# Recent trends in eLearning environment for effective content dissemination to online learners

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*Abstract*— **Learning is an interactive process that involves the learners, teachers and the contents. With the massive growth in WWW technologies, learning has become a ubiquitous process where there are no restrictions on the time and place of learning for the learners. The support for online learning has paved the way for easy access to the educational resources and also given the learners the comfort of learning from their home. This paper focuses on the related works in the field of e-learning and highlights the importance of the contributions being made towards addressing the issues with the learning contents and the effectiveness of content delivery for the learners. The contents of this paper are organized under the topics viz. Introduction, learning contents, learning object repositories, learning object metadata, learner profiles, generating learning experiences and adaptive content recommendation.**

**Keyword -** eLearning, Learning Objects, Learner Profile, Content Recommendation, effective learning

## I. INTRODUCTION

e-learning should be considered as a means of learning rather than the mode of learning. Since e-learning is not a separate system of education by itself, it is to be only used a means of delivering the learning contents by being a part of the well-established education systems [1]. The electronic form of learning used alongside of the traditional face to face learning has led to blended learning environments that improve the effectiveness of traditional learning even further. The use of e-learning tools in such blended learning environments should reflect the pedagogy of the course in the way the contents are organized and sequenced for delivery. The use of technology should also assist the learners in presenting them the appropriate contents that can cater their learning requirements at different stages of learning. The two major aspects of an e-learning environment are the presentation of contents and facilitation of learning. With the technological advancements capable of supporting the effective dissemination of learning contents, facilitating the learning process is a cumbersome task as it requires thorough understanding about the learners. The facilitation process begins with understanding the requirements of the learners and then providing them the necessary contents based on that. The knowledge about the learners should help to retrieve the contents selectively or to retrieve the parts of contents that have the capability to cater the learner requirements and assemble them in such a way that it caters the current learning needs of the learners. Also the contents thus retrieved should be grouped together based on the learning context in order to classify them based on the type of requirements they cater [2].

However, understanding the learners requires necessary information that gets generated during the learning cycle on different aspects that has a direct impact on the effectiveness of learning. Such information is usually obtained through two different means, one by taking it explicitly from the learners and the other by deriving it from the learner actions over the e-learning environment. Reference [3] highlights the importance of the different forms of interactions that the learner experiences in a virtual learning environment. The level of interaction that the learning environments support has a direct impact on the effectiveness of the learning. The interactions that the learner has with the contents greatly help in understanding their implicit requirements that were not explicitly stated otherwise. Such implicit requirements helps to refine the contents presented to the learners thereby improving the understanding about them. The information generated in collaborative learning environments from the learner-teacher interactions or the learner-learner interactions (through the discussion forums) also helps to refine the learners' requirements and classify them under appropriate learning contexts.

Content personalization is an important aspect of any learning environment as the learning needs of learners vary greatly based on their learning background, skills and knowledge. Since each learner has specific ways of learning, the LMSs should identify the appropriate policy for picking the right contents and presenting them to the learners. This is possible only when the information obtained explicitly and implicitly over the learning cycle is used effectively in the process of retrieving the contents. The service based approach proposed by [4] focuses on isolating the services being provided in the process of retrieving the contents for the learners. Here, the user query is reviewed and rewritten using the query rewriting service which adds additional information to the query that can better explain the learner's requirements. The recommendation service finds the appropriate contents to be recommended for the learners based on the requirements obtained from their profile. Finally, the linking service finds either the alternative forms of contents that can assist the learner for better understanding or the contents that could be used to learn the future topics based on the current one. The parameter used for personalization was the information about the learner's background knowledge on the topic of study. This information was used to identify the appropriate contents that could help the learners to go ahead in the learning cycle based on whatever they know already.

With the rapid increase in the use of hand held, mobile devices, the learning contents are delivered to the learners straight away in to their devices. Such advancements in the content delivery also demanded for Quality of Service (QoS) considerations as the form factor and battery life of mobile devices are not on par with that of desktop machines. The need for adaptive content delivery arises out of the fact that the contents being delivered should be modified to match with the QoS requirements of the mobile devices and hence the different forms of contents were made for different types of devices. The introduction of standards like eXtended Markup Language (XML) helped to overcome the difficulties with making different forms of contents for different learning platforms by allowing the content created once to be used anywhere. This was achieved by isolating the contents form formatting aspects so that the contents are created independent of the devices on which they are to be delivered.

## II. LEARNING CONTENT

Since the e-learning environments focus mainly on the contents being delivered to the learners, much attention is given on designing the contents being delivered through these platforms. The digital learning contents delivered through the e-learning environments should be capable of addressing the needs of the learners while catering the specific learning objective. The content structure plays an important role in an e-learning environment as it helps to define the scope of the content and the learning objective that it can cater. The growth of WWW and access to the media through the handheld devices has stressed the need for the improving the quality of contents and its representation in order to improve the effectiveness of learning. The support for various forms of contents like text, image, audio, video and animation has improved the scope for presenting the learning resources effectively to the learners. This in turn also demanded the need for their structural organization that could help the learners to search and re-use the LOs effectively. So, the content providers have to devise new methods for creating the contents that can cater a specific learning objective as well as reused in different learning scenarios. Also, the different content authoring platforms and their repositories that store those contents should have necessary provision to deliver the right contents at right time for the learners. The tagging of learning contents with additional information that is unique for them greatly help in matching the learner's requirements with that of the capability of the objects [5].

Separating the learning design from the object creation is the key for effective reusability of LOs. The Generative LOs (GLOs) created using the popular tools like GLO maker can be easily reused across the learning scenarios where the LO can serve a similar objective. This greatly reduces the time required in creating the replica objects for different subject domains. The GLO maker adopts a two-step procedure to build the learning contents with a planner tool for learning design and a designer tool for structural design. The planner tool follows the procedure given in figure 1 to design the outline/ pedagogical layout that could benefit the learners of the environment and the designer tool helps to create the structure for assembling the LOs. The independent LOs are then assembled inside the structure and presented to the learners as a part of the course content [6]. The use of successful pedagogical design and course structuring has benefited the authors by giving them the freedom to assemble the LOs that can cater the learners. Representing the LOs through feature diagram was proposed by [7]. Here, the generic level features are represented in the form of a hierarchy, followed by the structure of the content and the actual content itself. The advantage of using the feature model for LO representation is to separate the generic and specific aspects of the content. Also, it helps to highlight the properties of the LOs with respect to different levels of abstraction.

Reference [8] represents the LO as a class based on the object oriented software engineering approach with each class having four parts, namely, pre-knowledge questions, the learning material (content), self-evaluation questions and metadata. The additional information surrounding the content helps to understand the relevance of the content with respect to the learner. The importance of creating fine granular objects and its impact on the learners of e-learning environments was pointed out in [9]. This work showcases the method for creating learning objects using the object-oriented principles. Each learning concept was represented as a class that takes appropriate inputs from the user through interaction and instantiates the LO dynamically.

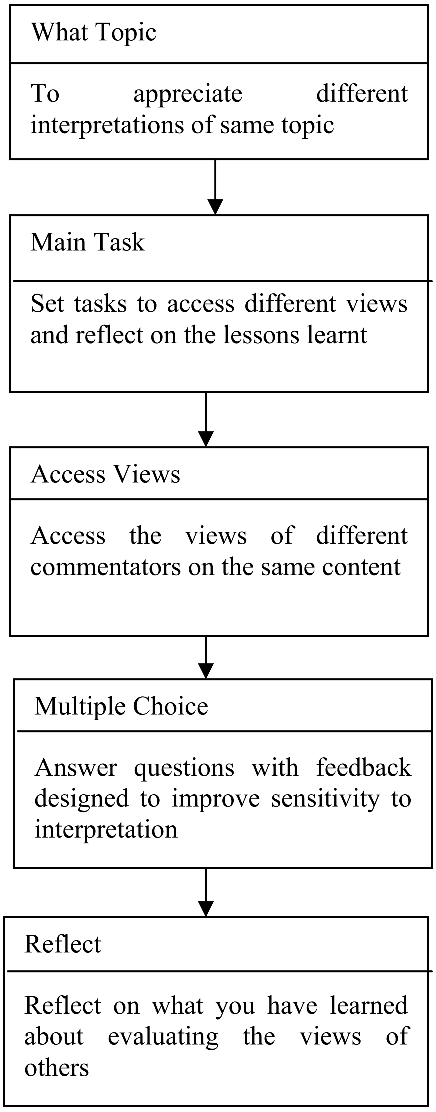


Fig. 1 GLO planner for designing the content

The interactive LOs proposed by [10] highlights how the LOs created through animations for a specific pedagogy can be used in a different learning scenario by using the additional APIs that can control the usage of LOs with respect to the learning scenario. Here, the explanation of Dijikstra's algorithm to find the shortest distance between a pair of nodes was created as an explanatory LO using flash animation. The additional APIs created to map the nodes to the cities helps to use the algorithm in a scenario where the learner wants to use it to find the shortest distance between a pair of cities in Germany. The third party APIs created to work on the LO helps to customize the base version of the LO in order to make use of it in different learning scenarios without having to modify the original LO. This approach improves the reusability of the LOs in cases where the specific solutions require only explicit changes to the basic object.

The Location based Interactive LOs (LILO) proposed by [11] showcases the need for structuring the LOs in to different sections viz. the objective, the procedure, the assessment, the meta-information and the type of object (experience or knowledge). The wandering system proposed in their work allows the learners to learn beyond their classrooms by taking up a physical activity based on the instructions. The result of the activity creates a LO which can further be used as a case study for the learners who do not have the chance to take part in a physical activity.

## III. LEARNING OBJECT REPOSITORIES

LOR is a collection of digital learning materials that can be accessed through a network without the need for having any prior knowledge about the structure of content (IMS global). The e-learning environments utilize the services of LORs in order to create, store, index, search and discover the LOs [12]. The popular repositories across the world includes the Multimedia Educational Resource for Learning and Online Teaching (MERLOT) repository that offers learning materials organized under categories such as animation, open book, presentations, exercises, quiz, etc. MERLOT supports content creation in different formats like HTML, PDF, Adobe Flash, image, SCORM, VRML, etc. and also allow linking of content web pages hosted on the WWW [13].

The National Learning Network (NLN) repository has a collection of learning materials hosted on its server and also supports creating small sized contents that can cater the specific learning requirements of the learners [14]. Blackboard LMS supports organizing the contents which are in different formats like text, image, audio, video, etc. through the Blackboard Drive technology. The centralized management of files helps to create the objects by making use of them whenever required by simply dragging them in to the content structure. In some repositories, the LOs are presented as a collection of freely expandable, interlinked hypertext web pages called wikis [15]. Educational wikis present the content collection to the learners in the form of a hierarchy of hyperlinks that enables easy navigation. The supplementary wiki hosted for the mechanics course at MIT university by the Research in Learning, Assessing and Tutor Effectively (RELATE) group, helps the learners to use the learning materials more easily and effectively than a traditional e-book. The provision for giving topic wise feedback on the contents and the support for interactions with the learning peers and teachers have led to the improved use of content in e-learning environment.

The need for the LORs to provide services other the storing and discovering of the LOs was highlighted by [16]. Their work focus on extending the services of LORs as knowledge management systems such that it can act as an assimilator of knowledge derived from the usage of contents and its effectiveness on different sections of learners. By that the repositories can assist the learners by recommending appropriate LOs based on the knowledge that it has gathered over the period of time rather than just acting as a delivery engine. This would enhance the scope of LORs by making it intelligent enough to understand the learner requirements and serve them accordingly. Integrating knowledge management aspects into LORs also help to recommend personalized contents without human intervention thereby making it a self-sustained learning environment for its learners. The authors also discussed about the other roles that can be played by the repositories of the future.

Reference [17] summarizes the quality of the contents available inside the repository by analysing their internal data and classifying them as good and non-good contents. The attributes used for classification were based on the appropriateness of the content to the query words, ratings, file size, etc. Their main objective was to project a summarized image of the contents being retrieved for the learners so that the time required for the learner to filter the contents manually can be reduced.

The visualization method proposed in [18] showcases the way the overall contents inside a repository can be visualized before refining the results. The visualization done using the squarified cushion tree maps, Venn diagram and hyperbolic tree explains the importance of filtering the LOs based on their metadata at the first level to give a complete picture of the overall availability of objects. The visual forms provide scope for the learners to filter the objects based on interaction or on the extent of their suitability to address the learner's preferences.

## IV. LEARNER PROFILES

The fragments of information about the learning activities of learners inside an e-learning environment greatly help to understand their requirements and determine their progress with respect to the course. This in turn enables the LMSs to device new methods to address the issues faced by the learners in coping up with the subject. With the LMSs focusing mainly on the information pertaining to the rating of contents or the performance of the learners as a means for recommending the suitable learning objects, the other aspects of the learners like their learning progress or the relationship among the LOs used could give an insight into their context specific learning requirements. Such information could assist the LMSs to take dynamic decisions towards imparting active learning for the learners.

The explicit representation of learner's requirements in an e-learning environment is achieved through learner profile (LP), which links up the entry level competencies, learning participation and outcomes attained by the learner [19]. The IEEE Public And Private Information (PAPI) and IMS Learner Information Package (LIP) standards classifies the learner information under the major categories like personal, preferences, security, relations, performance, and portfolio. These standards have explicitly defined the profile attributes in such a way that they can be used uniformly across LMSs. The attributes of these LP standards mainly falls under the categories like learner identification, skills, knowledge and preferences.

Reference [20] uses the information in the learner profile to dynamically create assessment questions. The learner profile attributes like the responses to the questions and the characteristics of the learning devices used by the learners are used as the key factors for creating personalized quizzes. The implicit feedback derived based on the learner actions also at times plays an important role to determine the level of understanding of the learner. Reference [21] highlights the way of handling such implicit feedback to assist the learner by giving appropriate hints on the ways of improving the solution to a problem. Such an adaptive method for improvising the learner's actions greatly helps to engage the learners in the learning environment as well as improves their learning skills.

The initial information about the learners is very much vital as it is the only means for the LMSs to assist the beginners of a subject. However, such initial information must be obtained explicitly from the learners at the beginning of each and every course. The basic information that the LMSs could use at initial stages of learning cycle may include the learner preferences, pre-requisite knowledge and the set of skills possessed by the learners in relevant to the subject.

Reference [22] proposes the model for measuring such initial information about the learners in terms of their exposure to subject domains and their learning styles using a set of questions prepared in compliance with Blooms Taxonomy. The learner responses to these questions are used to build the basic profile of the learner which is then used to recommend them the LOs initially. A set of rules were framed to determine the proficiency of the learners in a specific subject domain and recorded in their profile.

The changes in the learning style of the learners over the learning cycle also needed to be considered for recommending the LOs as the recommendation based on a fixed learning style across the different topics may not be appropriate for the learners all the times. Reference [23] shows the way of handling the fluctuations in learning styles by giving preference to the styles that have been mostly preferred and enabling the link to objects that match with the preferred style. Reference [24] proposes the literature based learning style determination for adaptive content delivery wherein, the LMS analyses the learning behaviour of the learners to determine their learning styles. The behaviour based learning style determination dynamically records the changing learning styles over the learning cycle and recommends the LOs based on that.

The need for deriving the information about the learners is not only to identify the right contents for them but also to guide them through the learning path and to decide on the alternate path that suits their interests over the period of learning. Reference [25] highlights the competency based approach for personalizing the learning path of the learner and recommending the appropriate LOs based on that. The competency of the learner is derived based on their knowledge and the ways they have used it to obtain the necessary skills. Reference [26] showcase the methods of matching the learner preferences with the LO metadata attributes in order to retrieve the objects that can cater the changing preferences of the learner. The contents frequently visited by the learner were used to find the most similar materials and the most similar learners and then the LOs were recommended by matching the two.

The study of the existing systems has revealed the fact that only certain attributes of the learner profile viz. learning style, performance, or preference are frequently used in recommending the LOs [27] [28]. The importance of matching the appropriate attributes of learning contents with that of learner profiles was highlighted in [29]. Here, the historical rating on the learning materials was used to match the learner profile attributes with the LOM in order to determine the pattern of content utilization by the learners.

## V. LEARNING EXPERIENCES

An interactive e-learning environment should not only allow the learner to reflect on the content but also should understand what the content is meant for the learners from that. With a provision to know whether the learner liked the content or not through the rating given by the learner, the LMSs should device new methods to determine what makes the learner to like or dislike the content. Such an observation on the type of contents that the learners are comfortable with makes the environment more effective towards addressing the needs of the learners. Learning analytics is the method for measuring, collecting, analysing and reporting of information about the learners for better understanding of their requirements and that of their environment [30]. It is also used to determine the effectiveness of the contents being delivered over the e-learning environment wherein, the facts on the type of learners the content has catered, number of attempts being made by the learners towards understanding the content, fraction of positive/ negative ratings on content, etc. could be derived through statistical analysis. The importance of learning analytics is largely felt in Massively Open Online Courses (MOOCs) like environments where the sentiments of the learners is considered to be the key factor for deciding the effectiveness of a course.

Reference [31] shows how the attention of the learner can be used as a parameter to highlight the status of the learner in an e-learning environment. Here, the number of interactions that learners have with LOs over a period of time is used to identify their interests towards a particular subject domain. Such interaction based determination of interests helps to address the issues of learners who struggle to cope up with the domain by recommending and motivating them with appropriate LOs. The importance of using the activity level information for monitoring the learners was highlighted in [32]. In their work the information extracted from the learner activity logs of MOODLE LMS were used for recommending LOs. The log information was filtered appropriately based on the context and represented in the Java Script Object Notation (JSON) format so that they could be analysed easily with the help of existing tools. The actuator indicator model used in their work has four layers viz. sensor layer (obtains the activity information), context abstraction (filters activities), control layer (interprets activities) and indicator layer (displaying the output). The representation of learner activities in

JSON format and analysing the information generated to monitor the learners have paved the way for effective recommendation of contents based on the learners' interests.

Understanding the mobility of the learners across different learning platforms and other content sources is a key factor in determining the appropriate policy for recommending LOs. The knowledge attained by the learner from learning through the sources other than the LMS like video sharing sites, online repositories, magazines, etc. should be taken into account for getting a complete picture on the learner. The information thus obtained should be represented properly such that it conveys exactly the learning needs of the learners and the suitability of the contents at different learning instances. With the standards like SCORM having the provision to track the learner activities inside the LMSs, the representation of such activities in a meaningful manner was addressed with the help of experience API specification. The learner actions represented in the form of <subject> <action> <object> was very much useful for analysis and deriving conclusions on the effectiveness of the content.

Reference [33] highlights the importance of "mobler card" application that runs on the mobile devices used for learning and records the learning activities. The "mobler card" also records the learner interactions with the questions/exercises using the verbs like "attempted" or "achieved" that reflects the learner actions. The experience statements thus recorded are then analysed statistically and the performance of the learner with respect to the questions being attempted were summarized and displayed. Reference [34] focuses on the new models devised for representing the activities in an industrial training environment where the employees have to learn by using a particular device. Here, certain part of the training is given through the hand held devices and the learning activities are recorded. This information is then used to determine whether an employee is qualified for the physical training to be taken by interacting with machinery. The responses of the activities are then gathered and analysed to evaluate the labours and highlight their skills.

The Learner Records Store (LRS) act as a storehouse of experience statements generated through the xAPIs embedded in to browsers, reader tools, etc. and also provides the basic tools for analyzing the experiences. One such LRS is the "Watershed LRS" which was created with the intention of storing the learning experiences of the employees of an organization. It records the learning activities of the employees taking place even beyond the LMSs and allows the organizations to generate correlations between the learning data and real-world performance of employees [35].

Another implementation of xAPI specification is the BookOnPublish, where the books are created in digital form with additional support for interactive contents in the form of quiz. The learning experiences generated through interaction are then analyzed to derive conclusions about the usage pattern, effectiveness of content etc. that could help the author to make necessary reforms to the contents in order to address the needs of the learners. The interaction information represented in the form of experience statements has made the task of analyzing the information on multiple perspectives easy for the LMS and also helps to obtain useful knowledge from that. Moreover, the generated experiences could be classified based on the context (topic, type of learner, region) in order to visualize the impact of the content on various sections of users across the globe [35].

Tappestry is a mobile based social network for learning built on the top of xAPI specification. It helps to learn by socially interacting with the peers and sharing the information on whatever the learner has experienced. Tagging of the learning experiences benefits the other learners who have similar interests and enable the content to get a widespread reach among the learning audience. This application helps the organizations to monitor the learning progress of their employees and identify the employees who have got the customized skill set requirements. Also, there are options to visualize the individual performance of the employees with respect to a particular domain of study. Tappestry has options to manage events like a debate, discussion or a problem that the members of the organization can participate and address. Altogether, it offers a comprehensive learning experience for the learners and also multiplies their learning experiences through social interaction [36].

## VI. CONTENT RECOMMENDATION AND PERSONALIZATION

The need for content personalization arises with the increasing number of LOs available across the repositories that in turn force the learners to refine the contents manually in order to suit their requirements. The learner profile plays a major role in content recommendation as it has the potential information about the learners on different aspects of learning.

When it comes to recommendation of LOs, the most basic form is the content based recommendation, wherein the LMS recommends the contents based on the extent to which the learner profile matches with that of the its metadata. The suitability of learning contents for a specific learner in such cases is decided based on the number of instances in which the learner has used similar contents before. Also, the content based recommenders consider the feedback given for the contents in order to decide its appropriateness for a specific learner. The effectiveness of content based recommenders relies on its potential to identify the suitable learner profile parameter that can play a vital role in deciding the contents needed by the learner.

The user information should represent the preferences and the interactions of the learners with the recommendation system. It is based on these explicitly stated preferences and the implicit details of interaction, the recommenders can derive the requirements of the learner in a specific learning context. Reference [38] suggests the different methods for finding the relevance between the learner activities and the kind of contents that suits the current requirements of the learners. The Decision tree classifier based approach for classifying the items used and deriving the rules that can represent the requirements of the learner, the nearest neighbour approach to determine the similarity between the kind of contents utilized, the relevance feedback approach that takes the learner feedback and reduces the weight for non-relevant results, the incremental method of predicting the relevant results through linear classifiers and probabilistic approach to determine the similarity among the contents used were the popular approaches discussed in their work.

Reference [39] proposes the LO sequencing based on the knowledge on the learner activities stored in the knowledge base. Here, the LOs already used by the learners were analysed and the kind of objects that could help the learners to go ahead further in the course was identified. The competency gap between the learner's knowledge and the object's objective is used as a factor to identify the next suitable LOs for the learning path sequence.

Reference [40] highlighted the drawbacks with pure content based recommenders with respect of the appropriateness of the keywords used in identifying the contents. It also suggests the folksonomy based approach wherein the taxonomy of the LOs were attributed with the tags given by the users in addition to the content based tags. Their work highlights the effectiveness of the appropriate tags generated over the period of time and its impact on the accuracy of recommendation. Since there is a massive growth in the volume of user generated contents hosted through the web repositories, more importance was given to collaborative annotation.

With the content based recommenders mostly considering the explicit aspects of the learners and the contents to recommend the appropriate LOs, some work has been done towards generating new information from the existing information for recommendation. Reference [41] proposes a method to derive the emotion of the music from its metadata and use that for recommendation. Feature similarity is another method where the features derived from the content's metadata are used for the purpose of recommendation. Reference [42] stresses the importance of determining the feature vector of media objects from their metadata and uses them in order to identify the objects with least distance among their features. The recommendation based on the features of the objects used by the learner gives the scope for the recommender to identify the contents that caters the learning style and preferences of the learners.

The importance given to the content features and the user's profile in identifying the right contents for recommendation may be appropriate in cases where there is enough information available about the learner. But in cases where there is no or less information available on the learners beforehand, then the content based retrieval faces the cold start problem. To overcome the cold start issue with content based recommendation, the LMSs should be trained by allowing the learners to make use of the LOs for a threshold number of iterations. However, in modern day learning environments the LMSs cannot take such a long time to understand the learner as the chances that the learner may leave the course due to lack of support is high. In such cases, the experiences of similar learners could be used for initial recommendations. Since all the beginners with same level of exposure to a particular course have the tendency to like similar kind of objects that can cater their basic requirements, the collaborative recommendation approach would be effective enough to recommend the contents until a clear picture on the learner's requirements is obtained over the learning cycle.

Collaborative recommendation is of two types, memory based and model based. In memory based recommendation, the similarity between the actions carried out by the learners are used for recommending the appropriate LOs using the cosine similarity or Pearson coefficient methods and the missing rate is used to determine the accuracy of recommendation. The drawback with memory based approach is that the assumption on the number of learners for the recommendation has to be made is to be determined beforehand. Whereas, in the model based recommendation, the learners are grouped based on their actions performed and the system then learns about the learner's behaviour over a period of time. In an environment where the similarity cannot be established directly among the users, the model based approach is an effective method for recommendation. However, the drawback with model based approach is that the model derived cannot be used for recommendation under different contexts as the behaviour of the users varies with the context.

Reference [43] proposes the social network based collaborative recommendation wherein the user's social interactions and the association with other users in terms of the track records, friendships and tagging of contents were used as the means for calculating the similarity weights among the users. It is based on this similarity weight the type of contents that can suit a specific user is predicted.

The collaborative recommendation based on associative rule mining proposed in [44] uses the association between the users and the items to assign the weights to items based on the ratings given by the users. Here, the mining process extracts all possible rules and then filters them based on the best support and confidence values. The addition of weights based on the ratings has increased the scope of contents being liked by similar learners.

Reference [45] highlights the importance of collaborative recommendation in an environment where the users were recommended the television programs based on the interests of other users who watched similar contents. The television, internet and mobile based video activity recorders were networked together and the data generated by them were analysed in order to identify the viewing behaviour of the user. This viewing behaviour of similar users was then used for recommending the programs.

The collaborative recommendation systems do have certain limitations when it comes to recommending users with varying tastes or recommending contents in different learning contexts. The cases where the recommendation fails to cater the needs of the learners should be attended with great care as it hinders the further recommendation process. Handling the generic and specific cases in recommending the contents was proposed in [46] where, the collective data of all the users of the environment were used for initial recommendations that are common for all the users. The cases where the specific recommendation seems to be more helpful, a separate ranking based approach was used to filter the recommendations based on the learner activities that are specific for the learner. The importance of having a specific approach in cases where the generic recommendation is not possible was highlighted appropriately.

The use of content and collaborative filtering together neutralizes the shortfalls of each approach in such a way that the overall effectiveness of recommendation is improved. The advantage of hybrid recommendation systems which is a combination of different types of recommendation strategies was highlighted in [47]. The Fab recommendation engine proposed in [47] combines the features of content based recommendation with recommendation based on the similar contents liked by the other users. Their system presents the results of each type of recommendation separately as well as the results of the combined filtering and analysed the effects of combination.

The Entree recommender proposed in [48] recommends the suitable restaurants based on the user's profile and the similarity between the restaurants in terms of their cuisine. The three types of knowledge that used for recommendation are: the catalogue knowledge, functional knowledge and the user knowledge. The catalogue knowledge is the knowledge about the objects being recommended e.g. identifying the category of a particular food type (Indian cuisine is a part of Asian cuisine). The functional knowledge is the knowledge used to map the user's needs with the objects that can satisfy that e.g. (a romantic dinner requires a restaurant that has the provision for candle light dinner). Finally, the user knowledge concerns about the information about the user and the inferences based on the likes and their dislikes.

With hybrid recommenders combining different types of recommendation techniques together, the combination is made in many different ways. These are weighted, switching, mixed, feature combination, cascade, feature augmentation and meta-level. All these methods either focus on the proportion of combination or the order of combination in order to suit the requirements of the users in an environment.

Due to the non-availability of proper metadata for LOs, the recommenders at times have to rely on the semantic information generated dynamically [49]. Such methods have focused on deriving new information from the existing contents as a means of recommending the LOs. The primary aspect of learner profile that greatly helps in identifying the suitable contents for them is their learning style or learning pattern [50]. The Intelligent Tutoring Interface for Technology Enhanced Learning (INTUITEL) system orders the knowledge objects to be recommended based on the learner's profile requirements and their learning history inside the current learning requirement [51]. Since feedback based improvisation of actions would help to refine the overall understanding of the actors of an interactive environment [52], in e-learning environments also the feedback plays a major role as it supports the decision making process towards taking the corrective action to recommend the LOs.

## VII. SUMMARY AND FUTURE DIRECTIONS

In this paper an attempt was made to provide an insight into the contributions being made in the e-learning environment towards addressing the issues with learning content, metadata, learner profiles, content personalization and recommendation. The importance of structuring the content and maintaining proper metadata for the contents was stressed. Also, the role of learner profiles in improving the effectiveness of retrieving the appropriate contents was highlighted. The need for content recommendation and personalization in environments that deals with a large collection of contents inside its repository was represented.

The following observations were made based out on the study of the existing works:

- The content structure plays an important role towards catering the learning objective of the learners. The LMSs should provide necessary support to aggregate the contents based on the requirements of the learner.
- The usage of proper metadata for the LOs greatly helps the LMSs to precisely identify the suitable LOs for the learners. The evolutionary nature o f learning environments has demanded the need for representing the dynamic aspects of the LOs like its usage under different scenarios as a part of the LOM. The e-learning environments apart from having the necessary technological support to

effectively deliver the contents to the learners, it should also provide timely assistance to them by understanding their requirements at various stages of learning.

- The increased availability of the learning contents across the repositories adds additional burden to the learners in terms of manually filtering the relevant contents. The lack of proper assistance from the recommenders in identifying the suitable contents at different learning instances would further aggravate the problems with the quality of learning over the online environments. The use of application profiles stressed the importance of custom built metadata schema that could effectively represent the object's capacity towards addressing the requirements of the learners. Altogether, the completeness of the LOM over the period of time benefits the learners of the environment and also improves the chances of the right contents being used in right time.
- The vast amount of LOs available across the online repositories like MERLOT, Wikipedia, etc. has exposed the learners to a vast amount of learning contents. In such a scenario, unless the experiences of the learners are known by the LMSs at regular intervals, the recommendation won't be appropriate. In spite of the standards like xAPI allow embedding of experience statements inside the learning path, it is an overhead for the content authors to do so for every granular LO considering the volume of LOs. Also, the learning experiences generated should be properly analyzed over the period of the learning cycle in order to determine the learning pattern of learners and recommend the appropriate LOs based on that. Also, the drawback with the existing methods for profiling is that the parameters used for recommending the LOs are given arbitrary weights that remain fixed throughout the learning cycle. In a typical learning environment where the chances of learners having more distinctive requirements are high, the learner profile parameters that cater one learner may not cater the other. So, dynamic approaches must be used to determine the weight of the parameters for each learner and recommend the LOs based on the feedback obtained.

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