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Development of an Ontology-Based Personalised E-Learning Recommender System

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Abstract

E-learning has become an active field of research with a lot of investment towards web-based delivery of personalised learning contents to learners. Some issues of e-learning arise from the heterogeneity and interoperability of learning content to suit learner's style and preferences in order to improve the e-learning environment. Hence, this paper developed an ontology-based personalised recommender system that is needed to recommend suitable learning contents to learners using collaborative filtering and ontology. A pre-test is carried out for users in order to segment them in learning categories to suit their skill level. The learning contents are structured using ontology; and collaborative filtering is used to collects preferences from many users and then recommending the highest rated contents to users. The system is implemented using JAVA programming language with Structured Query Language (MySQL) as database management system. Performance evaluation of the system is carried out using survey and standard metrics such as precision, recall and F1-Measrure. The results from the two performance evaluation models showed that the system is suitable for recommending the required learning contents to learners.

Keywords: Personalised; E-learning; Recommender; Ontology; Collaborative filtering.

1. Introduction

E-learning brings changes not only in digitized materials but also in learning styles and pedagogical activities. E-learning paradigm shift focuses on two main aspects: to eradicate the barriers of time and distance; and the personalisation of the learner's experience [1].

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One of the reasons for personalisation is to ensure information meet learner's need. personalised e-learning provides an important alternative to the one-size- fits- all approach of online learning. Moreover, it offers the potential to uniquely address the specific learning goal, prior knowledge and context of a learner so as to improve that learner's satisfaction [2]. Ontology for recommending learning materials has been developed in recent times, however, there are some drawbacks such as time, performance required to process the recommendation contents [3] and recommending intelligent for individual preferences based on skill level [4]. In an e-learning environment, different learners have different learning characteristics, preferences and knowledge, it is important to provide an intelligent personalised recommender system to recommend useful content to learners based on their skill level, knowledge and preference to improve learning among learners. In this paper, an ontology based e-learning recommender system is developed to help resolve the issue of personalsation and help recommend suitable learning content to learners based on their skill level and knowledge.

2. Related Work

Recommender system has been efficiently used for educational purposes for offline and web delivery of contents to learners. Reference [1] developed a semantic recommendation system for e-learning. The motivation came from the inability to find suitable learning content for learners and providing web services for the user. To achieve better performance, a web based semantic recommendation system is developed and ontology is used to gather learning content and rule based system consist of rules and reasoning engine for providing suitable recommendation but the re-usability and interoperability of learning content is not considered when carrying out this design. Alexsandra and his colleagues [5] developed an e-learning personalisation based hybrid recommendation strategy and learning style identification. A recommendation module of a programming tutoring system – Protus is used. The system recognises different patterns of learning style and learners' habits through testing the learning styles of learners and mining their server logs. AprioriAll algorithm is used to analyse the habits and the interests of the learner through mining the frequent sequences, however, the chronological recommendation of materials for students is not considered. Adewale and his colleagues [6] presented the use of ontology for e-learning system, the research focused on resolving some of the problems learner's encounter when taking courses online. Students skip necessary courses when taking a course thereby reducing learning performance when taking other courses. This brought about the objective of this course which presented the use of ontology for e-learning process such as course syllabus, teaching methods, learning activities, learning styles and also prevent student from skipping prerequisite courses. Quantitative and qualitative methodology are used to find the specific requirements of academia with respect to e-learning. The outcome of the study showed that academia needs an efficient e-learning framework which gives relevant results. There are improvements for students who took pre-requisite courses before learning than those who did not. The system, however, is used for a specific class of students but not carried out on a large number of students. Reference [7] designed a recommender system for an e-learning platform to provide prompt, accurate and relevant recommendations to users of the e-learning platform based on their existing as well as difficulties. Their reason is the need to adapt and improve student progress in an existing e-learning environment based on the users' strengths, flaws and preferences. Collaborative filtering, Object-Relational Mapping (ORM) and JAX-RS API are used to develop the system. The drawback of this system is the slow time performance required to process the recommended contents. Also, ORM is not considered to be efficient enough in handling every transaction within the database. John and his colleagues [8] said that e-learning recommender system faces issues arising from the lack in learner characteristics such as learning style, skill level and study level. As a result, conventional recommendation techniques cannot guarantee accurate recommendations to learners, therefore, the use of ontology collaborative filtering is proposed to achieve personalisation and accuracy online by recommending learning materials to learners. The first part of the recommendation process incorporated learners' characteristics such as learning style, skill level which alleviate cold-start problem at the initial stages of recommendation in the absence of ratings. The second phase aggregated both ratings and ontological knowledge in computing similarities and generates recommendations to learners. The drawback of the system is the inability to segment learners' skill level when recommending contents. Stuart and his colleagues [9] developed an ontological recommender system to help monitor users' behaviour and provide relevance feedback to help improve user profiling. The reason for this is to solve the recommendation problem on academic research papers. The methodology adopted is the use of ontology and collaborative filtering. Collaborative filtering is used to find set of interesting papers to be recommended to users and ontology is used to improve user profiling. External Ontological Inference is successfully bootstrap a recommender system and profile visualization employed to improve profiling accuracy. The limitation is that there is no usage of real time data to help improve users profiling. Reference [10] stated that collaborative filtering creates personalised recommendations by combining the knowledge of similar users in the system. In collaborative filtering (CF) technique, the recommendation process is automated by building on users' opinions of items in a community. Collaborative filtering is based on the principle that the finest recommendations for an individual are given by people who have similar flavor. It identifies users with choice similar to the target user and then computes predictions based on the score of the neighbors. It progresses recommendation system. The recommendation for a target item is based on other users' ranking of item instead of study contents. The job in collaborative filtering is to guess the usefulness of product to a particular user which is based on a database of user votes. Both collaborative filtering and ontology is used for curriculum structuring and recommend content's that are rated by similar users to other learners. Jeevamol and his colleagues [11] designed an ontology model that encapsulates both the learner profile and learning object characteristics which can be used for learning content recommendation in an adaptive learning environment. The static and dynamic characteristics of a learner are considered in the model. The static data is directly gathered from the learner using forms and questionnaires; and dynamic data is collected by tracking the behaviour of learners while interacting with the learning management system. The proposed model has not been implemented and evaluated to attest to the efficiency of the model. Reference [12] presented a hybrid recommender system that adapts appropriate learning material to students based on student profiling which consists of learning preferences, the student's confidence level in the required topics and the course enrolment by the students. Implicit and explicit learning object ratings are incorporated into the system to enhance the recommendation. The system would perform better when incorporates automatic generation of students profile through learning process.

3. System Design

This section discusses the system architecture, ontology structuring of the learning contents and system model.

3.1 System Architecture

The system architecture consists of components such as user interface, content model, user repository and personalised recommendation engine which are described as follows:

i. USER INTERFACE: The user interface is where the learners perform all the functions that the recommendation system provides. The user or learner has access to register, take the pre-test, rate the system and get recommendations from the system. The admin is in charge of developing and maintaining the system. The goal of the user interface is to allow effective control and operation of the proposed system.
ii. CONTENT MODEL (ONTOLOGY): This is where the learning objects are designed and structured using Ontology web language (OWL) in protégé ontology editor 4.3.The Ontology Web Language (OWL) is used to describe the classes and relations between the learning contents used in designing the system. It captures the relationships between different concepts that are related to the learner. Ontology web language (owl) is used for modeling the courses that are recommended to users. The structured learning content is then inserted into the recommender system.
iii. USER REPOSITORY: This is where the user profile and activities are stored. It houses all users action on his/her interface.
iv. PERSONALISED RECOMMENDATION ENGINE: This is where the user's recommendation is filtered and contents are generated based on historical preferences of similar users (collaborating) to learners. Each learner takes a pre-test in order to get recommendation of personalised learning contents. The learners get recommendations from similar collaborative ratings of previous learners.

The Ontology components are connected through relations. This ontology contains concepts which are classes, instances (individuals) and relations (properties). There are two main classes; the student and learning content. The learning content for each level contains forty (40) instances; with three relations ("pdf", "audio", "video"). Figure 2 shows that the instance relation of "Introduction_to_the_art_computer_science "is localised in the Beginner level class which is applicable to the intermediate, advanced and expert classes. Ontology is a formal explicit specification of a shared conceptualization. Ontology is a language used to describe the classes and relations between them that are inherent in web documents and applications [13]. Collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences from many learners (collaborating) and then recommend items rated highly by these similar users, but not rated by the current user. The main reason for the use of ontology is to structure the learning content curriculum and incorporate learners study level and skill level into the recommendation process while Collaborative filtering is used to aggregate both ratings and ontological knowledge in computing similarities and generate recommendations for the learners.

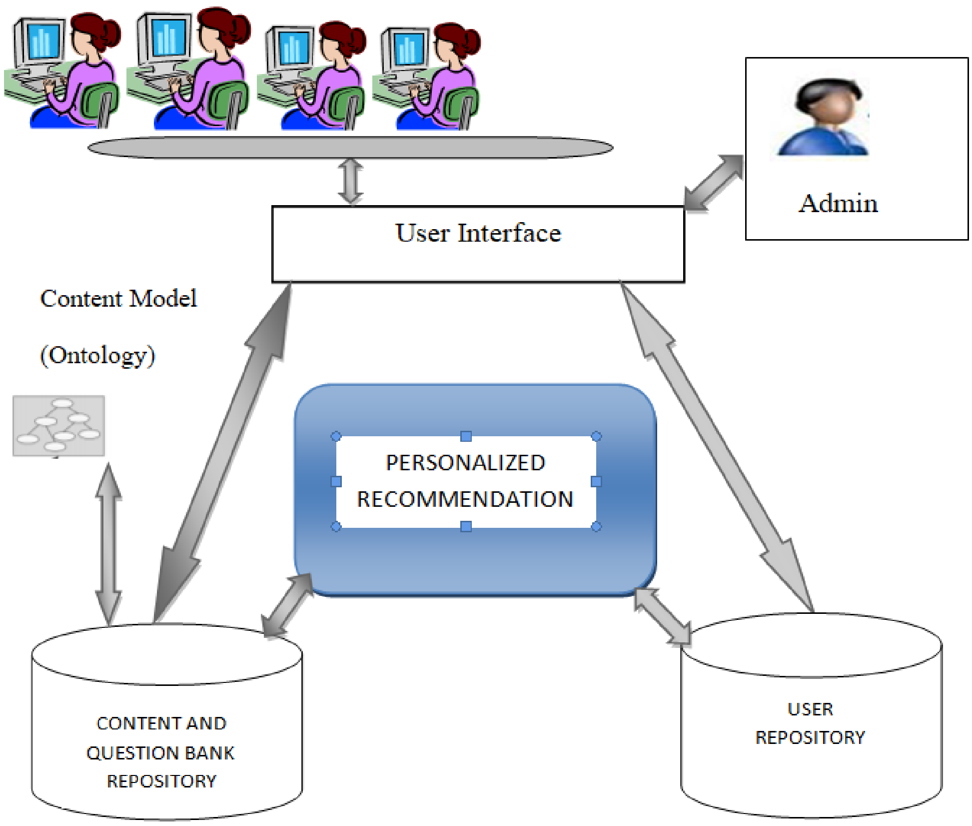

Figure 1: System Architecture

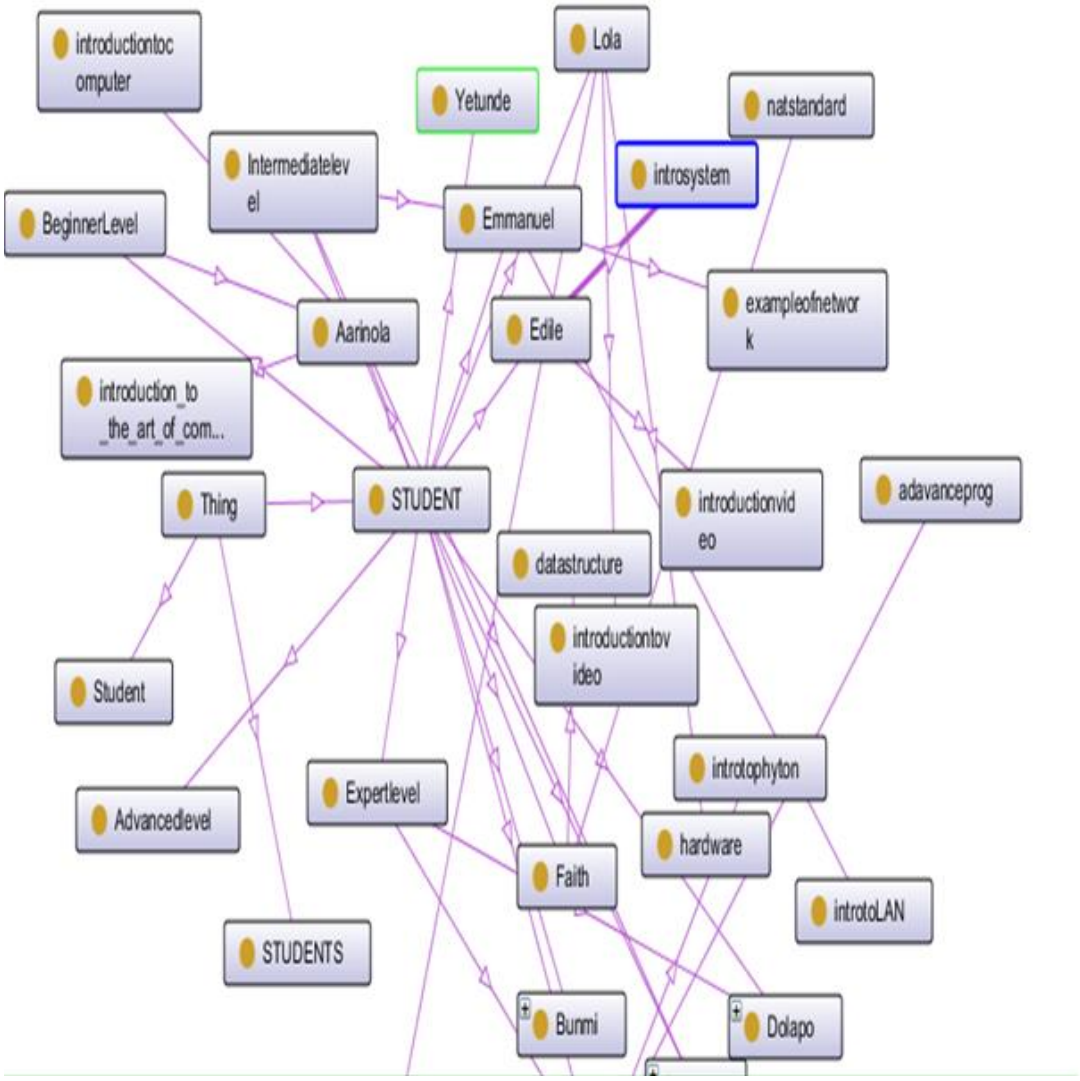

Figure 2: Ontology Structuring using Protégé 4.3

3.2 System Model

The system uses the adjusted cosine similarities where average user ratings are taken into account and transform the original ratings. Equation (1) is used to make prediction of learning content.

$$Sim\ (i,j) = \frac{\sum_{p\varepsilon P}\left(r_{p,i-\overline{r_p}}\right)\left(r_{p,j-\overline{r_p}}\right)}{\sqrt{\sum p\varepsilon P\left(r_{p,i-\overline{r_p}}\right)^2}\sqrt{\sum p\varepsilon P\left(r_{p,j-\overline{r_p}}\right)^2}} \qquad (1)$$

where:

P is the set of users or learners who have rated both learning objects i and j

$r_{p,i}$ is the rating given to learning object i by learner P

r_p is the mean rating of all the ratings provided by *P learners* based on ontology knowledge

Equation (2) is used to compute the predictions of the ratings. The higher the value of similarity in the similarity matrix, the more similar (nearest neighbors) the learning objects are. Predictions of the ratings are computed using the q most similar learning objects who have rated learning object i.

$$Pred_{p,q} = \frac{\sum_{i \in ratedobjectP} (Sim(i,q) * r_{p,i})}{\sum_{i \in ratedobjectP} Sim(i,q)} \quad (2)$$

where: p is the learner, i represents the learning object, q represents similar learning objects, N is for the top recommendations. For each learning object i, the ontological similarities between learning content and the predicted ratings is computed. The top N predictions are then recommended for the target learner.

4. Results and Discussion

This section discusses the results of the test cases and the evaluation of the system performance.

4.1 System Result

The ontology collaborative filtering model is tested using 150 learning materials with 100 learners. 50 users registered and are allowed to take a pre-test and rate the contents. This score from the pre-test shows the skill level of the learners. The skill level includes a Beginner, Intermediate, Advanced and Experts level. Other Subsequent learners' would get recommendations of learning contents based on preferences from other learners. The ontology personalised system recommends learning contents to learners according to their pre-test knowledge and then segments them into beginner, intermediate, advanced or expert level. The learners rate the contents on a scale of 1 – 5 (1 – very irrelevant, 2 – fairly irrelevant, 3 – irrelevant, 4 – relevant, 5 – very relevant). The system then does automatic predictions (filtering) by collecting preferences from many users through ratings and then recommends content to users.

4.2 Performance Evaluation of the System

Precision, recall and F1-measure are standard measures that express the quality of information retrieval methods [14]. Precision, recall and F1-measure is used to evaluate the performance of the system. Precision is the proportion of the number of relevant items that is recovered to the total number of irrelevant and relevant items recovered, while Recall is the proportion of the number of relevant items recovered to the total number of relevant items present in the database. The values of precision and recall are usually expressed in percentage.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

TP = number of relevant learning contents that satisfy the user out of the recommended content.

FP = number of relevant learning contents that do not satisfy the user out of the recommended content.

FN = number of irrelevant learning contents that do not satisfy the user out of the recommended content.

Precision, recall and the F1-measure can also be defined with respect to true positives TP, false positives FP, true negatives TN and false negatives FN [14]. F1 measure combines both precision and recall into a single value for ease of comparison and at the same time, giving equal weight to precision and recall**.**

$$F1 = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (5)$$

Based on these metrics, the system has precision (80%), recall (77%) and f-measure (78%) which demonstrates that there is relatively a great significance of the system in recommending the appropriate learning contents to learners.

4.3 Performance Evaluation of System Using Questionnaire

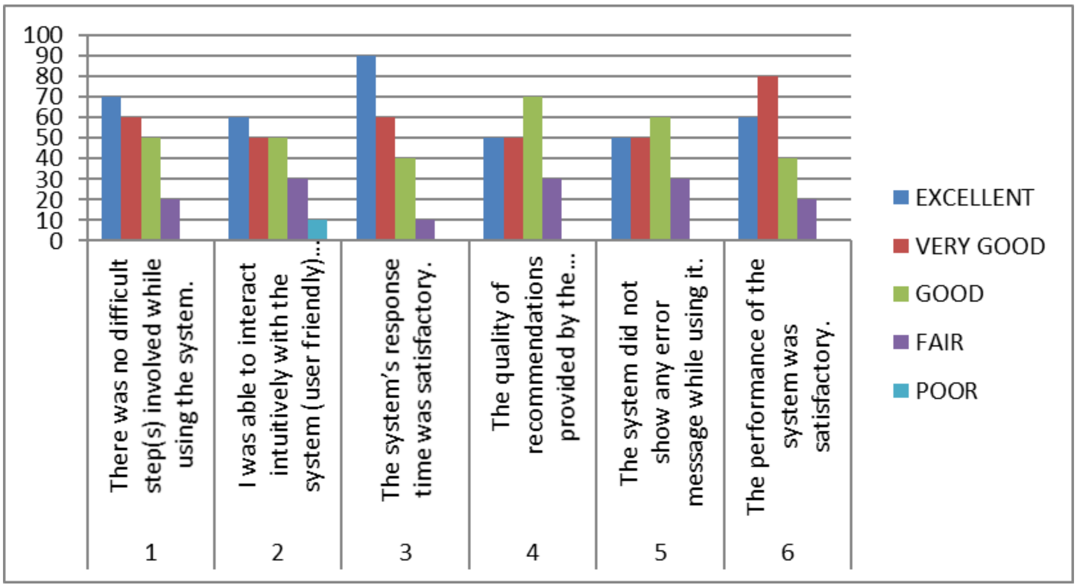

Figure 3: Result of Evaluation based on User Experience

The ontology recommender system is presented to a group of 20 users for evaluation with the aid of questionnaire. The questionnaires use a five point likert scale for evaluation which include Excellent, Very Good, Good, Fair and Pair. Figures 3, 4 and 5 show the results of the user experience, efficiency and effectiveness of the system.

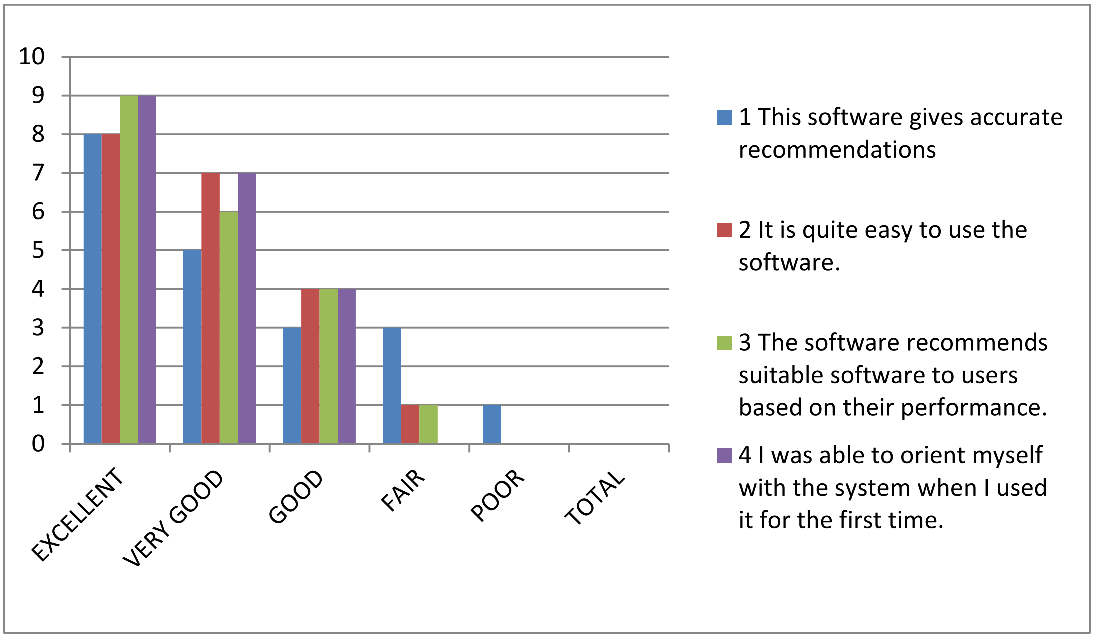

Figure 4: Result of Evaluation based on Efficiency of the System

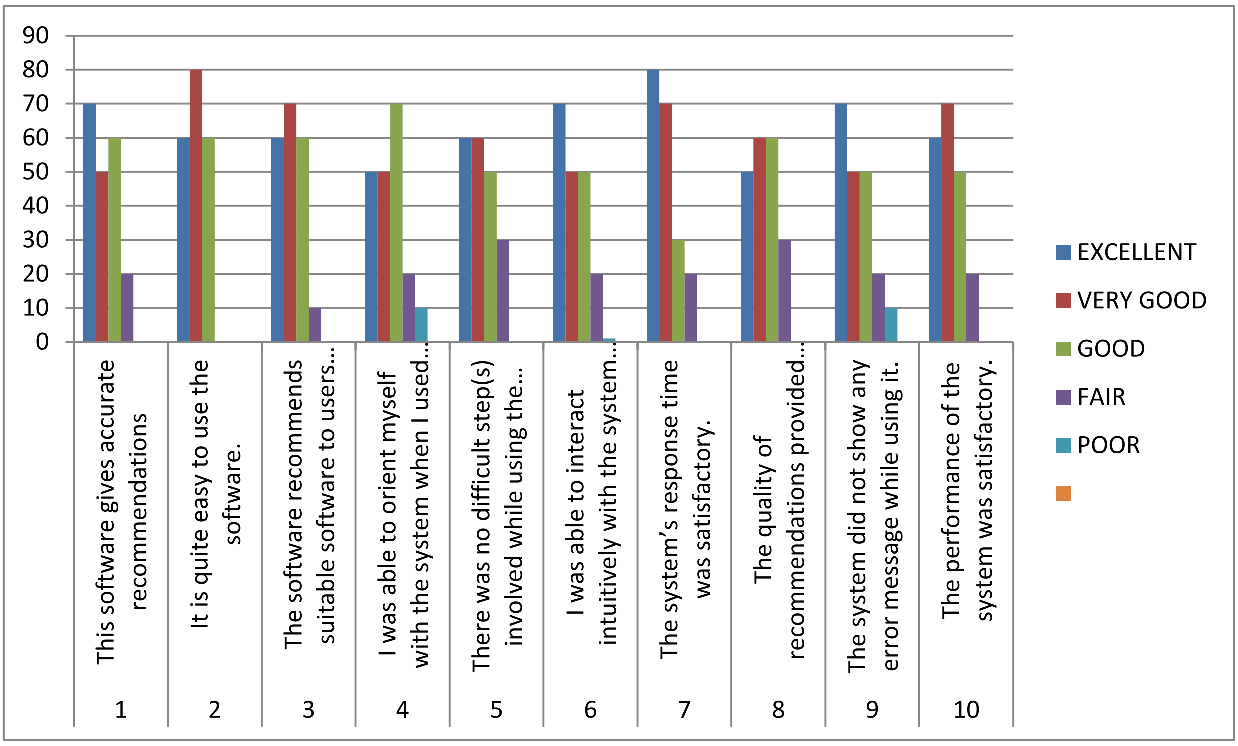

Figure 5: Result of Evaluation based on Effectiveness of the System

. Figure 6 shows the overall result from the performance evaluation of the system based on user experience, efficiency and effectiveness. The results show that 88% of users are satisfied with the user experience and the interaction of the system, 92% of users are in the opinion that the learning content response time is fast and efficient while 95% also agreed that the learning content recommendation is adequate and satisfactory.

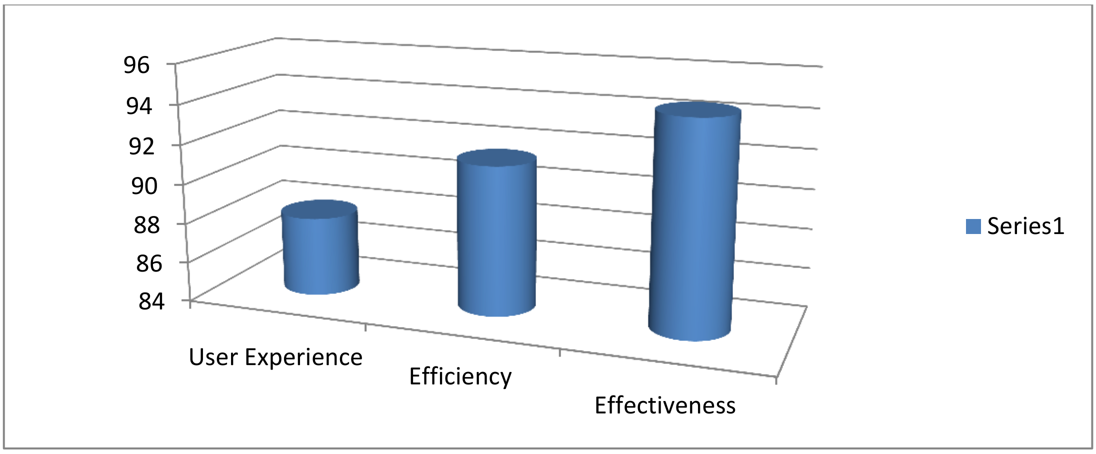

Figure 6: Overall Performance of the System based on User Experience, System Efficiency and Effectiveness

5. Conclusion

Recommendation system is a technique that is widely used in various fields and primarily has benefited the e-learning environment. It offers a variety of personalised learning contents to learners to suit their learning preference. However, in the most existing recommender system, learning contents are not tailored to learners' preferences. In this paper, an ontology based personalised recommender system developed to tailor learning contents to meet learners' learning preference. The system allows learners to take a pre-test prior to getting recommendations. In the conventional recommendation system, this is not provided before recommendations are given. Recommendations are suggested to users based on collaborative preferences of existing users who have rated the system. This system recommends leaning contents based on collaborative users and pre-test knowledge. Performance evaluation of the system is carried out using standard metrics and questionnaire. The results obtained showed that the system is appropriate to recommend the learning contents to learners based on their learning preference.

6. Recommendation

The ontology based personalised e-learning recommender system provides a means to assist students learn in a better and more efficient way. The future research work could incorporate hybrid approach to ensure learners track their progress as they learn and they complete their modules before getting further recommendations. If future work includes this approach, learners would learn efficiently, thus, improves their knowledge.

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