-based recommendation approach for e-learning with other recommendation approaches such as CB, CF, fuzzy-based, context-aware based, trust-aware based or social-network based recommendation techniques. Hybridization of other techniques with ontology-based recommendation approach has the potential to significantly improve the effectiveness and quality of recommendations. In addition, the benefits of hybridization of ontology-based recommendation approaches with other existing recommendation methods can help to alleviate recommendation drawbacks that are common with conventional recommendation approaches such as sparsity and cold start problems. Previous research studies show that hybridization of recommendation methods alleviates some of the challenges associated with individual recommendation approaches. Therefore further research studies on hybridization of ontology-based recommendation approach with other recommendation approaches should be carried out with the goal of improving the effectiveness of ontology-based recommendation approaches for e-learning.

Hybridization of knowledge structures: Hybridization of different types of knowledge structures is another interesting and notable trend in OB recommendation systems for e-learning. Hybridization of other knowledge structures with ontology facilitates the capture and incorporation of more useful knowledge about the learner and learning resources into the recommendation process which is likely to improve the effectiveness and quality of recommendations. Though ontology is currently the most commonly used tool for knowledge modeling and representation in e-learning recommender systems, there is an opportunity to combine ontology domain knowledge with other existing knowledge structures with a view to improving the effectiveness of recommendations. Other existing knowledge structures that can be hybridized with ontology include social knowledge [133], knowledge vectors [134], constraint-based reasoning [135] and case-based reasoning [136]. This trend goes hand in hand with the advancements in research on knowledge-based systems.

Diversification of ontology knowledge sources: Future ontology-based e-learning recommender systems will most likely rely on diverse sources both implicitly and explicitly in acquisition of ontology knowledge for both learners and learning resources. There is a wealthy of ontology knowledge about the learner and learning resources available on the web, social media and other sources that may be useful and relevant in enriching the recommendation process. Extraction of ontology knowledge from these diverse sources of knowledge can improve the quality of ontology knowledge and by extension personalization of recommendations to meet the learner's learning needs. This trend goes hand in hand with research in other related fields such as semantic web, machine learning and web mining.

2.4 Context Awareness in E-Learning Recommendation

Hybrid and context-aware (CA) recommendation approaches have gained popularity among the researchers in recent years as alternative recommendation techniques for e-learning. As a result, a number of related studies have been carried out on hybrid and CA recommender systems for e-learning. For instance, Verbert et al. [31] present a comprehensive review on context awareness in recommendation systems deployed in TEL settings. It was evident in their survey that a lot of advancement in the development of CA recommender systems for TEL has been achieved in recent years. Abbas et al. [137] similarly conducted a review of CA recommendation based on computational intelligence. The key results of their survey are the presentation of taxonomy of the computational intelligence approaches and challenges pertaining to CA recommender systems. A recommendation strategy based on context awareness was also proposed by [104]. Their recommender system was for recommendation of educational resources such as questions, lecture notes and exercises to learners taking computer science course. Their recommender system incorporates contextual information about the learner such as knowledge about that particular field. Gallego et al. [138] presented a framework for generation of proactive CA recommendations for learners using e-learning. Their recommendation technique uses contextual information such as location and user context. Similarly, Do et al. [3] proposed a CA recommendation model that can suggest suitable learning items for learners in online environment. Evaluation of their recommendation model revealed that aggregation of context information into the recommender system improved the performance and quality of recommendations.

Furthermore, Hu et al. [139] presented a personalized CA recommender system that uses a rules engine for e-learning. In this system, learner's contextual information is captured from external social networks whereas rules engine is used to manage the set of rules for each learner to offer personalized recommendations. Salazar et al. [140] proposed an approach of incorporating context information within an adaptive ubiquitous multi-agent system called U-MAS which is a learning environment for recommending educational resources. Their experimental evaluations showed some effectiveness of their approach in virtual learning environments and also an improvement in learning processes. Similarly, Huang et al. [37] proposed a CA recommendation method by extracting, measuring and then incorporating significant context information into their recommendation process. In their proposed method, significant attributes were extracted to represent context information and also measured to identify the recommended items based on the rough set theory. Their experimental results show that the proposed CA approach is useful in improving the quality of recommendations. Moreover, Anderson et al. [141] described a reasoning framework based on ontology for creating CA applications. Ontology was aggregated in their recommender system and contextual information described semantically. Liu and Wu [142] proposed a generic framework to learn CA latent representations for CA collaborative filtering. Experimental results demonstrated improved performance by their CA model. Zheng et al. [33] proposed context similarity as an alternative approach for contextual modeling. Their experimental results revealed that learning context similarity is a more effective approach to CA recommendation than modeling contextual rating deviations.

2.5 Sequential Pattern Mining

Sequential pattern mining (SPM) was discovered and first introduced by Agrawal & Srikant [143]. SPM refers to the process of discovering all sub-sequences that appear more frequently on a sequence database [144], [145]. A sequence refers to an ordered list of itemsets. SPM algorithm is used for mining the sequence database by looking for any repeating patterns (also called frequent sequences) that are useful for finding any association between different items in their database for purposes of making predictions. The widely used algorithms for SPM include Generalized Sequential Pattern (GSP), PrefixSpan, FreeSpan and Sequential PAttern Discovery using Equivalence classes (SPADE) [144]. PrefixSpan and GSP are the commonly used sequential pattern mining algorithms. GSP mines sequential access patterns through adoption of a candidate subsequence generation-and-test technique based on the popular apriori principle [143], [146]. The apriori principle states that "*All nonempty subsets of a frequent itemset must also be frequent*" [144]. The major strength of GSP sequence mining algorithm is pruning by apriori, hence reducing significantly the search space. However, GSP algorithm is not efficient for mining large sequence databases that have numerous patterns. SPADE is a SPM algorithm that works through apriori candidate generation and performs the mining of sequential patterns by growing the subsequences one item at a time [147]. It adopts vertical data format by decomposing the search space into sub-lattices so that they can be processed independently in the main memory. The weaknesses of SPADE algorithm arises from its huge set of candidates that generate multiple scans of database making it inefficient especially in mining long sequential patterns. FreeSpan algorithm mines the sequential patterns first by partitioning the search space and then projecting the sequence subdatabases recursively based on the projected itemsets [148]. It starts by creating a list of frequent 1-sequences from the sequence database called the *frequent item list (f-list)*, and then constructs a lower triangular matrix of the items in this list. The major strength of FreeSpan algorithm is that it searches smaller projected database for every subsequent database projection. However, the major weakness of FreeSpan algorithm is that it has to generate a lot of nontrivial projected databases. For instance, if a pattern appears in every sequence of a database, then its projected database will not shrink [146]. On the contrary, PrefixSpan is a projection-based algorithm for pattern mining. It starts by scanning the whole projected database in order to find the frequent sequences and count their supports. PrefixSpan algorithm examines the prefix subsequences and then projects only their corresponding postfix subsequences into the projected databases [148]. The key advantage of PrefixSpan is that it does not generate any candidates. It works by counting the frequency of the local items and then uses a divide-and-conquer approach by creating subsets of the sequential patterns (projected databases) that can be divided further where necessary. The major overhead of PrefixSpan algorithm is in construction of the projected databases recursively [144].

A few researches in recommender systems have employed SPM in their recommendation processes. For instance, Romero et al. [149] described an e-learning recommendation system for recommending personalized links to students. Their recommender system employs clustering and SPM algorithm for discovering personalized recommendation links. Hariri et al. [150] presented a music recommender system that uses latent topic sequential patterns. Their recommendation system uses the patterns discovered by PrefixSpan algorithm for predicting the next topic automatically in the playlist. However, our proposed recommendation approach is different from previous researches since we combine CF, ontology and SPM algorithm in one proposed recommendation method (Chapter 3) and CF, context awareness and SPM in another proposed recommendation algorithm (Chapter 4). Furthermore, ontological knowledge and contextual information are taken into account in our study for computing similarities of learners as well as generating recommendations. GSP algorithm is used in our proposed recommendation methods for mining web logs and discovering learner's sequential access patterns for use in filtering the final recommendations.

2.6 Challenges of E-Learning Recommender Systems

Recommender systems are widely used to support retrieval of online learning materials in educational institutions. However, there are some challenges experienced by learners and researchers hindering the full implementation and utilization of recommender systems in e-learning environments. In this sub-section, we present a review of the main learner and researcher related challenges of e-learning recommender systems. This was achieved by carrying out a systematic literature review of relevant journal papers on e-learning recommender systems with a view to identifying and classifying the challenges as either learner or researcher challenges. The survey revealed that successful implementation and utilization of recommender systems for e-learning is hindered by some challenges categorized in this review as learner and researcher related challenges.

Though previous studies have addressed some of the issues affecting recommender systems in various domains, a gap still exists which necessitates this specific review on learner and researcher related challenges of recommender systems for e-learning. Most previous studies focused on general challenges of recommender systems for e-learning.

In this review, we focus on learner and researcher related challenges of recommender systems for e-learning. This review makes two major contributions. First, we review and classify the main learner and researcher related challenges of recommender systems for e-learning. Secondly, based on the review of the challenges, we discuss possible solutions for alleviating those challenges and highlight the limitations of the existing solutions.

2.6.1 Overview of Challenges of Recommender Systems

Recommender systems play a major educational role in supporting online learning by providing personalized recommendations of learning resources to the learners for better achievement of their learning goals [15], [16]. Although recommender systems have been used widely in e-learning environments in recent years, they still face some challenges hindering its full implementation and utilization by the learners, teachers, and researchers. Previous studies show that implementation of recommender systems still face some challenges. As a result, research studies have been carried out over the years with a view to identifying and addressing these challenges. For instance, Verbert et al. [31] presented a survey as well as future challenges of CA recommender systems for TEL. Among the challenges identified include context-acquisition, presentation challenges and evaluation challenges. Similarly, Tarus et al. [77] proposed a learning resources recommendation approach by combining collaborative filtering, ontology and sequential pattern mining and suggested solutions for alleviating cold-start problem and sparsity problem by using ontology domain knowledge and learner’s sequential access patterns in the absence of sufficient ratings. Mika [151] investigated on challenges of recommender systems in the area of nutrition and further discussed ways to deal with those challenges. He et al. [152] analyzed the several interactive recommender systems and presented the research challenges facing such interactive recommender systems. The challenges identified include cold-start problem and diversity problem. Khusro et al. [153] investigated issues and research opportunities facing recommender systems. Among the challenges they identified include data sparsity, latency, cold-start and grey sheep problems.

2.6.2 Selection of publications reviewed in this survey

This review was guided by the methodological guidelines recommended by Kitchenham and Charters [154] for carrying out systematic literature reviews in the area of software engineering. The relevant papers were retrieved by searching the digital databases for research papers that included Science direct, Engineering Index, ACM, IEEE Xplore, Springer and Web of Science. In order to search the digital data-bases exhaustively, Boolean operators “OR” and “AND” were used to combine the various search strings. The inclusion criteria applied to the retrieved papers include: (i) papers on recommender systems whose application domain is e-learning (ii) papers that investigate or discuss one or more learner and researcher challenges affecting e-learning recommender systems. Only peer reviewed journal papers were considered in this study due to the quality, details in content and reliability of their results.

After retrieval of the publications, the authors reviewed the papers and selected the relevant papers that met the inclusion criteria. The information of interest that was extracted during review and analysis of the selected publications include the author(s); the recommendation challenges and solutions; and the affected recommendation technique(s). The challenges were identified in the selected papers and classified as either learner or researcher related challenges. Those challenges that affect learners who use e-learning recommender systems were categorized as learner challenges. Similarly, the challenges that limited the researchers from evaluating e-learning recommender systems successfully were classified as researcher challenges. Fig. 2.4 shows our classification model of the learner and researcher related challenges of e-learning recommender systems.

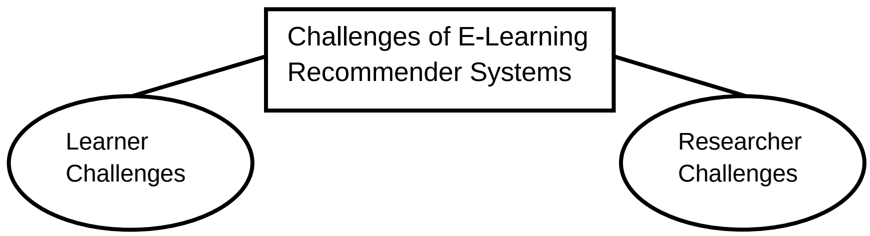

Figure 2.4: Classification of challenges of e-learning recommender systems

2.6.3 Learner and Researcher Related Challenges of E-Learning

In this sub-section, we present the results and discussion of our review of learner and researcher related challenges of e-learning recommender systems alongside the possible solutions for alleviating them. In presenting the review results, we focus mainly on the name of challenge, the affected recommendation technique, and the relevant references (Tables 2.3 and 2.4). Some challenges affect more than one recommendation technique. For clarity, the results are grouped into two categories namely learner related (Table 2.3) and researcher related (Table 2.4) challenges. Tables 2.3 and 2.4 presents the two categories of the challenges namely learner and researcher related challenges respectively.

Table 2.3: Learner related challenges of e-learning recommender systems

Challenge	**Affected Recommendation Technique(s)**	**References**
Privacy issue	All recommender systems	Verbert et al. [31], Khusro et al. [153], Su and Khoshgoftaar [155], Garcia-Martinez and Hamou-Lhadj [72], He et al. [152]
Lack of trust in recommendations	Collaborative filtering & Content-based	Jannach et al. [36], Martinez-cruz et al. [95], Eirinaki et al. [156]
Lack of motivation to rate items	Collaborative filtering	Ekstrand et al. [157], Salehi & Kamalabadi [71]
Changing learner characteristics	Collaborative filtering & content-based	Khusro et al. [153], Tarus et al. [77], Verbert et al. [31]

Table 2.4: Researcher related challenges of e-learning recommender systems

Challenge	**Affected Recommendation Technique(s)**	**References**
Evaluation challenges	All recommender systems	He et al. [152], Verbert et al. [158], Verbert et al. [31], Erdt et al. [17], Tarus et al. [77]
Dataset sharing challenges	All recommender systems	Verbert et al. [158], Verbert et al. [31], Erdt et al. [17], Tarus et al. [57]

2.6.3.1 Learner Related Challenges and Solutions

The first category of challenges reviewed in this survey is learner related challenges of e-learning recommender systems. Table 2.3 illustrates the learner related challenges of recommender systems for e-learning identified in this review. The main learner related challenges include: *privacy issues*; lack of *trust in recommendations*; *lack of motivation to rate items*; and *changing learner characteristics*.

Privacy issues: Concerns on privacy issues hinders learners from providing relevant data necessary for enhancing the effectiveness of recommender systems. Ricci et al. [7] points out that to generate good quality recommendations, e-learning recommender systems need to collect as much learner information as possible. However, learners may fear that their privacy is likely to be comprised. Similarly, user data in unsecure recommender systems is likely to be compromised and misused in some cases [153], [155]. Generally, recommendation systems require the learner's demographic and ratings information in order to provide personalized and accurate recommendations.

A good recommender system for learning materials should guarantee privacy and security of learner's personal data stored in the recommender system. This can be realized by making use of privacy preserving algorithms that preserve learner's identity [31], [152], [153], [155].

Lack of trust in recommendations: Lack of trust in recommendations by learners is also a challenge experienced by learners who interact with recommender systems in e-learning. Most recommendation systems for e-learning do not explain to the learners how the recommended items were selected, hence learners may have little trust in the recommendations.

To address this issue, recommender systems should provide explanations alongside the recommendations. Explanations should provide information as to why one item was preferred over another so as to build trust in the learners concerning recommendations to reduce the uncertainty about the reliability of recommendations [36]. Additionally, trust models can be incorporated in e-learning recommender systems [95], [156].

Lack of motivation to rate items: Most learners are reluctant to rate learning materials in situations where explicit ratings are required by the recommender system. This is mainly because they of lack the motivation and awareness on the importance of rating learning materials. Collaborative filtering which is the commonly used recommendation technique requires ratings so as to generate recommendations [20], [95]. Few ratings or lack of it in a recommender system limits the recommender system from personalizing and providing accurate recommendations to the learner.

To alleviate this problem, recommender systems used in e-learning should be designed to acquire ratings both explicitly and implicitly. Implicit ratings are acquired when the learner navigates, reads or downloads learning resources. Other recommender systems such as content-based provide recommendations based on content similarity while knowledge-based recommendation systems use knowledge structures such as ontologies to represent knowledge about the learners and learning materials [77]. These recommendation approaches that do not use ratings can be hybridized with collaborative filtering technique. Other solutions include using hybrid-based filtering by incorporating learner’s sequential learning patterns into the recommendation process which can predict learning resource’s for the target learner without relying on ratings [5], [71], [77].

Changing learner characteristics: Some learner characteristics such as study level, knowledge level, skills and learner’s context change over time as situations change and these changes influence the learner preferences [77]. Most recommender systems such as CF and CB do not consider the changing learner characteristics in their recommendation processes. This may result in recommendation of some learning items that are not personalized to the learner preferences.

To overcome the challenge of changing learner characteristics, recommendation techniques that integrate additional learner information such as knowledge level, study level, learning styles, and learner context among others should be employed by developers of recommender systems for use in e-learning domains [31], [77], [153].

2.6.3.2 Researcher Related Challenges and Solutions

The second category of the reviewed challenges of recommender systems for e-learning is the researcher related challenges. Table 2.4 illustrates the researcher related challenges of recommendation systems for e-learning. The identified challenges include: *evaluation challenges* and *dataset sharing challenges*.

Evaluation challenges: Despite the success in research on e-learning recommender systems, there is still scarcity of public e-learning datasets for evaluating such recommender systems [17], [31], [77]. Without public datasets for e-learning recommendation systems, it becomes difficult to evaluate and compare results of one study with other previous studies.

As a remedy to scarcity of public datasets for e-learning recommender systems, researchers have suggested that real world data be collected and used for evaluation at the initial stage [158]. Secondly, public datasets from other domains such as MovieLens[9] dataset may be used by researchers for initial testing and evaluation. However, a real public e-learning dataset will be a necessity for final verification of evaluation results and comparison of performance [17], [57].

Dataset sharing challenges: Data sharing is equally a challenge experienced by researchers in the field of recommender systems for e-learning. Although some researchers and relevant organizations have managed to collect e-learning recommender systems data for evaluation purposes overtime, most of these datasets still remain private mainly because of privacy concerns, hence hindering progress in research on e-learning recommender systems [57], [158].

[9] https://grouplens.org/datasets/movielens/

To address this issue, researchers and relevant organizations need to work on strategies for dataset sharing to facilitate standardization in evaluation of e-learning recommender systems. Such strategies can be attained by addressing legal and privacy issues pertaining to dataset sharing [17], [158].

2.6.4 Limitations

The major limitation of the review is that our study focused only on the major learner and researcher related challenges facing e-learning recommender systems. However, there is possibility that there are other challenges that previous research studies have not brought to the fore. In addition, technological challenges of e-learning recommender systems were not reviewed in this study. Similarly, challenges of more recent recommendation techniques such as trust-aware, group-based, social-network based and ontology-based recommender systems have not been explored widely. Therefore, there is need for further research to investigate the challenges and propose solutions associated with these new recommendation techniques in the context of e-learning. Furthermore, challenges of e-learning recommender systems relating to pedagogy have not been investigated widely.

Secondly, the reviewed previous research studies revealed that the optimum solutions to the challenges have not been fully achieved. More research studies therefore need to be carried out with a view to finding more optimum solutions for alleviating these challenges to a higher degree.

2.7 Evaluation of E-Learning Recommender Systems

There are a number metrics for evaluating accuracy and performance of e-learning recommender systems. These include Mean Absolute Error (MAE), Recall, Precision, F1 measure and user satisfaction among others [17]. MAE is used to evaluate prediction accuracy. On the other hand, recall metric, precision metric and F1 measure are used to evaluate the performance of the recommender system. Recall metric, precision metric and F1 measure are computed with the aid of the confusion matrix shown in Table 2.5 [7], [159].

Table 2.5: Confusion matrix for computing recall and precision

	Recommended	Not Recommended
Used	True Positive *(tp)*	False Negative *(fn)*
Not Used	False Positive *(fp)*	True Negative *(tn)*

The contingency table (Table 2.5) contains four different sets of values which reflects the four possibilities of retrieval and recommendation decisions namely True Positive (*tp*), True Negative (*tn*), False Positive (*fp*) and False Negative (*fn*) [159], [160]. True Positive and True Negative refers to classes of learning items that were classified correctly as positive and negative respectively. On the other hand, False Positive and false Negative are those classes of learning items that were inaccurately classified as positive and negative respectively. Only the true positive and false positively classified items are recommended by the recommender system to the learner. The following sub-sections describe the relevant evaluation metrics for e-learning recommender systems.

2.7.1 Mean Absolute Error

The MAE [83], [161], [162] measures the average deviation between the predicted and the actual ratings. Lower value of MAE implies higher accuracy while higher value implies lower accuracy. MAE is among the commonly used measures of accuracy of predictions in e-learning recommender systems [45]. To compute the value of MAE in recommender systems, the following formula is used (eq. 2.3):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | p_i - r_i | \tag{2.3}$$

where p_i is the value of predicted rating for learning material i, r_i represents the value of the actual rating given to learning material i by the learner, and n is the number of cases.

2.7.2 Precision

Precision is one of the widely used metrics for testing the performance of a recommender system. Precision refers to the ratio of the relevant items that were selected by the recommender system to the number of items selected. A learning resource is said to be relevant if it is liked by the learner [7].

$$\Pr ecision = \frac{Correctly\ recommended\ items}{Total\ recommended} = \frac{tp}{tp + fp} \tag{2.4}$$

where *Correctly recommended items* refers to the number of learning items classified as relevant by the learner that are recommended by the recommender system. *Total recommended* is the total number of learning items recommended by the recommender system.

2.7.3 Recall

Recall is the ratio of the relevant learning items selected to the number of relevant learning items. It is the recommenders' ability to suggest as few non-relevant learning items as possible. A learning item is considered to be non-relevant if it is disliked by the learner [7].

$$Recall = \frac{Correctly\ recommended\ items}{Relevant\ items} = \frac{tp}{tp + fn} \tag{2.5}$$

where *Correctly recommended items* is the same as in Precision metric and *Relevant items* is the number of learning items classified as relevant by the learner.

2.7.4 F-Measure

F-measure metric combines both recall and precision into a single value for ease of comparison as well as to get a balanced view of the performance of the recommender system [163]. The F1 measure metric gives equal weight to recall metric and precision metric.

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{2.6}$$

2.8 Summary

This chapter reviewed the literature related to e-learning recommender systems. First, it described the common recommendation techniques for recommender systems that include content-based, collaborative filtering, knowledge-based, hybrid filtering, context-aware based and ontology-based among others. Secondly, an overview of ontology and its usage in e-learning recommender systems was discussed. In addition, recommender systems for e-learning and context awareness in e-learning recommendation were discussed. Thirdly, the chapter reviewed the learner and researcher related challenges facing the implementation and utilization of recommender systems in e-learning. Solutions for addressing each of the challenges were also discussed. The review found out that successful utilization and improvement of e-learning recommender systems can be achieved if the identified learner and researcher related challenges can be addressed. Finally, the commonly used evaluation measures for e-learning recommender systems e.g. MAE, recall, precision and F1-measure were described.

Literature review of related work revealed that a number of research studies related to e-learning recommender systems have been published. Previous researches proposed various methods of recommendation of learning resources in e-learning environments. However, this thesis focuses specifically on hybrid recommendation of learning resources by incorporating additional learner information into the recommendation process by using tools such as ontologies, context awareness and SPM algorithm among others. Our approach in this thesis is different from previous studies since in our study, we take into account the additional information about the learner such as learner characteristics, learner's contextual information and learner's sequential access patterns in providing recommendations.

Chapter 3

Hybrid Knowledge-based Recommendation Approach for E-Learning based on Ontology and Sequential Pattern Mining

Recent years has witnessed exponential growth in the use of online learning resources available on the web. The rapid increase of these online learning resources on the Internet has resulted in challenges in retrieval of the relevant learning items by learners due to information overload. As a result, many learners especially those with less internet and computing skills are experiencing difficulties of retrieval of relevant learning resources that are useful to their learning needs. To overcome this difficulty, recommendation systems are used and deployed for recommending learning resources to learners according to their preferences. However, conventional recommendation techniques such as CF and CB and also other existing recommendation methods are unable to provide accurate and personalized suggestions of learning items in scenarios where learners possess different characteristics. Different learners have different characteristics in terms of knowledge level, skills, learning style and study level among others. Besides, learners have differences in sequential access patterns. Most existing recommendation methods do not consider these learner differences in their recommendation process. This problem can be addressed by incorporation of additional learner information into the recommendation process. Conventional recommendation approaches such as CB and CF consider only similarity in content features and ratings respectively in generating recommendations. In this chapter, we propose a hybrid knowledge-based recommendation approach using ontology and SPM for recommending learning items to learners in e-learning environments. In the proposed recommendation method, ontology was used for modeling and representation of knowledge about the learners and learning items whereas SPM algorithm was used for mining the web logs and discovering the learner's sequential access patterns. The proposed recommendation method involves four main steps: (1) creation of ontology to represent the learner's additional information and learning resources knowledge; (2) computing similarity of ratings based on ontology domain knowledge and also computing predictions of ratings for the active learner; (3) generation of *top-N* recommendation list of learning items using CF recommendation engine; and (4) application of GSP algorithm to the *top-N* recommendation list of learning items to generate the final recommendations for the learner based on learner's sequential access patterns. We evaluated the proposed hybrid recommendation approach and compared results with other existing recommendation techniques using a real world dataset. Experimental results showed that the proposed hybrid knowledge-based recommendation approach provides good accuracy of recommendations and improved performance. Furthermore, the proposed recommendation method can alleviate the rating sparsity problem and cold-start problem by making use of learner's sequential access patterns and ontology domain knowledge respectively in cases of new learners with insufficient ratings during the initial stages of recommendation.

3.1 Introduction

The Internet has witnessed a rapid increase in the amount of learning resources available on the web. This explosion in increase of online learning items over the years on the World Wide Web has been as a result of increasing demand for online learning resources by learners using e-learning. However, with the ever increasing volumes of learning items on the web, online learners encounter difficulties in choosing appropriate learning items that meets their learning needs because of information overload. Recommender systems can address the problem of information overload by filtering out what is irrelevant to the learner and automatically recommending only the relevant learning items that are personalized to the learner preferences [13], [14]. Learner preference refers to the relevant learning items that meet the learner's interests and learning needs. Recommender systems are information retrieval tools that make suggestions of suitable items to a user by predicting the user's preference on the item [7]. The goal of a recommender system in e-learning environments is to predict the target learner's rating of unseen learning item for the purpose of generating recommendations of relevant learning items [17]. Conventional recommendation methods such as CB and CF have been quite successful in application in different recommendation domains such as e-commerce and movies. Books recommendation in Amazon, movie recommendation in Netflix and course recommendation in Coursera are some of the examples of application areas of recommender systems [8]. CF automatically suggests items to the target user that other users with similar preferences also liked in the past. Similarity in preferences between users is measured based on similarity of ratings between the users in the case of CF [20], [21] and similarity of content features in case of CB recommendation technique [22], [23].

However, in recommendation of learning resources to learners in e-learning, additional characteristics and information about the learner such as knowledge level, learning style, background knowledge, skills, learning goals and learner's sequential access patterns among others is required for personalization and accuracy of recommendations. CF, CB and many other existing recommendation methods do not consider these additional learner information in generating their recommendations, hence they cannot guarantee accurate recommendation of relevant learning items. To overcome this recommendation problem in e-learning resource recommendation, tools such as ontology [49] and SPM algorithm [5], [164] can be employed to incorporate the additional learner information into the recommendation process with the goal of improving personalization of preferences and recommendations to the learner. A number research studies on recommender systems have attempted to address this problem of differences in user characteristics in other recommendation domains such as leisure and medication with a view to improving the accuracy of recommendations. For instance, in [49], a CA recommender system for movie recommendation that uses ontology to model the user context in leisure domain is proposed. Similarly, [164] proposed a recommendation approach that makes predictions of medications by using SPM. To generate personalized and accurate recommendations, recommender systems for e-learning should incorporate additional information such as learning styles, study level, background knowledge and learner's sequential access patterns into the recommendation process. This additional learner information influences the learner's preference for a learning resource and helps with personalization of the recommendations. Though previous studies like Chen et al. [5] proposed a recommender system that combines CF with SPM for recommendation of learning materials, however, in their method, they did not consider additional learner information and learner characteristics such as knowledge level, learning style and study level among others in their recommendation approach. Our recommendation method is enriched by incorporation of additional learner information using ontology as well as using SPM algorithm for discovering learner's sequential access patterns.

In this study, we propose a hybrid knowledge-based recommendation approach that combines CF, SPM and ontology for recommending relevant learning items to the learners. In this proposed method, ontology was used to represent and model the knowledge about the learner and learning items while SPM algorithm was used to discover the learner's sequential access patterns from the web logs. CF was used to measure similarities of ratings and compute predictions for the target learner taking into account the learner's ontological knowledge. The advantage of hybridization of recommendation methods is to benefit from the strengths of each individual technique and at the same time address the limitations of individual recommendation approaches [165]. Although a number of previous researches have employed different approaches in their recommendation methods, the benefit of our approach is in using ontology and SPM to incorporate additional learner information into the hybrid recommendation process.

This proposed hybrid recommendation method makes significant contributions to the research on recommender systems for e-learning.

First, the proposed knowledge-based recommendation method for learning resources takes into account additional learner information represented by ontological knowledge and the learner's sequential access patterns discovered by SPM algorithm. Incorporation of these additional learner characteristics and learner's sequential access patterns into the recommendation process helps to personalize recommendations according to the learner preferences.

Secondly, learner's ontological knowledge is taken into account together with the ratings in computing similarities of learners and learning items, as well as in generation of predictions of ratings, hence assisting in improvement of accuracy of predictions.

Thirdly, the proposed hybrid recommendation method can help alleviate the cold-start problem in the absence of ratings for new learners by using available ontology domain knowledge acquired through integration of ontology into the recommender system. Besides, the proposed hybrid recommendation approach can alleviate rating sparsity problem by using the learner's sequential access patterns in predicting the learner's preferred learning items in cases where the ratings are sparse.

Lastly, the experimental results show improvement in performance by the proposed hybrid KB recommendation approach. In comparison to other recommendation approaches, the proposed hybrid recommendation method outperformed other related recommendation approaches that do not aggregate ontology and learner's sequential access patterns in their recommendation processes.

3.2 Background

Ontology-based recommender systems refers to knowledge-based recommender systems that make use of ontology for knowledge modeling or representation in their recommendation process [56], [57]. In e-learning recommendation domain, ontology is used to infer learner interests or preferences and enrich the learner profile. In the case of hybrid ontology-based recommendation systems, the learner ratings of learning items are coupled with ontological domain knowledge not only to improve similarity matching but also to improve personalization of recommendations according to the learner preferences. Once ontological knowledge and concepts are mapped, any normal recommendation method can be applied to generate recommendations [166]. Unlike in other fields of recommendation, ontology in e-learning recommender systems is commonly used to represent and model knowledge about the learner and learning items [50], [53]. Like KB recommendation techniques, ontology-based recommendation systems are least affected by most of the drawbacks which affect conventional recommendation techniques such as over specialization, rating sparsity and cold-start problems due to their use of ontology domain knowledge to represent and model user's knowledge. Personalization of learner preferences and profile using ontology results in recommendations that are tailored specifically to the preferences and needs of the learner. Moreover, improved personalization of learner preferences with the aid of ontology makes ontology-based recommendation for learning resources ideal for e-learning [58]. In addition, ontology-based recommendation approach uses ontologies in modeling the learner profile alongside the features of the learning items in the domain [167], [168]. In general, ontology-based recommendation systems in e-learning take into account the knowledge about the learner and learning items for incorporation into the recommendation process. Additional information about the learner such as study level, knowledge level, learning style, learning goals and other learner characteristics are integrated into the recommendation process using ontology. Fig. 4.1 shows an example of the general structure of the top level ontology for e-learning.

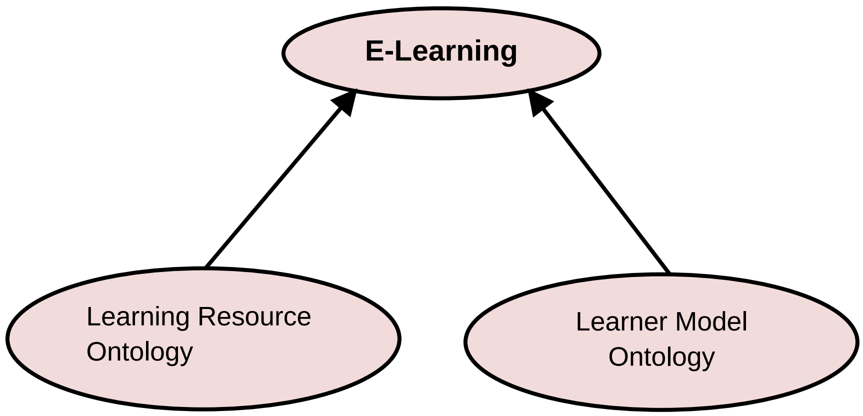

Figure 3.1: General structure of the top-level ontology for e-learning

The general structure of a top level ontology for e-learning shown in Fig. 3.1 contains two main classes namely learning resource and learner ontologies. The learner ontology class represents the knowledge about the learner such as learner's personal and demographic details, study level, knowledge level, skills and learning style among others. The learning resource ontology represents the knowledge about the learning resources such as format of the learning items and type of the learning item. Learning item formats can be image, audio, video or text while the learning item type can be lecture notes, assignment, exam etc. In the proposed hybrid knowledge-based recommendation approach for learning resources, the additional learner information captured by using the e-learning ontology is incorporated into the recommendation process.

3.2.1 Sequential Pattern Mining in E-Learning Recommendation

Sequential pattern mining is a web mining algorithm than can discover all sub-sequences that appear frequently in a given sequence database [144]. The main objective of the SPM algorithm is to discover frequent sequential patterns by mining the web logs with a view to knowing the users historical web access pattern and navigational behavior. The web logs contains information related to web access and content such as client IP address, access date/time, HTTP request method, the URL page requested and the name of the browser used to access the page. These web log raw data needs to be prepared and preprocessed before use by the recommender system. When a learner visits the web and accesses learning items from a website, a sequence of web pages visited during that session from the time of starting to the time of exiting the browser is generated [54]. Let this sequence pattern be denoted by S = i_1, i_2,… i_k where i_{m} (m = [1…k]) is the pageID of the m^{th} visited learning item by the learner. Nguyen, et al. [54] pointed out that given the current visited learning item on a web page and k previously visited learning items on web pages, the learning items that will be visited in the next navigation step can be predicted.

SPM algorithm is useful in recommendation systems for e-learning since it can discover the learner’s frequent sequential access patterns from the web logs. SPMs role is vital in enhancing recommendation of learning items based on the learner’s sequential access patterns in an e-learning recommender system. The sequential access pattern of the target learner is constructed based on the frequently accessed learning items mined from the web logs. To illustrate the importance of learner’s sequential access patterns in a recommender system, [5] observes that in a typical learning environment, a learner will probably learn starting with easy learning materials then eventually move to difficult learning materials; for a single knowledge point, a learner will probably start the learning from theoretical learning then practical learning, hence during recommendation, this learner’s historical learning sequence pattern should be captured and incorporated into the recommender system using the SPM algorithm. There are many SPM algorithms that can be used for mining the web logs and discover the sub-sequences that appear frequently in the web logs. The widely used SPM algorithms include PrefixSpan, GSP algorithm, FreeSpan and SPADE [169].

In the proposed hybrid knowledge-based recommendation approach, we adapted the GSP algorithm for mining learner’s sequential access patterns due to its suitability in e-learning recommender systems. GSP algorithm [5] is a sequence mining algorithm that is suitable for mining web logs to discover the learner’s historical sequential access patterns in e-learning applications. Learner's historical sequential access patterns mined by the GSP algorithm can be used to predict learning items that the learner is likely to access in the future visit to the web. Incorporating learner's sequential access patterns into the recommendation process in e-learning has the potential to improve the accuracy of predictions.

3.3 Our Recommendation Approach and Model

The proposed hybrid recommendation method is a knowledge-based recommendation approach for recommending learning resources based on ontology and GSP algorithm. The recommendation approach is demonstrated in the hybrid e-learning recommendation model shown in Fig. 3.2.

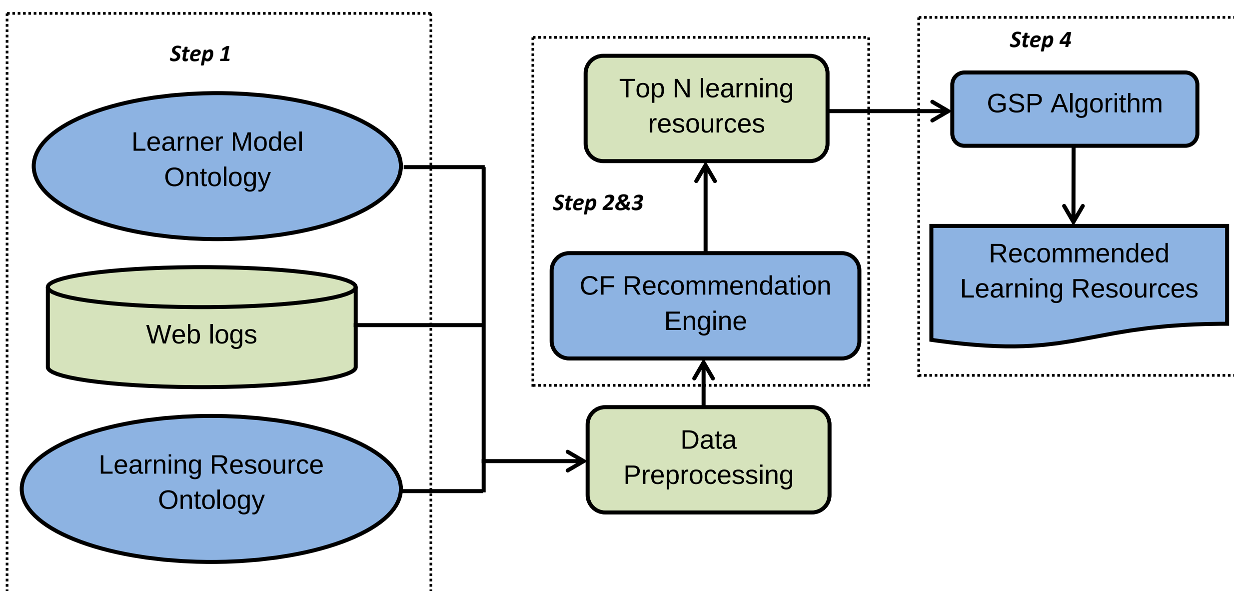

Figure 3.2: Knowledge-based recommendation model for e-learning resources based on ontology and GSP algorithm

The recommendation model contains five major components namely: the learner model ontology, learning resource ontology, CF recommendation engine, GSP algorithm and the recommended learning resources component. In this recommendation model, the process of generating recommendations of learning items involves four steps as illustrated in Fig. 3.2 and described as follows: (1) creating ontology for modeling and representing the learner and learning resources domain knowledge; (2) computing the rating similarities as well as predictions of ratings for unseen learning items for the target learner taking into account the ontological knowledge; (3) generation of *top-N* recommendation list of learning items by the CF recommendation engine; and (4) application of learner's sequential access patterns discovered by the GSP algorithm onto the *top-N* recommendation of learning items to produce the final recommendations for the target learner. The details of the proposed hybrid recommendation method are elaborated in the following sub-sections.

3.3.1 Creating the Learner Ontology and Learning Resources Ontology

The learner ontology shown in Fig. 3.3 represents the ontological knowledge about the learner such as personal data (gender, name, age); knowledge level (beginner, intermediate, advanced) and learning style. The sub classes of the learner ontology contain more specific ontology knowledge about the learner. For example, the learner's learning style would include the four dimensions of learning styles classification according to Felder-Silverman Learning Style Model namely active/reflective, sequential/global, visual/verbal and sensing/intuitive [170]. In our proposed recommendation method, we considered only the learning style and knowledge level as additional learner information to be incorporated into the recommendation process using ontology. Whereas more additional learner characteristics such as study level, learner skills and background knowledge among others can be incorporated into the proposed hybrid recommendation system to improve learner preferences personalization and profile, the downside is it results in increase in utilization of computational resources and also time complexity. To capture the learner's learning style information for incorporation into the recommender system, the standard online learning style questionnaire "*Index of Learning Styles Questionnaire*[10]" [170] was administered to the learners using an e-learning LMS with recommender system during the time of account registration process. Similarly, to capture the learner's knowledge level, a random online test for measuring the knowledge-level (10 questions) was administered to the learners to evaluate their knowledge level according to the test scores (*beginner = 0 - 3, intermediate = 4 - 6, advanced = 8 - 10*). For computational

[10] https://www.webtools.ncsu.edu/learningstyles/

purposes, the levels of knowledge and learning styles were assigned numerical values as follows:

Knowledge-level = {beginner, intermediate, advanced} = {1,2,3}

Learning style = {sequential/global, active/reflective, visual/verbal, sensing/intuitive} = {1, 2, 3, 4}

Once the learner's level of knowledge and learning style has been obtained, the learner ontology (Fig. 3.3) is automatically updated and ready for use by the recommender system. The recommendation engine (Fig. 3.2) makes use of this additional knowledge about the learner during the measurement of similarities of learners and in generating recommendations for the target learner. Fig. 3.3 illustrates the layout of the constructed learner ontology for the proposed knowledge-based recommendation approach.

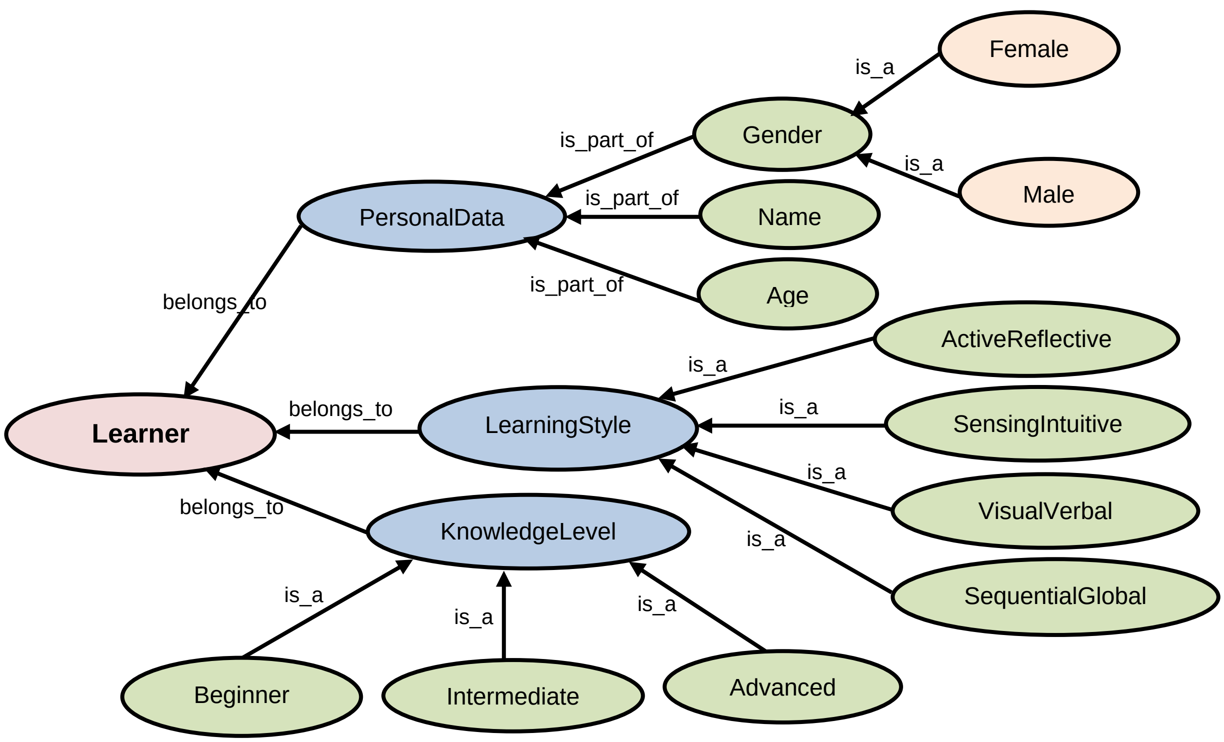

Figure 3.3: Layout of the constructed learner ontology model

Similarly, the learning resource ontology models and represents the ontology knowledge about the learning items (Fig. 3.4). Knowledge represented in this ontology class include: learning resources format which may be text, image, video or audio; and learning resource type which can be lecture notes, exam or assignments. In this proposed knowledge-based recommendation method, ontological knowledge about the learner and learning items have been used to improve personalization of the learner profile and preferences and also modeling the ontology knowledge about the learning resources. To encode the ontology domain knowledge of the learner and learning items, OWL encoding language was used for creation of the ontology in the proposed knowledge-based recommendation approach. To facilitate the creation of the learning resources ontology and learner model ontology classes (together with their sub-classes), concepts and their relationships, Protégé ontology editor was used. The recommendation engine (Fig. 3.2) makes use of the learning resources ontology and learner domain ontology knowledge by aggregating this additional information alongside the ratings of learning items in measuring the similarity and predictions of ratings for the learner. Subsequently, once the learning resource and the learner ontologies have been constructed, the learner and learning resource information represented in these ontologies are preprocessed together with the mined web logs into a suitable format required by the recommendation engine (Fig. 3.2). Figure 3.4 shows the graphical layout of the constructed learning resource ontology for the proposed hybrid recommendation method for learning resources using ontology.

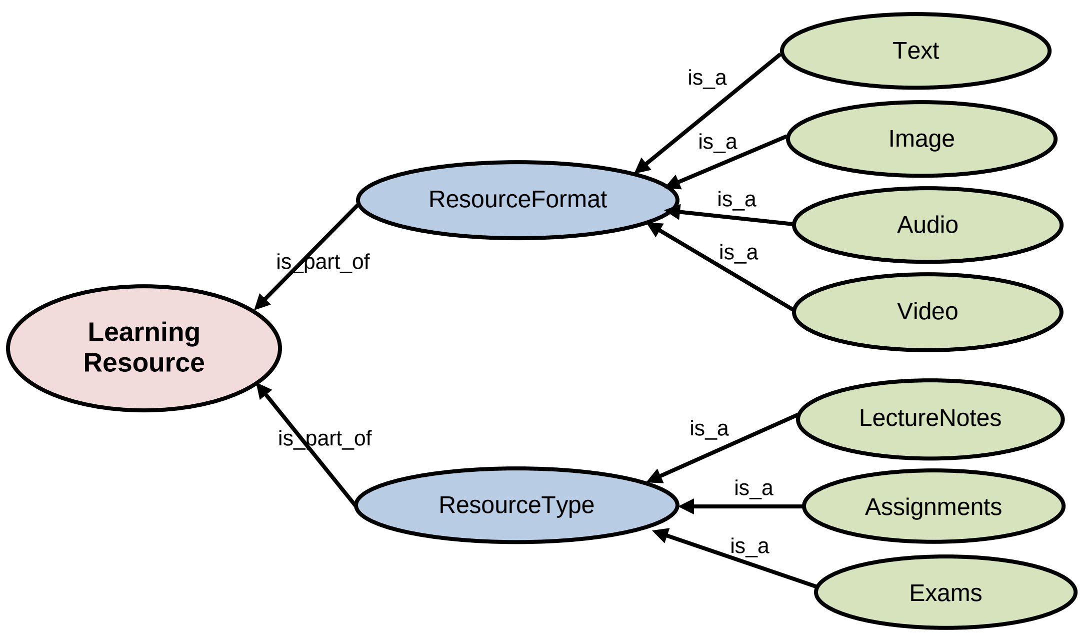

Figure 3.4: Layout of the constructed learning resource ontology

3.3.2 Computing Similarities and Predictions

After the ontology domain knowledge about the learner and learning item characteristics has been prepared, preprocessed and aggregated with the ratings information of the learner, the CF recommendation engine (Fig. 3.2) uses this information to compute the similarities of ratings and learner preferences and generate predictions of ratings of unseen learning items for the target learner. In computing the similarities of learners and learning items, both the ratings and ontology domain knowledge about the learner are considered. In the proposed recommendation approach, we used an extension of the popular Adjusted Cosine Similarity [7], [36] to compute the ontologically based similarities. Ontological similarity *Sim*(o_i, o_j) between any two learning items *i* and *j* is computed using eq. 3.1.

$$Sim(o_i, o_j) = \frac{\sum (\mathrm{r}_{l,i} - \overline{r_l})(\mathrm{r}_{l,j} - \overline{r_l})}{\sqrt{\sum (\mathrm{r}_{l,i} - \overline{r_l})^2} \sqrt{\sum (\mathrm{r}_{l,j} - \overline{r_l})^2}} \tag{3.1}$$

where $r_{l,i}$ is the rating given to the learning resource *i* by a learner *l*, $\overline{r_l}$ is the ontologically based mean rating of all ratings provided by learner *l*. Unlike in CF technique, ontological domain knowledge is considered in computation of the mean rating $\overline{r_l}$ and similarity in the proposed hybrid KB recommendation approach.

The next task is computation of predictions of ratings for unrated learning items for the target learner. The predicted ratings of learning items are computed based on the most similar learning items (*k*NN[11]) obtained in (3.1). The goal of prediction in this case is to predict the rating $r_{l,t}$ for a target learner *l* on a learning item *t* using the rating given to *t* by other learners who are most similar to the target learner *l* (nearest neighbors). To measure the predicted rating for a learning item *t* by a target learner *l*, we use the following prediction algorithm (eq. 3.2):

$$P_{l,t} = \frac{\sum_{i \in S} (Sim(i,t) \times \mathrm{r}_{l,i})}{\sum_{i \in S} (|Sim(i,t)|)} \tag{3.2}$$

where S denotes the learning item *t*'s similar learning item set, and $r_{l,i}$ is the rating given to learning item *i* by target learner *l*.

[11] k Nearest Neighbors (kNN) refers to the most similar k number of users/items to a given user/item.

3.3.3 Generation of *top-N* List of Recommended Learning Resources

The *top-N* recommended list of learning items is generated by the CF recommendation engine based on the predicted ratings of learning items for the target learner and the ontological information of the learner. The recommendation problem in the context of e-learning is defined as the problem of measuring the predictions of ratings for the learning items that have not been seen by the target learner [171]. In the proposed knowledge-based recommendation approach for learning items, the similarity, prediction of ratings and recommendations are all based on:

- Ratings of the target learner on learning items
- Ratings given to a learning item by other learners
- Ontological knowledge of learner and learning items

Extending and modifying the recommendation problem formulation described in [32], the new proposed recommendation problem in the context of e-learning can be formulated as follows: Let L denote the *set consisting of all learners* $L = \{l_1, l_2, ..., l_m\}$, let I be the *set consisting of all possible learning items* $I = \{i_1, i_2, ..., i_n\}$ that can be recommended; and let O be the *set consisting of all ontological domain knowledge* $O = \{o_1, o_2, ..., o_p\}$ about the learner and learning items. The rating R measures the degree of usefulness of a learning item to a learner. The possible values that a rating can take are defined on a numerical scale ranging from 1 (very irrelevant) to 5 (very relevant).

Let f be the recommendation function of L, I and O. The *top-N* denotes the sets of recommendation results. The recommendation function can thus be expressed as:

$$f: L \text{ x } I \text{ x } O \rightarrow top\text{-}N \tag{3.3}$$

The recommended list of learning items (*top-N*) generated is ranked according to their similarities with learning item i. Algorithm 3.1 shows how the *top-N* recommendation list is generated.

Let $r_{l,i}$ be the rating of learning item i by target learner l and $P_{l,t}$ be the predicted rating for learning item t by the target learner l. The steps for generating the recommendation list of learning items (*top-N*) are illustrated in Algorithm 3.1.

Algorithm 3.1: Generate *top-N* Recommendation List
Input Set of learning items $I = \{i_1, i_2, i_3, \ldots\ldots, i_n\}$ Ontology Domain Knowledge $O= \{learner, learning\ resources\}$ Rating value of Learners r $r \in \{1, 2, 3, 4, 5\}$
Output Predicted ratings & *top-N* recommendation list
Method 1: **for each** $i \in I, j \in I, o \in O$, **do** 2: Compute ontological similarity Sim(o_i, o_j) using eq. (3.1) **end for each** 3: Compute predicted ratings $P_{l,t}$ using eq. (3.2)
4: Output the *top-N* recommendation list for target learner *l*.

3.3.4 Generation of Final Recommendations based on GSP Algorithm

The last step is to generate the final recommendations to the target learner by applying the GSP algorithm to the *top-N* recommendation list to filter the recommendation list according to the learner's historical sequential access patterns. The GSP algorithm is a widely used sequence mining algorithm [172]. How the GSP algorithm works to discover the learner's historical sequential access patterns by mining the sequence from web logs is described in the following three phase process:

First pass: determine the support of each learning item, i.e., the number of data sequences to know which learning items are frequent.

Candidate sequences generation: this phase involves generating new potentially frequent sequences called candidate sequences and then determining which of the candidates are actually frequent.

Pruning phase: pruning phase involves deletion of candidate sequences whose support count is less than the minimum support.

The GSP algorithm was applied to the *top-N* recommendation list to filter the recommendation list according to the target learner's sequential access patterns and provide the final recommendations to the target learner. This is a weighted approach that applies the GSP algorithm to the *top-N* recommendation list generated from CF with ontology and discovers the learner's sequence access patterns in the item sets. In the context of e-learning recommender systems, some sequences are more important and others are less important in a sequential pattern. Furthermore, the number of frequent sequential access patterns increases as the minimum support becomes lower and vice versa. As a result, it becomes quite difficult to find more important sequences in a sequential pattern. To address this problem, a weighted SPM approach described in [173], [174] is used whereby the weights are assigned to items according to their relative importance in the sequence. The weight of a learning item i is a non-negative real number w that shows the importance of each learning item. Important sequential access patterns are generated by giving more weights to learning items within the important sequences. Furthermore, weights are useful for adjusting the number of sequential access patterns. Table 3.1 shows the recommendation results with an example, before and after application of GSP algorithm to *top-N* recommendation list.

Table 3.1: Example of application of GSP algorithm to recommendation list

Learner	Before CF+Ontology	After SPM+Ontology+CF
l_1	$<i_1, i_2, i_3, i_4>$	$<i_3, i_2, i_4, i_1>$
l_2	$<i_2, i_5, i_3, i_6>$	$<i_2, i_6, i_5, i_3>$
l_3	$<i_3, i_2, i_1, i_5>$	$<i_1, i_3, i_2, i_5>$

Before application of GSP algorithm to the recommendation list (Table 3.1, column 2), the result is *top-N* recommendation list of learning items. However, after application of the GSP sequence mining algorithm to the *top-N* recommendation list (Table 3.1, column 3), the final recommended learning items are filtered and sequenced according to the learner's historical sequential access patterns mined from the web logs which reflect the personalized learner's preference for learning items. The advantage of this approach is that each learning item is assigned a certain weight according to its importance in the sequence, hence even if there are few or more sequences in the initial sequential access patterns, only the most important sequences will be used in generating the final recommendation results, hence improving the quality of recommendations [173], [174]. The final recommendation of learning items suggested to the target learner will be as a result of aggregating both ontology domain knowledge and learner's sequential access patterns.

3.4 Experimental Evaluation

In order to evaluate the effectiveness of the proposed hybrid knowledge-based recommendation approach, a number of experiments were carried out and the proposed knowledge-based recommendation approach was evaluated on a real world e-learning dataset. To determine the effectiveness and performance of our approach, the experimental results from the proposed hybrid recommendation method were compared with those of other existing related recommendation methods. The proposed hybrid knowledge-based recommendation approach combines CF, ontology and SPM algorithm (SPM+Onto+CF). The two other recommendation methods evaluated for purposes of comparison of effectiveness of recommendations include CF and a combination of ontology with CF (CF+Onto). The main objective of carrying out the experiments was to measure the prediction accuracy and performance of the proposed hybrid recommendation approach for learning items which aggregates ontology domain knowledge (learner and learning resources) and learner's historical sequential access patterns into the recommendation process. Furthermore, learner satisfaction with recommendation results from the different recommendation methods was also evaluated and results compared.

3.4.1 Experimental Setup

The experiments were conducted on a class of 50 undergraduate students in their third year of study pursuing computer science course in a university. The students use a Learning Management System (LMS) to access learning resources and support their learning. Lecturers can create and upload learning items to the LMS. Once learners are registered into the LMS, they can access the learning items. The recommender system in the LMS generates recommendations of relevant learning items to the learners based on ratings and similarity of the learner’s ontological knowledge. The experiments were carried out over a period of four months (one semester). Every semester, third year computer science students choose an average of six courses. The learners were required to rate the learning items in the LMS according to the relevance to their learning needs using a 5 point rating scale ranging from 1 – “Very irrelevant” to 5 – “Very relevant”. During the initial registration of learners to the LMS with recommender system, the learners were tested with some online quiz to evaluate their knowledge level and learning style. Similarly, they were required to rate at least a few learning items initially to enhance their learner profile and ontology. Subsequently, the recommender system was able to predict the learner’s ratings for unrated learning items and provide recommendations of learning items to learners based on the learner’s ratings and the ontology domain knowledge. Ratings and ontological information of learners were collected over the entire period of experiment spanning four months. Learners sequential access patterns from web logs were mined as well using the GSP algorithm during the experimental period. The implementation and evaluation of recommendation algorithms was done using Python programming language.

3.4.2 The Dataset

A real world dataset containing ratings of learning items and ontological information about the learners collected from an LMS used in a university was used to evaluate the performance and effectiveness of the proposed hybrid knowledge-based recommendation algorithm (SPM+Onto+CF) and two other related recommendation algorithms (CF on its own and CF+Onto). The total number of learning items contained in the database was 240. At the end of the experimental period, a total of 4000 ratings of learning items had been collected. For purposes of experimental evaluation, the e-learning dataset was split into two sub datasets. The first sub dataset was a training set while the second set was a test set, divided at the ratio of 70% training sub dataset to 30% test sub dataset. Table 3.2 shows the description of the e-learning dataset used to evaluate the proposed hybrid recommendation approach.

Table 3.2: Description of the e-learning dataset

No. of Learners	Learning Items	Ratings	Rating Scale	Learner Ontology Information	
				Knowledge Level	*Learning Style*
50	240	4000	1 – 5	1 – 3	1 – 4

3.4.3 Experimental Results

In this sub-section, we present the experimental results of the proposed hybrid knowledge-based recommendation approach (SPM+Onto+CF) and also comparison of results of two other related approaches namely CF and CF+Onto algorithms. A real world dataset (Table 3.2) was used for evaluation of our proposed recommendation method since public standard datasets are scarce in the area of e-learning recommender systems. This scarcity of public datasets for recommender systems for e-learning was also pointed out by [14] who observed that the performance results of different studies in e-learning recommender systems cannot be easily compared due to lack of public e-learning datasets. The goal of the experiments in this study was to test the accuracy of predictions and performance of the proposed hybrid recommendation approach (SPM+Onto+CF) and compare the results with the two other related recommendation algorithms over the same dataset. Furthermore, learner satisfaction with the recommendation results from the three recommendation algorithms was equally evaluated. In a bid to carry out comparisons of effectiveness of the proposed hybrid knowledge-based recommendation algorithm (SPM+Onto+CF) with the other related recommendation approaches, evaluation metrics such as MAE (eq. 2.3), precision (eq. 2.4), and recall (eq. 2.5) among others were used. Each set of the experiments was repeated 3 times using different randomly selected subsets of training set and test set each time, then the average values of the results taken for each of the metrics.

3.4.3.1 Sensitivity to neighborhood size and accuracy experiments

The size of similar items (neighborhood) in recommender systems determine the prediction accuracy and quality of recommendations [5], [163]. To evaluate the sensitivity to the size of neighborhood and prediction accuracy in the recommendation approaches, we measure the MAE for each of the recommendation algorithms using different sizes of neighborhood. MAE

[83], [161], [162] computes the average deviation between the predicted rating and actual rating in a recommender system. Lower value of MAE means the predicted rating is more accurate and vice versa. To measure MAE in e-learning recommender systems, we use the formula in eq. 2.3.

Sets of experiments were conducted while varying the size of neighborhood (Fig. 3.5) to find the neighborhood size that gives the optimum prediction accuracy for the proposed hybrid knowledge-based recommendation algorithm (SPM+Onto+CF) and the other two recommendation algorithms (CF and CF+Onto). The following diagram (Fig. 3.5) illustrates the experimental results of the sensitivity to size of neighborhood and accuracy of predictions for the three recommendation algorithms tested by varying the sizes of the neighborhood.

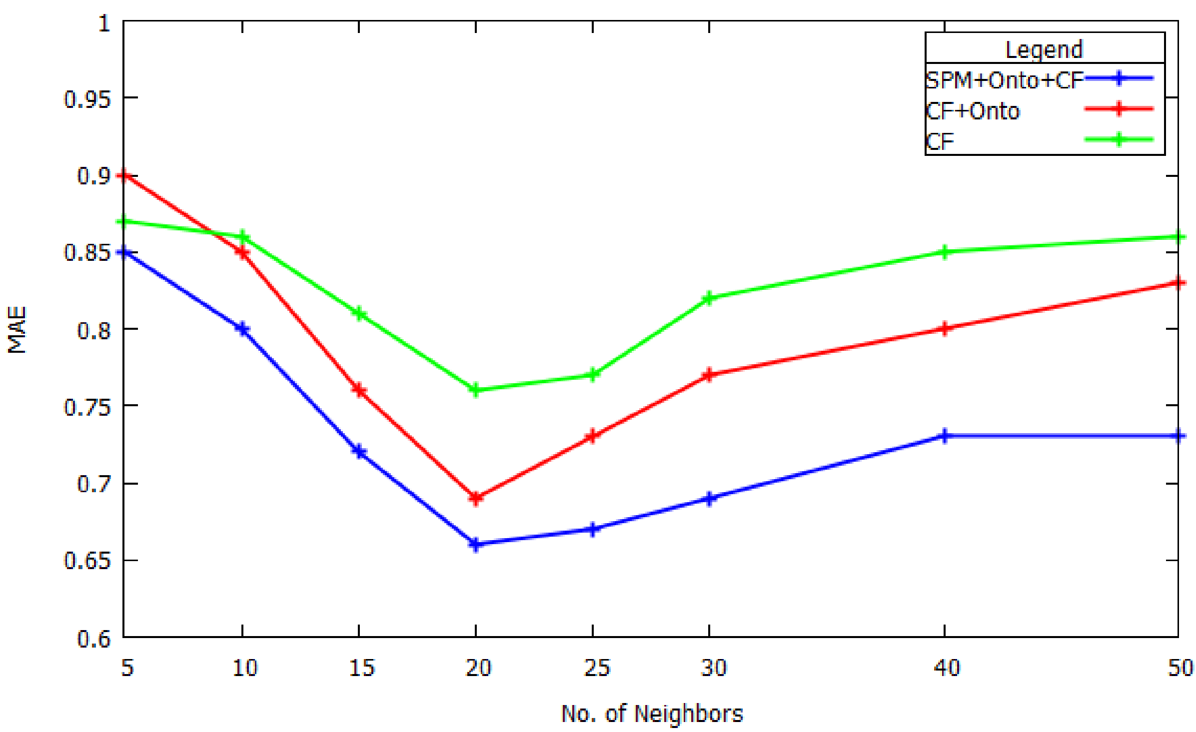

Figure 3.5: Measure of sensitivity to size of neighborhood and prediction accuracy

From Fig. 3.5, it can be observed that the optimal prediction of ratings is achieved when the size of neighborhood is 20. As the size of neighbors exceed 20, the prediction accuracy decrease for all the recommendation algorithms (Fig. 3.5). Therefore, the optimum neighborhood size of 20 will be used for the rest of the experiments.

Figure 3.5 further illustrates the comparisons in terms of accuracy of predictions using MAE between our proposed hybrid knowledge-based recommendation approach (SPM+Onto+CF) and the two other recommendation approaches (CF and CF+Onto). The value of MAE decreases steadily as the neighborhood size increase until when the size of neighborhood is 20, then MAE increases when the neighborhood size exceeds 20 neighbors for all the three recommendation algorithms. For instance, at an optimum neighborhood size of 20, the proposed hybrid recommendation approach has a MAE value of 0.66 while CF and CF+Onto have a MAE value of 0.76 and 0.69 respectively. Similarly, when the size of neighborhood increases to 40 neighbors, the MAE value for CF, CF+Onto and SPM+Onto+CF is 0.85, 0.8, and 0.73 respectively. It can be observed from Fig. 3.5 that the proposed hybrid knowledge-based recommendation method compared to CF results to an improvement of 0.1 MAE when the neighborhood size is 20 and 0.12 when the neighborhood size is 40. This shows that both SPM and ontology contribute to the improvement in accuracy. Although the MAE improvement of the proposed knowledge-based recommendation approach over the CF+Onto at optimum size of neighborhood of 20 appears small at 0.03, it is notable from the experimental results in Fig. 3.5 that the proposed hybrid recommendation approach outperforms the other two methods in terms of accuracy of predictions for all neighborhood sizes, hence translating to good quality recommendation results for the learner.

3.4.3.2 Accuracy experiments with different levels of sparsity

To measure the effects of level of sparsity on the accuracy of predictions and recommendations, a set of experiments were conducted to measure the prediction accuracy by varying the sparsity levels in the dataset. This test was carried out by randomly omitting some of the values in the training set so as to have a sparse training set while maintaining the test set. The experiments were repeated while varying sparsity level for each experiment. Sparsity is computed using the formula in eq. 3.4 [36]:

$$\text{Sparsity} = 1 - \frac{|ratings|}{|items|.|users|} \tag{3.4}$$

In the rating matrix, the original sparsity level was 66.7%. Figure 3.6 shows the prediction accuracy of our proposed hybrid recommendation method (SPM+Onto+CF) in comparison with the other two algorithms (CF and CF+Onto) at different sparsity levels.

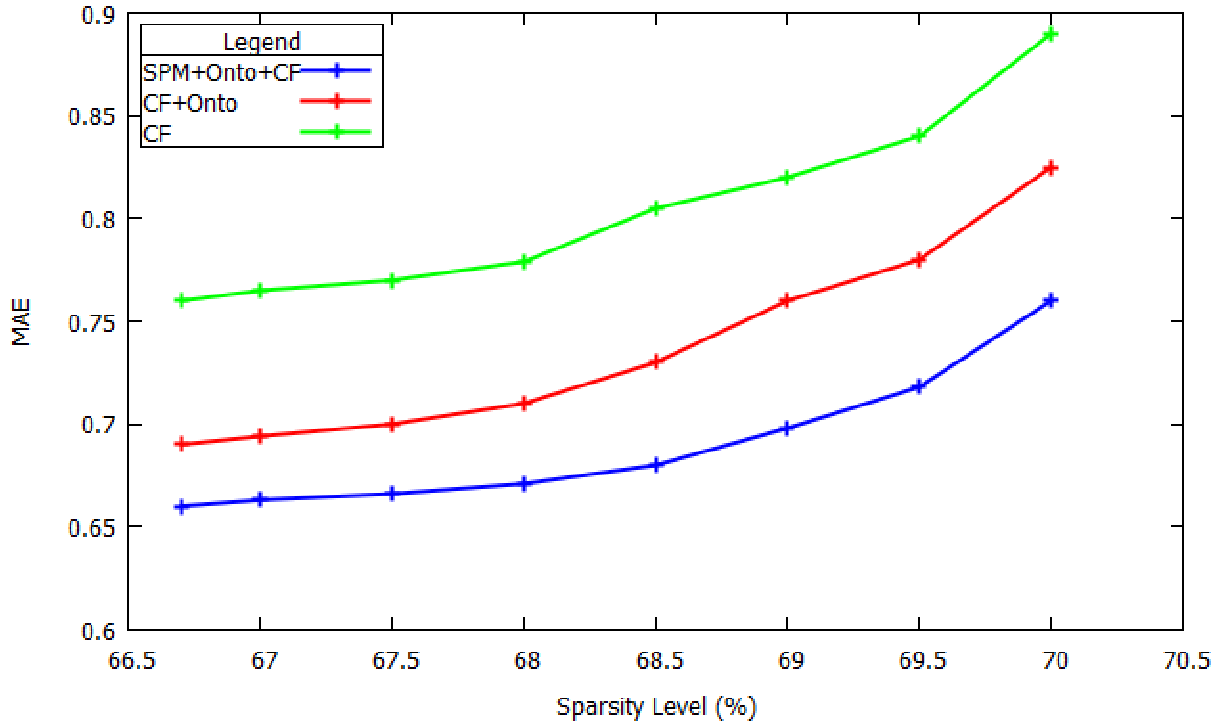

Figure 3.6: Measurement of accuracy at different levels of sparsity

Figure 3.6 shows that as sparsity level increases, the prediction accuracy decreases for all the recommendation algorithms. However, the proposed hybrid KB recommendation approach (SPM+Onto+CF) outperforms all the other recommendation algorithms for all levels of sparsity.

3.4.3.3 Performance evaluation

Experiments were equally conducted to test the performance of the proposed hybrid KB recommendation approach (SPM+Onto+CF). Recall and precision metrics were employed to evaluate the performance of the proposed hybrid KB recommendation algorithm and compared with the other related recommendation algorithms (CF and CF+Onto). Recall, precision and F1-measure are among the widely used evaluation metrics not only in information retrieval but also in e-learning recommender systems [17], [162]. Most researchers have adapted these evaluation metrics in the field of e-learning recommender systems [17]. In using recall and precision metrics, ratings of learning items are mapped onto a binary scale (not relevant vs relevant). In this research study, learning items rated from 1 – 3 are considered "not recommended" while those rated from 4 – 5 are considered "recommended".

Precision [45], [162] is measured with the aid of confusion matrix illustrated in Table 2.5. To evaluate the performance of the proposed hybrid knowledge-based recommendation approach, we use precision formula in eq. 2.4. Figure 3.7 illustrates the precision of the proposed hybrid recommendation approach (SPM+Onto+CF) and the other two recommendation methods against the number of recommendations. The experiments were repeated for different numbers of recommendations and their precisions recorded.

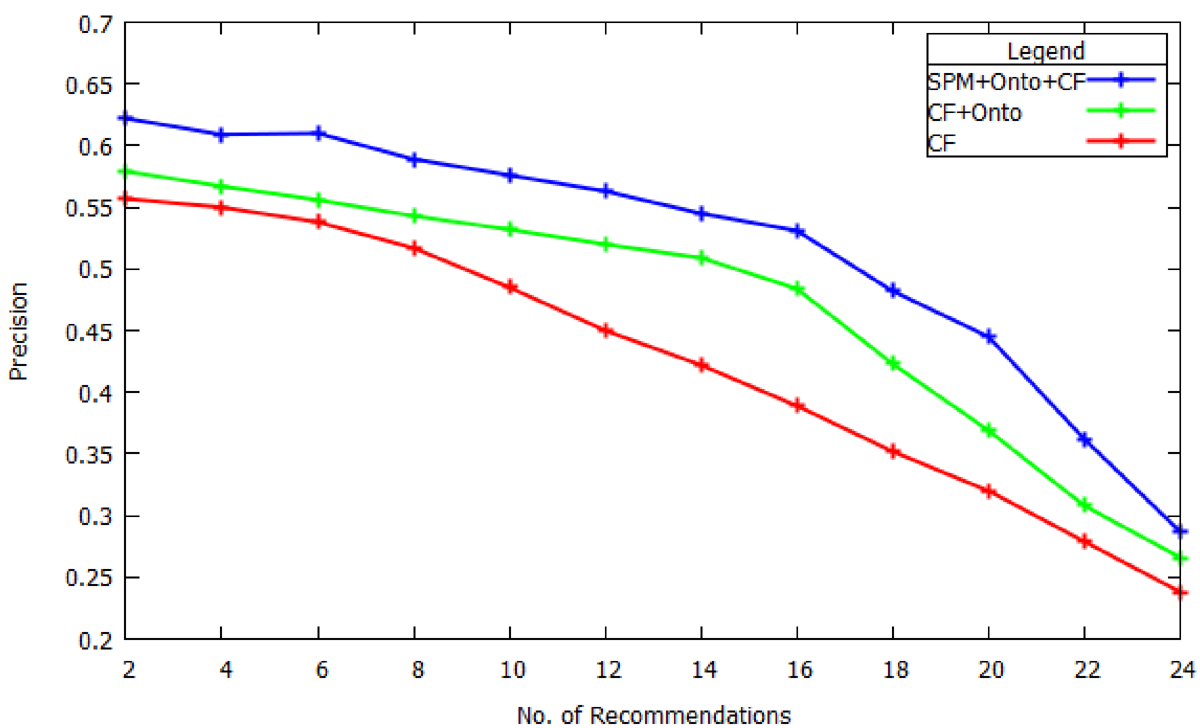

Figure 3.7: Precision measurement of the recommendation algorithms

It can be observed from Fig. 3.7 that the proposed hybrid knowledge-based recommendation algorithm (SPM+Onto+CF) outperforms the other two recommendation algorithms (CF and CF+Onto) in terms of precision for all number of recommendations.

Recall refers to the ratio of relevant learning items selected to the number of relevant learning items [45], [162]. To measure the recall of the proposed hybrid KB recommendation approach, we use the contingency table in Table 2.5 and the recall formula in eq. 2.5.

Figure 3.8 illustrates the comparisons of recall between the proposed hybrid KB recommendation algorithm (SPM+Onto+CF) and the two other recommendation algorithms (CF and CF+Onto). The recall experiments were repeated for different numbers of recommendations.

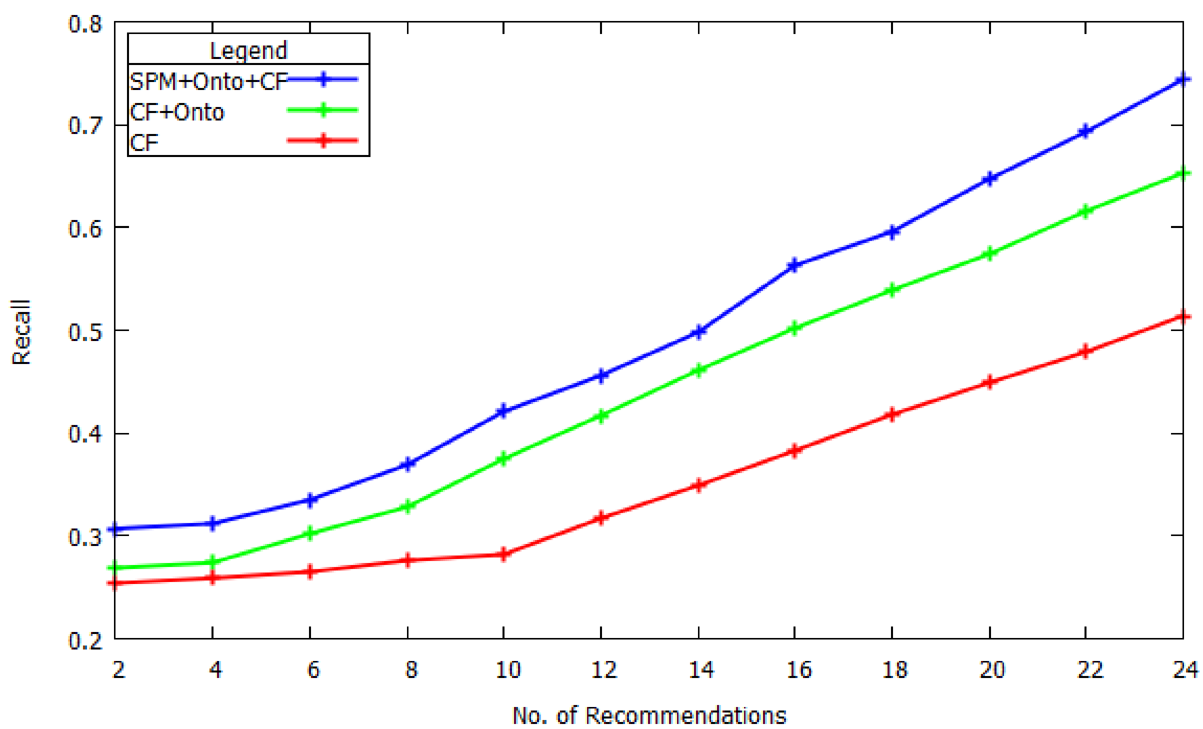

Figure 3.8: Recall measurement of the recommendation algorithms

It can be shown from Fig. 3.8 that the proposed hybrid KB recommendation approach (SPM+Onto+CF) provides better recall performance than the other recommendation methods for all number of recommendations.

3.4.3.4 Learner satisfaction evaluation

To measure the satisfaction of learners with the recommendation results from the recommendation algorithms, a closed-ended questionnaire was administered to the 50 learners who participated in the experiment. Previous researches on recommender systems for TEL have identified “user satisfaction” as among the important evaluation measures for e-learning recommender systems [17], [175]. The questionnaire sought to establish whether the learner was “satisfied” or “not satisfied” with the recommendation results. Figure 3.9 shows the responses of the learners on learner satisfaction with recommendation results from each of the three recommendation algorithms.

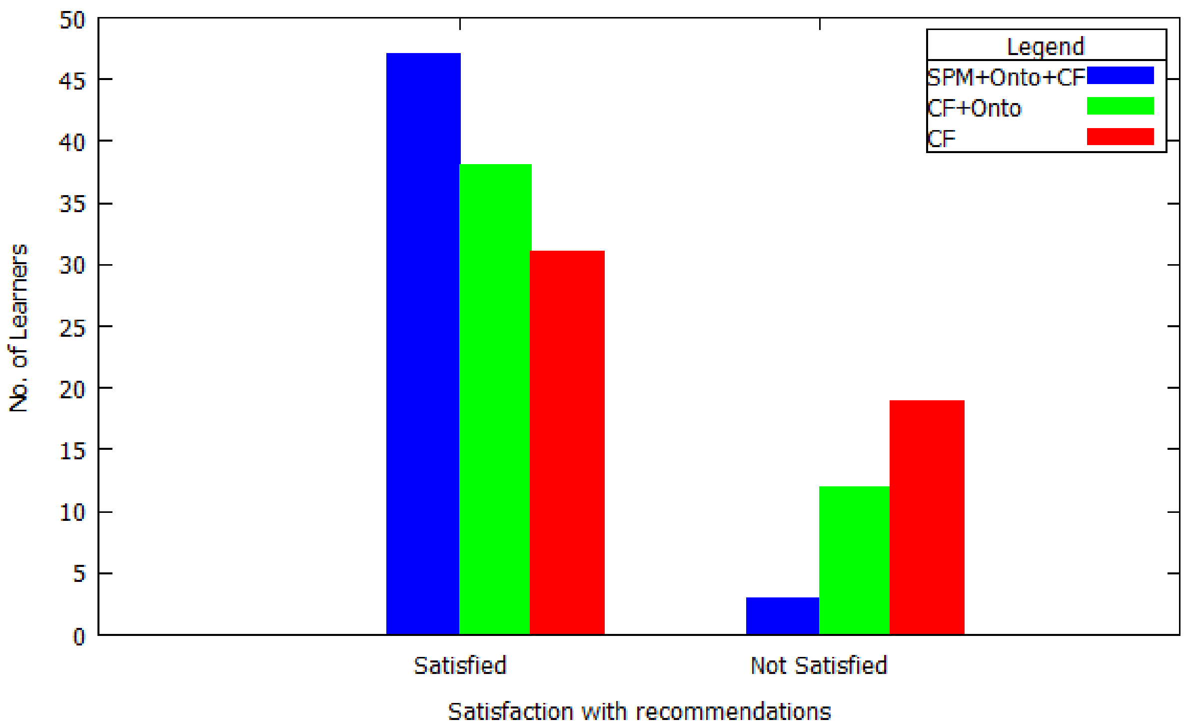

Figure 3.9: Learner satisfaction with recommendations

From Fig. 3.9, it can be observed that 94% majority of the learners expressed satisfaction with the recommendation results from the proposed hybrid KB recommendation approach (SPM+Onto+CF). Only 6% of the learners were not satisfied with the recommendation results from the proposed hybrid recommendation algorithm. On the other hand, 62% and 76% of the learners said they were satisfied with recommendation results from CF and CF-Onto recommendation methods respectively.

3.4.4 Discussion

The experiments conducted in this study reveal that the proposed hybrid KB recommendation approach (SPM+Onto+CF) provides results with good prediction accuracy and performance than the conventional CF and CF with ontology (CF+Onto) recommendation approaches. The advantage of the proposed hybrid recommendation method is that since ontological information about the learner is also used to measure learner similarities and comes earlier in the recommendation model (Fig. 3.2), then this method can help overcome cold-start problem encountered by conventional recommendation methods such as CF. Before the initial ratings to work on in cases of newly added learners to the recommender system, the recommender makes use of the ontological domain knowledge arising from aggregation of ontological knowledge to the recommendation system. Learner’s ontological information such as learning style and knowledge level are used in measuring similarity and prediction of learner preferences at the initial stage. Moreover, the proposed hybrid KB recommendation approach can address the rating sparsity problem by using GSP algorithm. The learner’s sequential access patterns discovered by mining of web logs reflects the preference for learning items by the learner and can be used for prediction of learning items that the learner would most likely access in the next visit to the web. Using the discovered learner’s sequential access patterns, the most likely learning items that the learner will access next time can easily be predicted even in cases where there is sparsity of ratings. Aggregating learner’s sequential access patterns for making predictions not only improves the accuracy of recommendation results but also helps to alleviate rating sparsity problem.

The experimental results of our proposed hybrid knowledge-based recommendation approach (SPM+Onto+CF) indicate that both SPM and ontology contributes to improvement in performance of the recommender system, hence making the proposed hybrid recommendation approach more effective. Additionally, using ontology in the proposed hybrid KB recommendation method to incorporate learner’s additional information such as knowledge level and learning style into the recommendation process results in recommendations that are more personalized according to learner preferences. In this study, we employed the recommended evaluation metrics that are suitable for e-learning recommender systems [17], [162] such as recall, precision and MAE to measure the performance and accuracy of the proposed hybrid KB recommendation approach. Additionally, we evaluate the learner's satisfaction with recommendation results from the proposed recommendation method.

It is clear from the experimental results that the proposed hybrid KB recommendation approach is more effective than other recommendation algorithms in terms of accuracy, recall and precision. Furthermore, majority of the learners (94%) were satisfied with the results of recommendations by the proposed hybrid knowledge-based recommendation algorithm (Fig. 3.9). The proposed hybrid recommendation method provides good quality recommendations of learning items to the learners and this is evident by a majority of learners who expressed their satisfaction with the recommendations.

3.5 Conclusion and Future Work

In this study, we proposed a hybrid knowledge-based recommendation approach based on ontology and sequential pattern mining algorithm for recommending relevant learning items to learners in e-learning environments. The proposed hybrid recommendation method incorporates additional learner information such as knowledge level and learning style using ontology while learner's historical sequential access patterns are integrated into the recommendation process using SPM algorithm. Ontology is used to model and represent knowledge about the learner and learning resources while SPM algorithm is used to mine the web logs and discover the learner's sequential access patterns. Experimental results show that the proposed hybrid knowledge-based recommendation approach provides better prediction accuracy and performance than other related recommendation methods. Furthermore, the proposed hybrid recommendation approach can help alleviate the ratings sparsity and cold-start problems by making use of learner's sequential access patterns and ontological domain knowledge respectively before the recommender system accumulates enough ratings.

Chapter 4

Hybrid Recommendation Approach for Learning Resources based on Context Awareness and Sequential Pattern Mining

The rapid evolution of the Internet has resulted in the availability of huge volumes of online learning resources on the web. However, many learners encounter difficulties in retrieval of suitable online learning materials due to information overload. Besides, different learners have different learning needs arising from their differences in learner's context and sequential access pattern behavior. Traditional recommender systems such as content-based and collaborative filtering use content features and ratings respectively to generate recommendations for learners. However, for accurate and personalized recommendation of learning materials, learner's context and sequential access patterns should be incorporated into the recommender system. Traditional recommendation techniques do not incorporate the learner's context and sequential access patterns in computing learner similarities and providing recommendations, hence they are likely to generate inaccurate recommendations. Furthermore, traditional recommender systems provide unreliable recommendations in cases of high rating sparsity.

In this chapter, we propose a hybrid recommendation approach combining context-awareness, sequential pattern mining (SPM) and collaborative filtering (CF) for recommending learning materials to the learners. In our recommendation approach, context-awareness is used to incorporate contextual information about the learner such as knowledge level and learning goals; SPM algorithm is used to mine the web logs and discover the learner's sequential access patterns; and CF computes predictions and generates recommendations for the target learner based on contextualized data and learner's sequential access patterns.

Furthermore, the proposed recommendation method uses both the ratings and learner's contextual information in computing similarities between the learners as well as generating predictions of ratings for learning materials, hence making recommendations more personalized to the learner. GSP algorithm is used in our method for sequence mining to discover the learner's historical sequential access patterns while CA incorporates learner's additional contextual information such as knowledge level and learning goals into the recommendation process. Recommender systems in e-learning differ from other domains since learner's contextual information such as knowledge level and learning goals are dynamic and change overtime according to situations, hence they have a bearing on learner preferences at that particular context. Evaluation of our proposed hybrid recommendation approach indicated that it can outperform other recommendation methods in terms of quality and accuracy of recommendations.

4.1 Introduction

As learning resources increase exponentially on the World Wide Web, learners in e-learning environments experience difficulty in choosing relevant learning materials due to information overload. Recommender systems can overcome this problem by filtering and recommending to the learner appropriate learning materials based on the personalized learner preferences. E-learning recommender systems can provide suggestions for relevant and useful online learning materials to learners using e-learning [7]. Recommender systems play an important role of automatic recommendation of relevant items to users in domains such as e-commerce and e-learning [12], [17].

Traditional recommendation techniques such as collaborative filtering (CF) and content-based (CB) recommendation approach rely on user/item rating and content features respectively in computing similarities, making predictions and generating recommendations of items to users. However, in e-learning recommender systems, learner preferences change from context to context. Traditional recommendation techniques such as CB and CF deal with only two types of entities namely *items* and *users* and do not consider their context when making recommendations [32], [33]. However, accurate recommendation of learning materials requires incorporation of learner's context information and sequential access patterns to improve personalization and accuracy of recommendations. Contextual information such as learning goals and knowledge level need to be taken into account in making recommendations to the target learner. Furthermore, since different learners may have different sequential access patterns, then sequential access patterns should also be integrated in computing learner's recommendations. By incorporating context-awareness and learner's sequential access patterns into the recommender system, the recommendation results will be more personalized to the learner preferences. A learner whose knowledge level is *beginner* at the current context may have different preferences for learning materials when the knowledge level of the same learner changes to *intermediate* in future context. The recommendation problem arising from differences in learner's contextual characteristics can be addressed by using context-aware (CA) recommendation method with SPM. In the context of e-learning, CA based recommender systems take into account the learner's context when modeling the learner preferences and generating recommendations. De Campos et al. [34] points out the importance of incorporating other additional information about the user including user's context information to improve the quality of recommendations.

In this study, we propose a hybrid recommendation approach for recommending learning materials to learners by incorporating context-awareness and SPM algorithm into the recommender system. In our method, we use context-awareness to incorporate additional contextual information about the learner while SPM algorithm is used to mine the web logs and discover the learner's sequential access patterns.

The contributions of this recommendation approach include: First, we incorporate context-awareness and learner's sequential access patterns into the recommendation process to achieve improved personalization of recommendations. Context-awareness is used to incorporate learner's contextual information such as knowledge level and learning goals while SPM algorithm is used to discover the learner's sequential access patterns and filter the recommendation results according to these sequential access patterns. Secondly, in computing the learner/learning item similarities, we take into account the learners contextual information to enhance the accuracy of predictions. Lastly, we show through experimental evidence that our recommendation approach combining CF, CA and SPM provide more accurate recommendations than other related recommendation methods.

4.2 Background

4.2.1 Collaborative Filtering

Collaborative filtering recommender systems deal with *user* and *item* entities. The rating function R in traditional CF recommendation technique can be defined as:

$$R : User \times Item \rightarrow Rating \tag{4.1}$$

This is a two-dimensional (2D) rating function since they consider only the *User* and *Item* dimensions in the recommendation technique. The traditional recommendation problem entails the estimation of ratings of items that the user has not yet seen [32]. The rating table (Table 4.1) illustrates the representation of a 2D CF rating matrix. Learner 1's rating of Item 3 can be predicted based on Learner 1's similarity to other learners in terms of their ratings of Item 1 and Item 2.

Table 4.1: Example of a rating matrix of CF recommendation technique

	Item 1	**Item 2**	**Item 3**
Learner 1	4	5	**?**
Learner 2	1	3	5
Learner 3	5	5	3
Learner 4	3	4	5
Learner 5	4	5	4

4.2.2 Context-Aware (CA) Recommendation

According to Dey et al. (2001) [66], context refers to any information that is used in characterization of the situation of an entity. An entity can either be a person, object or place that is considered to be relevant to that interaction between the user and the application, and it includes both the user and applications themselves. In the context of this study, the learner context information includes the *knowledge level* and *learning goals*. These contextual characteristics change according to situations as the learner acquires more knowledge. Context-aware recommender systems use context in their recommendation process for purposes of providing recommendations that are suitable for a specific user context [176]. In context-aware scenario, ratings are modeled as a function of users, items as well as context hence the rating function can be defined in three-dimensions (3D) as:

$$R : User \times Item \times Context \rightarrow Rating \tag{5.2}$$

where *User* and *Item* belongs to the domains of users and items while *Rating* belongs to the domain of ratings, and *Context* is the contextual information related to the application [32]. The user/item rating dimension was extended in order to add context dimensions which can help in personalization of recommendations according to user context. Table 4.2 illustrates an example of a rating matrix in CA recommender systems scenario with *knowledge level* as context.

Table 4.2: Example of rating matrix in CA recommender system

	Learning Material	**Knowledge Level**	**Rating**
Learner 1	i_1	Beginner	5
Learner 2	i_1	Advanced	3
Learner 3	i_1	Beginner	5
Learner 1	i_1	Intermediate	**?**
Learner 3	i_1	Intermediate	4

Different learner contexts in CA recommendation can impact on the learner preferences and ratings by the learners and also similarity and prediction of ratings for the target learner. For example, in Table 4.2, the change of *knowledge level* context of Learner 1 from *Beginner* to *Intermediate* can influence the rating of the learning material. Learner 1's rating for item i_1 when the knowledge level context changes from *Beginner* to *Intermediate* can be predicted using contextual similarity with other learners. Inclusion of learner context into the recommendation process helps improve personalization of recommendations to the target learner.

Contextual information can be acquired explicitly, implicitly or through inferring the context [32]. Explicit method involves physical and manual input from users while in implicit method, the contextual information is captured automatically from the environment. Contextual information can also be inferred through the use of data mining or statistical methods [31], [32]. Adomavicius and Tuzhilin [32] identifies three paradigms for incorporating contextual information in recommender systems namely contextual modeling, contextual pre-filtering and contextual post-filtering.

In contextual pre-filtering method, information about the current context denoted as c is used to select and construct the relevant set of data records or ratings [32]. Subsequently, the ratings can be predicted by using any of the traditional two dimensional (2D) recommendation techniques on the selected data [31].

4.2.3 Sequential Pattern Mining in E-Learning Recommendation

SPM is a sequence pattern mining algorithm that can discover the learner's sequential access patterns by mining the web logs. Generalized Sequential Patterns (GSP) algorithm is one of the commonly used sequence mining algorithms. A comparison of the SPM algorithms in previous studies in terms of performance shows that GSP algorithm outperforms both FreeSpan and SPADE in many situations. Although PrefixSpan is quite efficient than GSP algorithm in terms of memory usage and execution time for large databases, GSP algorithm on the other hand provides better performance due to apriori pruning for average sized databases [144], [145]. Furthermore, GSP algorithm has the advantage of good scale-up properties especially on average data sequence size. In this study, we adapted the GSP algorithm due to its good performance for medium sized sequence databases where execution time is negligible. Moreover, previous studies have shown that GSP algorithm is efficient and capable of generating all possible candidate sequences without missing any actual sequences hence it is suitable for application in e-learning environments due to its high accuracy [172], [177].

4.3 The Recommendation Model and the Hybrid Algorithm

The proposed hybrid recommendation approach in this study combines CF, CA and SPM in recommendation of e-learning materials. This section presents the recommendation model (Fig. 4.1) and also explains how the proposed recommendation algorithm works.

4.3.1 The Recommendation Model for E-Learning Materials Recommendation

The hybrid recommendation model in Fig. 4.1 summarizes the functionality of the proposed hybrid recommendation approach. The main components of the recommendation model are the learner profile, learning object model, contextualized data preparation, recommendation engine, SPM algorithm and contextual recommendations components. In this subsection, we explain the functions of the main components of the model.

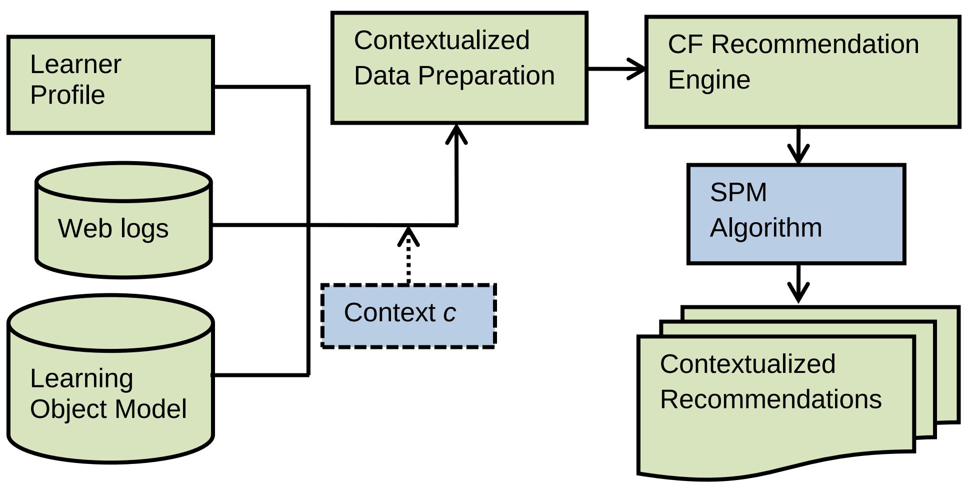

Figure 4.1: Recommendation model for the proposed hybrid recommendation approach

The *learner profile* component stores information and preferences about the learner. Information contained in the learner profile component is acquired using both implicit and explicit methods. Learner's data such as personal demographic data (name, gender, age etc.) as well as learner's contextual information such as knowledge level and learning goals among others is stored in the learner profile. The learner contextual information is used by the proposed hybrid recommender system to personalize the learner profile and preferences. Similarly, the *learning object model* component contains information about the learning materials. This component stores information about the learning materials that include format of the learning materials which may be text, image, audio or video. Learning materials will be recommended to the target learner based on learner's ratings on learning materials and contextual information.

In the *contextualized data preparation* component, cleaning of the web logs, preparation of learner's contextual information and learning material's data into a suitable format for the recommender system takes place. The r*ecommendation engine* component then analyzes the contextualized data arising from aggregation of learner preferences, contextual information and ratings. Using this contextualized data, the *CF recommendation engine* computes similarity and predicts the ratings for the target learner taking into consideration the learner's context. The recommendation engine then generates *top-N* recommendations of learning materials based on contextualized learner preferences.

The *SPM algorithm* is a sequence pattern mining algorithm. In our model, SPM algorithm is used for mining the web logs to discover the learner's sequential access patterns for the target learner. The sequential access patterns discovered by the algorithm are then applied to the *top-N* recommendation results to filter the recommendations according to the learner's sequential access patterns. Finally, the target learner receives the final c*ontextualized recommendations* based on the learner's contextual information and sequential access patterns.

4.3.2 Implementation of the Hybrid Algorithm

The proposed recommendation approach entails 3 main steps: (1) Incorporating context information *c* into the recommendation process using contextual pre-filtering method. (2) Computing learner similarities and prediction of ratings of learning materials based on contextualized data. (3) Generating *top-N* contextualized recommendations for the target learner and applying the GSP algorithm to the results to filter the final recommendations according to learner's sequential access patterns. These steps are summarized in the recommendation framework illustrated in Fig. 4.1 and explained in detail in this sub-section.

4.3.2.1 Incorporating context information into the recommender system

The paradigm adopted for incorporation of contextual information (Fig. 4.1) into the recommender system is contextual pre-filtering method proposed by [32]. The benefit of adapting context pre-filtering approach is easy integration with any traditional recommender system. In this study, one dimension of learner's contextual information namely *knowledge* *level* is considered. Knowledge level as context dimension in this proposed hybrid recommendation approach change with time and situations as the learner's knowledge improves. For example, a learner with little background knowledge on a subject may have knowledge level context as *beginner*. However, as the learner acquires more knowledge with time, the learner's knowledge level context can change to *intermediate*. The initial contextual data *knowledge level* is captured during new learner account registration. During registration into the system, the new learner is tested with some online evaluation questions to determine the knowledge level of the learner based on the test score. The recommender system then updates the learner profile and subsequently keeps track of the learner's knowledge level contextual change by administering the online knowledge level test at periodical intervals.

Contextualized data is used in computing the learner similarities and predictions of ratings of learning materials by the target learner. For example, in Table 4.2 in the previous section, for a target learner whose contextual *knowledge level* = {*beginner*} to receive recommendations of learning materials, only the ratings for other similar learners with context *knowledge level* = *{beginner}* will be considered in computation of rating similarity and predictions.

For purposes of computations in the dataset and use by the recommender system, we define *knowledge level* context with 3 values as follows:

Knowledge level = {beginner, intermediate, advanced} = {1, 2, 3}.

The assigned values of the elements of knowledge level {1, 2, 3} are used in the contextualized rating matrix of learners, learning materials and context values.

4.3.2.2 Measuring learner similarities and computing predictions of learning materials

Once the context information has been captured by the recommender system, similarities of learners and predictions of contextualized ratings of learning materials are computed by the recommendation engine component (Fig. 4.1). In computing similarities of ratings, contextual information is taken into account. In this study, *Pearson correlation coefficient* was used to compute learner similarities [36]. Contextual similarity $Sim(C_l,C_u)$ between the target learner l and learner u is calculated as follows (eq. 4.3):

$$Sim(C_l, C_u) = \frac{\sum_{a=1}^{m}(R_{l,a} - \overline{R_l})(R_{u,a} - \overline{R_u})}{\sqrt{\sum_{a=1}^{m}(R_{l,a} - \overline{R_l})^2}\sqrt{\sum_{a=1}^{m}(R_{u,a} - \overline{R_u})^2}} \tag{4.3}$$

where $R_{l,a}$ is the rating given to learning material a by target learner l, $\overline{R_l}$ is the mean rating of all the ratings provided by target learner l based on learner's contextual information. $R_{u,a}$ is the rating given by learner u to learning material a and $\overline{R_u}$ is the mean rating of all ratings provided by learner u based on learner's contextual information while m is the total number of learning materials. Unlike in CF, contextual information is utilized in computing the ratings and the mean rating.

To compute predictions of contextualized ratings of learning material b for the target learner, the *k*NN (*k* nearest neighbors) approach of the most similar learners obtained in eq. 4.3 who have rated the learning material b is used [36]. The goal is to predict the rating $R_{l,b}$ by target learner l for a new learning material b using the rating given to b by other similar learners (nearest neighbors). To compute the predicted rating $P_{l,b}$ of learning material b by target learner l, we use the following prediction formula [36] in eq. 4.4:

$$P_{l,b} = \overline{R}_l + \frac{\sum_{u=1}^{n}(R_{u,b} - \overline{R_u}) \times Sim(C_l, C_u)}{\sum_{u=1}^{n} Sim(C_l, C_u)} \tag{4.4}$$

where $P_{l,b}$ is the prediction for the target learner l for a learning material b, $\overline{R_l}$ is same as in eq. 4.3, n denotes the total number of learners in the neighborhood, $R_{u,b}$ is the rating given by learner u to learning material b, and $Sim(C_l, C_u)$ is the contextual similarity between target learner l and learner u.

4.3.2.3 Generating contextualized recommendations and application of GSP algorithm

To generate contextualized recommendations, GSP algorithm is applied to the *top-N* to filter the *top-N* recommendation results according to the learner's sequential access patterns. In this research, we adapted the GSP algorithm due to its suitability and efficiency in recommendation of e-learning materials. The *top-N* recommendations of the learning materials for the target learner l are generated based on contextualized learner similarities and predicted ratings. The recommendation process is illustrated in Algorithm 4.1 where M is a set of learning materials $\{a, b\}$ and learning material a has been rated by the target learner and learning material b represents unrated learning materials by the target learner of which predictions of ratings is being sought. C is the context representing knowledge level in this study. The elements of knowledge level are {*beginner, intermediate, advanced*} represented by values $\{1, 2, 3\}$. $R_{l,a}$ is the rating of learning material a by target learner l and $P_{l,b}$ is the predicted rating for unrated learning material b by the target learner l. Other learners denoted as u have rated learning material b. Once the *top-N* recommendations are being obtained, the GSP algorithm is applied on the recommendation results to filter the *top-N* recommendations according to the learner's sequential access patterns. Algorithm 4.1 shows the procedure of generating the final contextualized recommendations based on GSP algorithm.

Algorithm 4.1: Generate Recommendations

Input
Learners L = $\{l, u\}$
Learning Materials M = $\{a, b\}$
Context dimensions C = {*Knowledge Level*}
$C \in \{1, 2, 3\}$
Ratings
$R \in \{1, 2, 3, 4, 5\}$

Output
Predicted ratings, *top-N,* Final hybrid recommendations

Method
Initialization:
$l \in L, u \in L, a \in M, b \in M$
$u = u_1, u_2, u_3, \ldots, u_m$
for $(i = 1; i <= m; i{+}{+})$ **do**
  Compute target learner's contextual similarity $Sim(C_l, C_u)$ using eq. (4.3)
end for
Predict ratings $P_{l,b}$ for target learner l for unrated item b using eq. (4.4)
Generate contextualized *top-N* recommendations
Apply GSP algorithm to *top-N*
Output the final recommendations for target learner l

Discovering sequential access patterns using GSP algorithm involves three main phases: (i) determining the support of each learning material (*first phase*); (ii) generation of potential frequent sequences (*candidate sequence generation*); and (iii) deleting of candidate sequences whose support count is less than the minimum support (*pruning phase*). In e-learning materials recommendation, the learner's sequential access patterns are important and should be considered in the recommendation process. Therefore, the GSP algorithm is applied on the initial recommendation results *top-N* to filter the recommendation results according to the sequential learning access patterns of the learner. The final contextualized recommendations to be recommended to the target learner are based on both the learner's contextual information and sequential access patterns.

4.4 Experiments and Evaluation

4.4.1 Experimental Setup and Dataset

Sets of experiments were conducted in order to evaluate the performance of the proposed recommendation approach (*GSP-CA-CF)*. The dataset was obtained from a university that is using a learning management system (LMS) to support teaching and learning for students using e-learning. It was collected for a period of 6 months from September 2015 to March 2016. The total number of learners using the LMS to support their learning during the period of experiment was 1,200. The LMS allows learners to rate the learning materials on a scale of 1 – 5 (1 – very irrelevant, 2 – fairly irrelevant, 3 – irrelevant, 4 – relevant, 5 – very relevant). The recommender system is able to suggest learning materials to the learners by matching their preferences and contextual information. The initial context information (*knowledge level*) was collected during registration of learners to the LMS and is subsequently updated periodically as the learners use the LMS to access online learning materials. The contextual information of the learners namely knowledge level keep changing with time and situations as the learner's knowledge on a subject improves. Learner's knowledge level can change to *beginner, intermediate* or *advanced* as situations change. During the dataset collection periods, the learner ratings and learner's contextual information were extracted from the recommender system database and sequential access patterns obtained by mining the web logs using the GSP algorithm. The dataset was then split into training subset (80%) and test subset (20%) for purposes of experimental evaluation. The dataset description is shown in Table 4.3.

Table 4.3: Dataset description

No. of Learners	No. of Learning Materials	No. of Ratings	Context Scale	Rating Scale
1,200	756	57,153	1 – 3	1-5

For purposes of evaluating the effectiveness of the proposed hybrid recommendation approach, three other algorithms were evaluated over the same dataset described in Table 4.3 and their results compared. The algorithms that were evaluated are: (i) the proposed hybrid recommendation algorithm combining SPM, context-awareness, and CF (*GSP-CA-CF*) (ii) context-awareness combined with CF (*CF-CA*) (iii) GSP algorithm (iv) *CF* algorithm.

4.4.2 Experimental Results

The main goal of this study was to propose a hybrid recommendation approach based on SPM, CA and CF for recommending learning materials to learners in e-learning environments. In this sub-section, we analyze and present the experimental results and evaluation metrics to test the performance and effectiveness of the proposed recommendation approach (*GSP-CA-CF*).

4.4.2.1 Accuracy experiments

A series of experiments were conducted while varying the sizes of neighborhoods so as to establish the optimum size of neighborhood for best results to use in subsequent experiments. The size of nearest neighbors in recommender systems has an impact on both prediction accuracy and quality of recommendations [5], [163]. Similarly, experiments were carried out to measure the prediction accuracy for the four recommendation algorithms under different sizes of neighborhood. The accuracy of predictions is computed using the MAE (eq. 2.3). The lower the value of MAE, the higher is the prediction accuracy.

Figure 4.2 shows the sensitivity to neighborhood size and the accuracy of predictions against the number of nearest neighbors for the four recommendation algorithms measured using MAE.

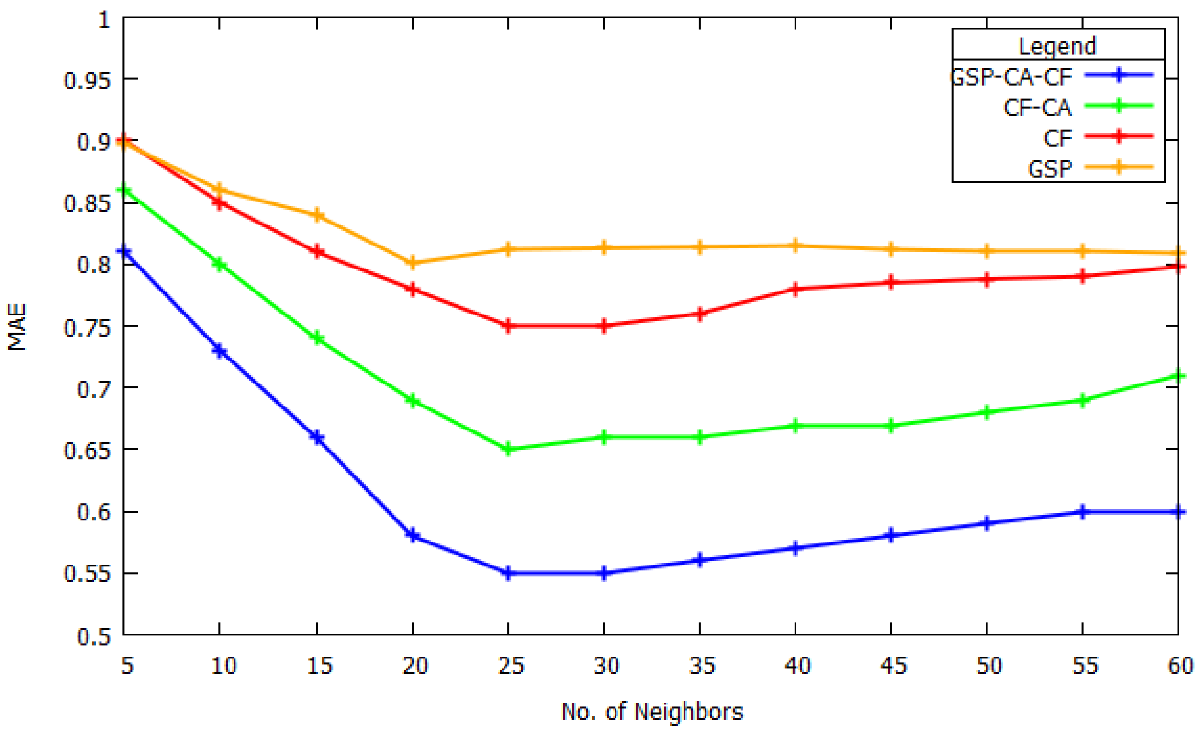

Figure 4.2: Accuracy of predictions and sensitivity to neighborhood size

From Fig. 4.2, it is evident that the accuracy of prediction for the proposed hybrid recommendation approach (*GSP-CA-CF*) as well the other three recommendation algorithms (*CF-CA, GSP* and *CF*) increase steadily as we increase the number of neighbors from 5 to 25 attaining the optimum prediction accuracy when the number of nearest neighbors is 25. After 25, the curve for the four algorithms *(GSP-CA-CF*, *CA-CF, GSP* and *CF*) begins to rise at smaller intervals, hence the accuracy of prediction decreases for the four algorithms as the number of neighbors increase beyond 25. Therefore, we selected 25 as the optimal size of neighborhood for the rest of the experiments. Furthermore, it can be observed from Fig. 4.2 that the proposed recommendation algorithm (*GSP-CA-CF*) provides better accuracy in comparison to the other three recommendation algorithms for any number of nearest neighbors.

4.4.2.2 Experiments on effect of sparsity level on prediction accuracy

Experiments to measure the effect of different levels of sparsity on prediction accuracy of the proposed hybrid recommendation algorithm were carried out. The test was carried out using a neighborhood size of 25 which was our optimum neighborhood from the previous experiment. Our original data sparsity level was 93.7%. Fig. 4.3 shows the results on the effect of level of sparsity on the prediction accuracy.

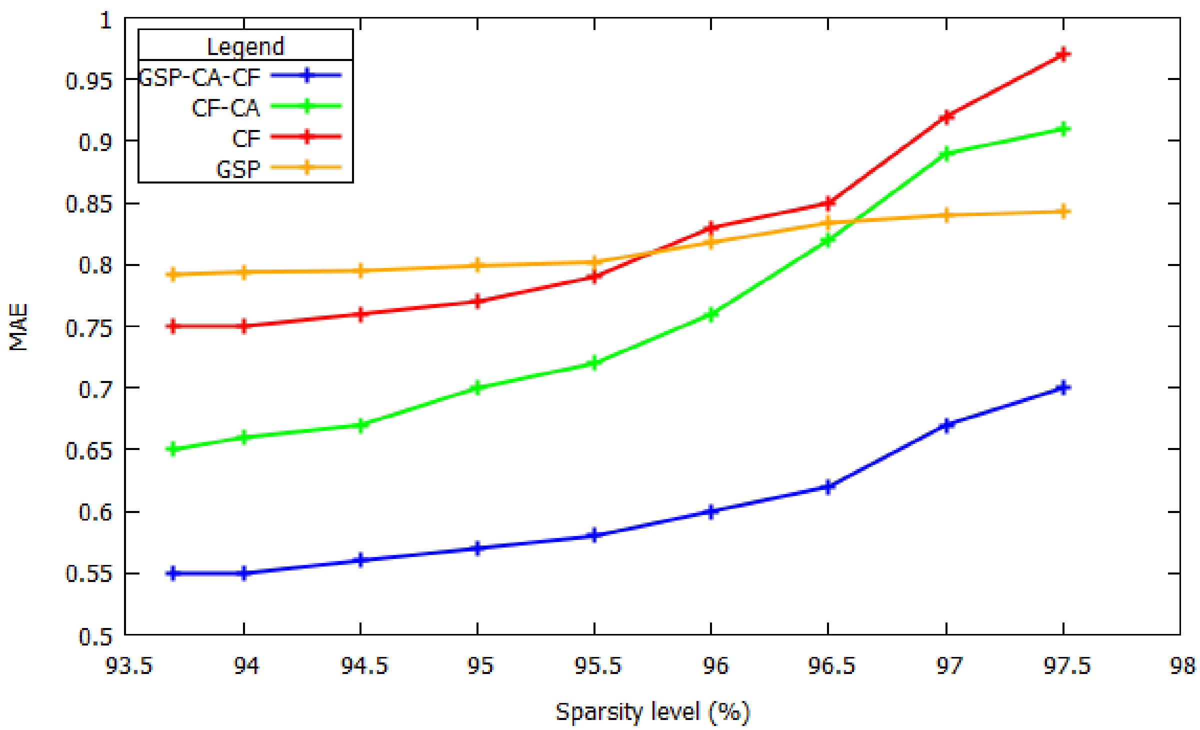

Figure 4.3: Effect of sparsity level on prediction accuracy

From Fig. 4.3, it can be observed that our proposed hybrid recommendation algorithm (*GSP-CA-CF*) has the lowest MAE compared to the other three recommendation algorithms at all levels of sparsity. As the sparsity level increases, the MAE also increases for three recommendation algorithms (*GSP-CA-CF, CA-CF, CF*). On the contrary, there was little change on the MAE of *GSP* algorithm as the sparsity level increases. It is evident from Fig. 4.3 that our proposed recommendation approach (*GSP-CA-CF*) outperforms the other three recommendation approaches with regard to accuracy of predictions at any level of sparsity.

4.4.2.3 Performance measure

The task of a recommender system in e-learning is to recommend useful learning materials to the learners. To measure the performance of the proposed recommendation method *(GSP-CA-CF)*, we use recall, precision and F1 measure metrics. We evaluate and compare the performance of the proposed hybrid recommendation approach (*GSP-CA-CF*) against three other recommendation algorithms namely *CF-CA*, *GSP* and *CF* in terms of recall, precision and F1 measure. Recall and precision can easily be computed with the aid of confusion matrix shown in Table 2.5.

In this study, learning materials are rated on a scale of 1 – 5. Learning materials rated 1–3 are considered "*not relevant*" while those rated 4–5 are considered "*relevant*". Recall is the ratio of correctly recommended learning materials to the relevant learning materials while Precision is the ratio of recommended learning materials to the number of learning materials selected [7], [159]. Precision and recall are computed using the formulas in eq. 2.4 and eq. 2.5 respectively.

Table 4.4 shows the performance of the proposed hybrid recommendation approach (*GSP-CA-CF*) in comparison to three other recommendation algorithms namely *CF-CA, GSP* and *CF* in terms of precision and recall for different numbers of recommendations.

Table 4.4: Performance of the recommendation algorithms in terms of precision and recall

No. of Recs	GSP		CF		CF-CA		GSP-CA-CF	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
4	0.390	0.219	0.412	0.220	0.449	0.231	**0.481**	**0.244**
8	0.364	0.221	0.397	0.233	0.443	0.242	**0.476**	**0.256**
12	0.356	0.226	0.384	0.234	0.438	0.248	**0.462**	**0.272**
16	0.348	0.235	0.371	0.242	0.419	0.267	**0.445**	**0.290**
20	0.342	0.248	0.356	0.259	0.388	0.301	**0.420**	**0.336**
24	0.324	0.259	0.332	0.268	0.359	0.321	**0.396**	**0.373**
28	0.302	0.268	0.311	0.290	0.339	0.352	**0.367**	**0.405**
32	0.245	0.277	0.263	0.304	0.314	0.379	**0.348**	**0.451**

It is evident from Table 4.4 that the proposed recommendation algorithm (*GSP-CA-CF*) outperforms all the other three recommendation algorithms in terms of both precision and recall metrics for any number of recommendations. It can also be observed that increase in number of recommendations results in decrease of precision for all the four algorithms. In contrast, as the number of recommendations increase, recall increases as well for all the four algorithms.

F1 measure metric combines both precision and recall into a single value for ease of comparison and to get a balanced view of performance [163]. To compute F1 measure, we use the formula in eq. 2.6. Figure 4.4 shows the performance in terms of F1 measure of the proposed hybrid recommendation approach (*GSP-CA-CF*) in comparison to the other three recommendation methods namely *CF-CA, GSP* and *CF*.

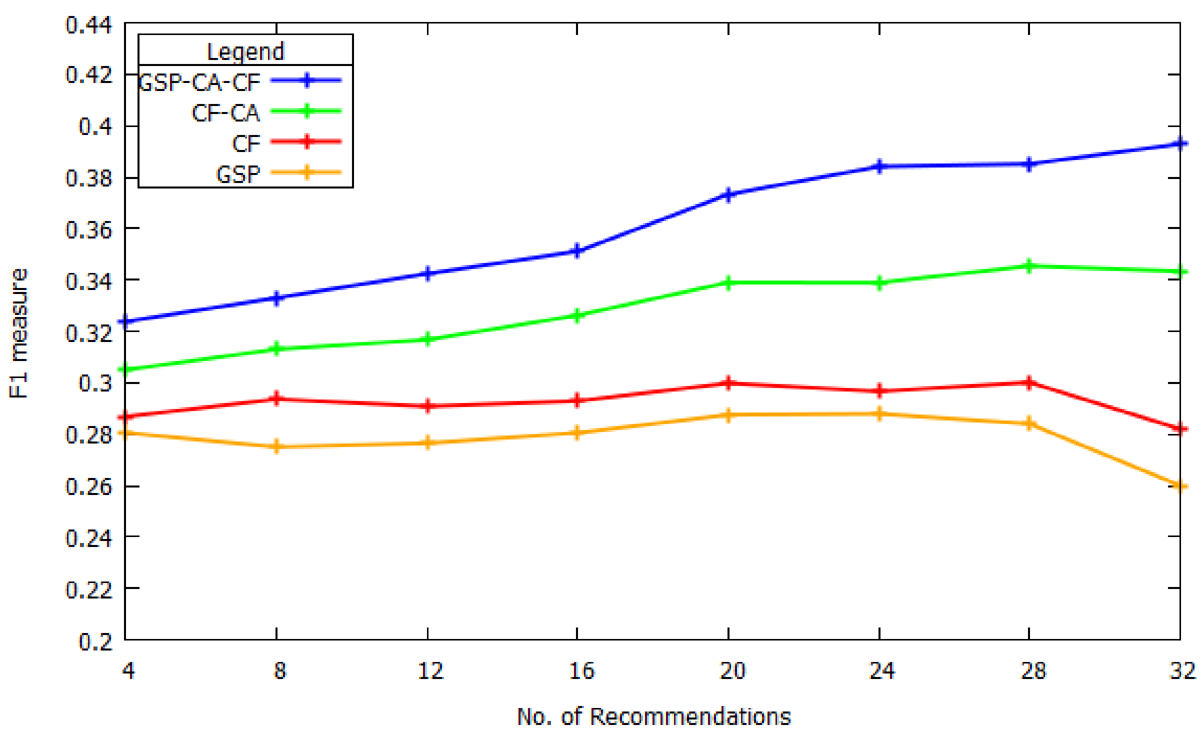

Figure 4.4: F1 measure of the recommendation algorithms against the number of recommendations

The proposed recommendation approach (*GSP-CA-CF*) shows good performance in comparison to the other three recommendation algorithms in terms of F1 measure (Fig. 4.4) for all number of recommendations.

4.4.3 Discussion

In order to evaluate the effectiveness of the proposed hybrid recommendation algorithm (*GSP-CA-CF*), similar experimental evaluations were conducted for the other three recommendation algorithms over the same e-learning dataset. The three other recommendation algorithms were collaborative filtering combined with context awareness (*CF-CA*), the GSP algorithm and the *CF* algorithm. From the experimental results of the proposed hybrid recommendation algorithm (*GSP-CA-CF*), it was evident that the proposed recommendation approach outperforms the other recommendation algorithms in all aspects. For instance, the proposed recommendation algorithm (*GSP-CA-CF*) generates more accurate predictions of ratings and recommendations than the other three recommendation approaches namely *CA-CF, GSP* and *CF*. The optimum prediction accuracy was obtained when the neighborhood size was 25. The proposed hybrid recommendation algorithm outperformed the other three recommendation approaches in terms of precision, recall and F1 measure. Moreover, the proposed recommendation approach provided better prediction accuracy than the other three recommendation algorithms at all levels of sparsity. However, there was an increase in MAE for *GSP-CA-CF, CA-CF* and *CF* algorithms with increase in level of sparsity. The GSP algorithm showed minimal change in MAE as the level of sparsity increases. This can be attributed to the use of learner's sequential access patterns rather than ratings in making predictions of learning materials. The experimental results demonstrate that combining SPM, CA and CF improves the performance and quality of recommendations.

The hybrid recommendation algorithm proposed in this research study is used for prediction and recommendation of online learning materials in e-learning environments. E-learning materials that can be recommended include lecture notes, exams, assignments, tutorial videos and audios among others. Even in cases of multi-course learner taking different unrelated subjects such as mathematics and physics, the proposed hybrid recommendation algorithm will predict the learning materials correctly by using SPM algorithm to mine the web logs and discover the learner's historical sequential access patterns that are useful for making predictions. The proposed hybrid recommendation method is flexible and with slight modifications, it can as well be used in other domain application fields such as movie recommendation and prediction of medical prescription.

4.4.4 Future Trends for Context-Aware Recommendation in E-Learning

An interesting future trend in research on CA recommendation approach in e-learning domain is the increased interest for research in use of context-awareness in e-learning recommendation systems. There is a clear trend towards hybridization of new recommendation techniques such as context-awareness with traditional recommendation techniques and also integration of other technologies including data mining and machine learning into the recommendation process. Techniques like context-aware based recommendation approach in e-learning incorporate context dimensions into the recommendation process such as knowledge level and learning goals among others making recommendations more personalized and relevant to the needs of the learner in an e-learning environment. Hybridization of recommendation techniques has the potential of improving the quality of recommendations in e-learning recommender systems.

Secondly, research in e-learning material recommendation using context awareness is likely to evolve and mature further alongside other evolutions in fields such as the web, artificial intelligence, knowledge management, data mining and machine learning.

4.5 Conclusion

In this study, we proposed a hybrid recommendation approach based on context-awareness and sequential pattern mining for recommending learning materials to learners in e-learning environments. The proposed hybrid recommendation algorithm uses GSP algorithm for mining the web logs and discovering the learner's sequential access patterns; context awareness for incorporating learner's contextual information such as knowledge level; and collaborative filtering for generating recommendations based on contextualized data. GSP algorithm is applied to the contextualized recommendations to filter the recommendations according to the learner's sequential access patterns and generate the final recommendation results for the learner. By combining recommendation techniques in this proposed hybrid recommendation approach, recommendations are personalized according to the learner's context and sequential access patterns. Experimental results reveal that the proposed recommendation approach provides better performance and recommendation quality. Moreover, the proposed recommendation algorithm helps in alleviation of rating sparsity problem by using the learner's sequential access patterns to predict probable learning materials in the absence of sufficient and overlapping learner ratings.

Chapter 5

Conclusion and Future Work

Recommender systems play an important role in e-learning by aiding learners to overcome the information overload problem and easily find relevant learning resources from large volumes of information available on the World Wide Web. Though conventional recommender systems such as content-based and collaborative filtering as well as other existing recommendation methods have helped in addressing the problem of information overload in many recommendation domains such as e-commerce, books, music and movies, they still face some challenges in e-learning domain arising from differences in learner's characteristics, context and sequential access patterns. Conventional recommendation techniques and most existing recommendation methods do not consider this additional information in their recommendation processes, hence they are likely to generate recommendations that are inaccurate and lacking personalization with learner preferences and learner's learning needs. Learners can have differences in learner contexts such as knowledge level and learning goals as well as learner characteristics such as background knowledge, study level and learning style among others. These learner characteristics and contexts can influence the learner's preferences on a learning resource. Besides, learners in e-learning environments have different sequential access patterns. These sequential access patterns should also be taken into account in making recommendations of learning resources for the target learner. Recommendation methods that do not incorporate these additional information about the learner namely learner characteristics, learner context and learner's sequential access patterns are likely to generate recommendations that are less accurate and lacking personalization. This recommendation problem arising from differences in learner characteristics, learner contexts and sequential access patterns among the learners in e-learning environments can be alleviated through incorporation of additional information about the learner into the recommendation process using recommendation tools such as ontology, context awareness and sequential pattern mining algorithm. These recommendation tools can help in personalization of recommendations as well as improvement of quality of recommendations to the learners.

The main objective of this thesis was to develop hybrid knowledge-based algorithms and techniques for recommending personalized and accurate learning resources to learners in e-learning environments taking into account additional information about the learner such as learner characteristics, context and learner's sequential access patterns. To achieve this goal, we employed recommendation tools such as ontology, context-awareness and sequential pattern mining. Furthermore, this thesis sought to explore the learner and researcher related challenges of e-learning recommender systems. It is the hope of the researcher that these findings will provide beneficial literature and solutions for researchers and stakeholders in the field of recommender systems for e-learning.

5.1 Thesis Summary

In this thesis, our main goal was to solve the problem of recommendation of online learning resources to learners in e-learning environments arising from differences in learner characteristics, learner context and sequential access patterns.

First, we carried out a comprehensive review of literature related to e-learning recommender systems such as common recommendation techniques, ontology-based recommender systems, context-aware recommender systems and sequential pattern mining. Furthermore, we explored the challenges of recommender systems with a focus on learner and researcher related challenges of e-learning recommender systems. This was achieved by carrying out a systematic literature review of journal papers on e-learning recommender systems with a view to identifying and classifying the challenges as either learner or researcher challenges. In addition, we discuss the solutions for addressing each of the challenges. It was evident from the review study that successful utilization and improvement of e-learning recommender systems can be achieved if the identified learner and researcher related challenges can be addressed adequately. The implications of the review study findings are vital in assisting the learners and educational institutions utilize recommender systems to support online teaching and learning.

Secondly, we proposed a hybrid knowledge-based recommender system based on ontology and sequential pattern mining for recommending learning resources to learners in an e-learning environment. The proposed hybrid KB recommendation approach incorporates additional information such as learner characteristics (knowledge level and learning style) and learner's sequential access patterns using ontology and SPM algorithm respectively. Ontology is used to represent the knowledge about the learner and learning resources while SPM algorithm is used to mine weblogs and discover the learner's historical sequential access patterns. The final recommendation results are filtered and personalized according to both the learner's sequential access patterns and ontology domain knowledge. Experimental results show that the proposed hybrid KB recommendation algorithm improves performance and quality of recommendations. Furthermore, the proposed approach can help alleviate the cold-start and data sparsity problems by making use of ontological domain knowledge and learner's sequential access patterns respectively before the recommender system accumulates enough ratings.

Lastly, we proposed a hybrid recommendation approach based on context-awareness and sequential pattern mining for recommending learning materials to learners in e-learning environments. The proposed recommendation algorithm combines GSP algorithm for discovering learner's sequential access patterns; context awareness for incorporating learner's contextual information such as knowledge level; and collaborative filtering for computing learner similarities and predictions of contextualized ratings. By combining recommendation techniques in this proposed hybrid recommendation algorithm, recommendations are personalized according to the learner's contextual information and sequential access patterns. Experimental results show that the proposed hybrid recommendation approach outperforms other related recommendation algorithms and provides better performance and recommendation accuracy. Moreover, the proposed hybrid recommendation approach can help alleviate the data sparsity problem by making use of learner's sequential access patterns to make predictions of probable learning materials in the absence of overlapping learner ratings.

5.2 Future Directions

Future work will focus on integrating other emerging and intelligent tools and technologies from fields such as artificial intelligence, data mining and machine learning into the recommendation process to further enhance the effectiveness of recommender systems as well as optimizing the recommendation results.

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Publications During PhD Study

1. **John Tarus**, Zhendong Niu, Abdalla Yousif (2017). A Hybrid Knowledge-based Recommender System for E-Learning based on Ontology and Sequential Pattern Mining. Future Generation Computer Systems. 72, 37–48. *(SCI)*
2. **John Tarus**, Zhendong Niu, Ghulam Mustafa (2017). Knowledge-based Recommendation: A Review of Ontology-based Recommender Systems for E-Learning. Artificial Intelligence Review. *(SCI)*
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