A Review on the Adaptive Features of E-Learning

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***Abstract*—The ever-increasing importance of interactive features in e-learning environment with the evolution of new dimensions of Information Technology has stimulated the introduction of adaptive e-learning. Although there has been a continuous effort from the researchers in last two decades to incorporate intelligent and adaptive features within e-learning software, they are mainly ad-hoc and serves partial perspectives. Due to the absence of any uniform structure, framework or standard, different perspectives of adaptive e-learning often possess overlapping and repetitive features. This paper identifies some primary components of adaptive e-learning with their individual perspectives. It presents a brief review on the existing methodologies for the different adaptive features of these components. It also introduces a hierarchical structure of different components of adaptive e-learning, which works as a framework for this review work.**

***Index Terms*—adaptive learning, curriculum sequencing, user modeling, adaptive navigation**

I. INTRODUCTION

The proliferation of internet has created huge potential for e-learning systems to offer flexibilities to learners to access the digital content independent of time, space, and proximity. Unfortunately, most of the web-based education systems are composed of certain predefined online contents that restrain a learner only to acquire generalized course material [1]. As a result they are nothing more than a network of static hypertext pages, unable to provide features that allow the learner to learn and update according to her level of competency and requirements in that learning domain. In order to overcome such limitations, there has been a continuous effort from the researchers to integrate intelligent components into the e-learning framework in terms of adaptivity and personalization. An adaptive e-learning environment is capable of providing some additional features like monitoring the activities of the learners, interpreting learner's behavior based on domain-specific models, inferring learner's new requirements and preferences out of the interpreted activities, and then appropriately representing this available knowledge in associated models to dynamically improving the learning process [2]. Contemporary strategies for web-based adaptive e-learning are mainly focused on four dimensions- curriculum sequencing, user modeling, adaptive navigation and adaptive presentation. This paper covers a general review on the existing methods and techniques for the above-mentioned dimensions. However, this classification of the features is not exhaustive and covers only the common and popular methods of adaptivity in e-learning. The words user, learner and student are used interchangeably throughout this paper in order to comply with the original terminology of the reviewed papers.

II. FRAMEWORK FOR THE REVIEW WORK

Substantial amount of work has been carried out to the integration of adaptive features within the e-learning environment. However, they are often ad-hoc and serves only partial perspectives. Therefore, in order to provide a systematic approach for this review work, we propose a hierarchical framework for the different models and techniques that are commonly employed in different dimensions of adaptive e-learning. However, since there is no precise boundary for the intelligent features that could be offered by an adaptive module, it is inevitable that features of different objects of the framework are often overlapping. Fig. 1 illustrates the framework for the adaptive features reviewed in this paper.

III. CIRRCULAM SEQUENCING

Curriculum sequencing is one of most common techniques used in many adaptive e-learning systems. It helps a learner to find out an optimal learning path through the available learning materials based on her knowledge level and need of learning. Different techniques have been used by the researchers to perform curriculum sequencing in e-learning environment; some of them are discussed below:

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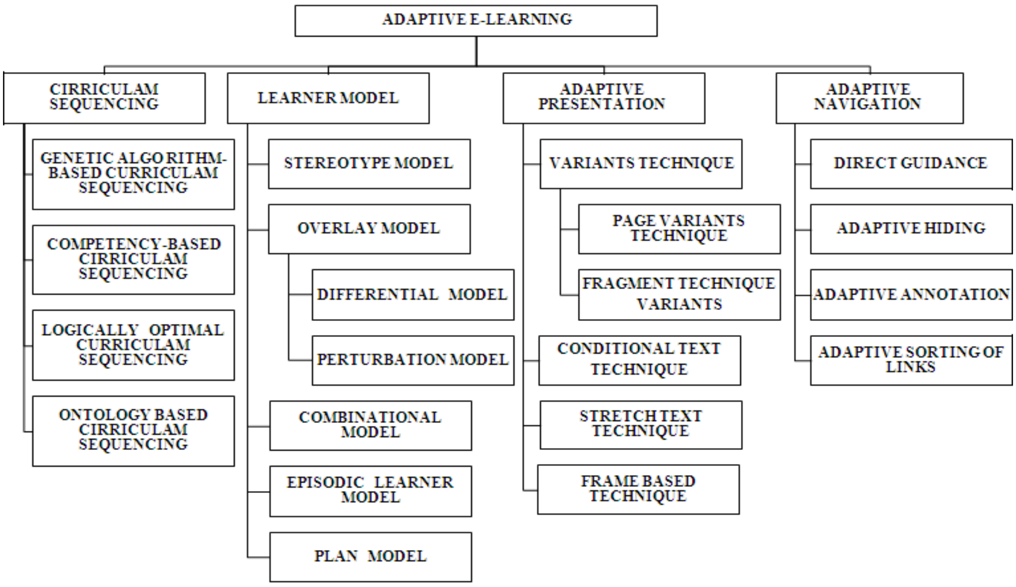

Figure 1. Hierarchical framework of the adaptive features

A. Genetic Algorithm Based Curriculum Sequencing

Genetic Algorithm (GA) is a well known method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population evolves toward an optimal solution. GA could be useful to construct personalized learning path in the context of adaptive e-learning by considering simultaneously both courseware difficulty level and the learners' ability. Chen [3] presented a GA-based curriculum sequencing approach to produce personalized learning path using the following steps:

Step 1. A learner performs a pre-test based on randomly selected testing items in a course unit for personalized learning path generation.

Step 2. The proposed system collects the incorrect testing items in the pre-test and their corresponding courseware in the testing items and courseware database.

Step 3. The corresponding courseware with the smallest difficulty parameter among the incorrect testing items is selected as the first courseware for personalized learning path generation.

Step 4. The system generates a near optimal learning path for an individual learner utilizing the genetic algorithm according to the incorrect response testing items.

Step 5. A learner performs personalized web-based learning according to the generated learning path.

Step 6. Terminate the learning process if the learner finishes courseware learning of the generated learning path; otherwise, return to Step I for next learning cycle.

Experimental results indicated that the proposed learning GA-based approach of curriculum sequencing could be advantageous in increasing learning effectiveness compared to the freely browsing learning mode used in most web-based learning systems, particularly for those who have very specific needs and has less time or patience to complete topics they have already learned.

B. Competency-based Curriculum Sequencing

IEEE defines a Learning Object (LO) as any entity, digital or non-digital, that may be used for learning, education or training. The task of sequencing reusable LOs for e-learning content creation is generally performed by human instructors, who create courses targeting generalized profiles rather than personalized materials. Marcos [4] proposed that the entire process of sequencing can be automated using Competency-based Intelligent Curriculum Sequencing. First, the model employs competencies as a mean for defining constraints to learning objects. Then a sequence of LOs is represented by relations among LOs with their competencies. Consequently, new sequences can be derived by permutation operations on the allowed set of LOs in the sequence. This is achieved with help of a proposed algorithm designed for this purpose.

C. Logically Optimal Curriculum Sequencing

A leaner in web based e-learning system navigates through its links structure to avail the content pages within a course. While following one of the possible page sequences, visiting some pages may become redundant, if its content has already been covered by some previously visited pages. Hübscher [5] presented an approach to avoid such situations using logically optimal curriculum sequencing. This approach is based on disjunctive and conjunctive nature of prerequisite combined with a propagating redundancy algorithm, which enables to find redundant pages on the fly without burdening the teaching model with that task. This work uses the following concepts:

Unit- A unit is the smallest description of some concept, topic, or method.

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Goal- A goal is a set of units that the learner wants to visit, but might not be able to do that until all units are enabled.

Enabled Unit- A unit is enabled if prerequisites are satisfied by the learner. If the prerequisite is a conjunction, then all of its prerequisite units need to be visited. If it is a disjunctive prerequisite, then at least one of the units needs to be visited.

Visited Unit- A unit is visited if the concept that the unit describes is assumed to be known/learned by the learner. Only enabled units can be visited.

Redundant Unit - A unit is redundant if it has not been visited, and visiting it does not enable any unit at any time in the future.

Prerequisite - A prerequisite can be either conjunctive or disjunctive. A conjunctive prerequisite in the form $u_1 \wedge u_2 \ldots \wedge u_n \rightarrow u$ asserts that all of the units $u_1, u_2, \ldots u_n$ need to be visited by the learner before unit u could be visited. Similarly, a disjunctive prerequisite $u_1 \vee u_2 \ldots \vee u_n \rightarrow u$ asserts that at least one of the units $u_1, u_2, \ldots u_n$ needs to be visited by the student before unit u could be visited.

Prerequisite Graph-A Pre-requisite graph G(V,E) is a directed acyclic AND-OR graph where the vertices(V) are the units and the edges(E) are prerequisites between the units. This work introduces the notion of virtual unit that represents intermediate elements in the prerequisite graph. It allows expressing any prerequisite in Conjunctive Normal Form (CNF) or Disjunctive Normal Form (DNF). For example, the expression u: $(u_1 \wedge u_2) \vee (u_1 \wedge u_3) \vee (u_2 \wedge u_3) \rightarrow u$ in DNF requires that the learner must visit at least two of the three units u_1, u_2, u_3 before visiting u. Fig. 2 represents the Pre-requisite graph for this expression, where the internal states are represented by U_X, U_Y, and U_Z.

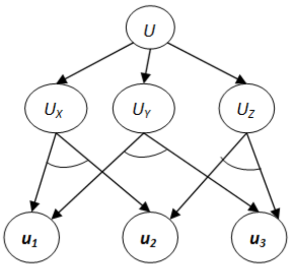

Figure 2. Prerequisite graph

Redundancy propagating path (RP) - An edge (v_i,v_j) is a Redundancy Propagating (RP) from v_j to v_i, if:

$$RP\ (v_i,\ v_j) = \begin{cases} \text{True} & \text{if } (v_i;\ v_j) \text{ represents a} \\ \text{conjunct} \wedge c\ (v_j) = c\ (v_i) + 1 & \\ \text{true} & \text{if } (vi;\ vj) \text{ represents a} \\ \text{disjunct} \wedge c\ (v_i) = c\ (v_j) & \\ \text{False} & \text{otherwise.} \end{cases}$$

In order to find a redundancy propagating path, an algorithm is proposed which generates a unique token for each conjunct and propagates it away from the goal. Each vertex v then counts c(v) which is the number of different tokens arrive at it. In Fig. 3, we consider an example of prerequisite graph $G = (V,E)$. Let $v_{i=}$ B and $v_{j=}$D. Edge (v_i,v_j)=E4. Considering edges E1 and E4 to be conjunct prerequisite, we get c(D)=2 i.e. there are two vertices A and B that must be learnt before arriving at concept D. Thus, the count of token for vertex D is 2. Similarly for c(B)=1. Since (v_i, v_j) satisfies the definition of redundancy propagating, i.e. RP(E4)=true as E4 represents a conjunct and c(D)=c(B)+1, so edge (v_i,v_j) is a redundancy propagating path from v_j to v_i,.

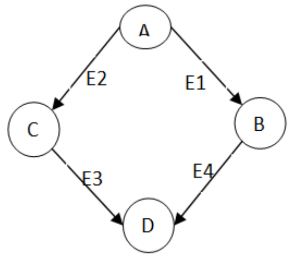

Figure 3. Redundancy propagating path

However, one limitation of this approach is that it can compute redundant units only if all the prerequisites are clear and the goal of the learner does not change while using the system.

D. Ontology-Based Curriculum Sequencing System with Semantic Rules

Composing a flexible learning route across multiple course publishers leads to sequencing complexity. Chi [6] proposed use of Ontology-based curriculum sequencing to reduce such complexity. This technique of curriculum sequencing uses semantic rules by means of ontology to create sequences and practical course materials in a general abstraction model. The ontology serves as a basis of the general structure of the knowledge base. It presents a knowledge-intensive approach to model curriculum sequencing. It shows how semantic rules in combination with a defined ontology can be used to create sequences and practical course materials in a general abstraction model. It then builds an OWL ontology to represent these models and specify SWRL rules to identify relationships between individuals of the OWL classes. This work proposes a curriculum sequencing system based on Java technology that integrates the OWL ontology, RacerPro engine and JESS rules engine. The proposed system provides knowledge maintenance mechanisms that both curriculum experts and course publishers can use to contribute to the knowledge base. The combination of semantic rules with ontologies tactfully manages intricate information of curriculum sequencing problems. The implementation tool provides a Java-based API that developers can use to integrate knowledge-based systems as part of a service related to e-learning systems.

IV. LEARNER MODEL

While curriculum sequencing deals with personalized learner content, in order to utilize this technique, we need to model the knowledge about the user of the system, which can be achieved by learner model. Learner model contains personalized information about individual learner that includes her domain knowledge, learning goals, preferences, style of learning etc. Learner's

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modeling helps the system to personalize the interaction between the learner and the contents. It supports to achieve effective learning by putting the content in a way that suited best for the learner to understand and to relate with the content [7]. There are different learner modeling techniques, some of them are discussed below.

A. Stereotype Model

Stereotypes are collection of facet-value combinations to describe a group of learners. A stereotype model constructs the learner model by classification of the learners into certain pre-defined stereotypes based on some characteristics. Stereotype-based reasoning takes an initial impression of the user and uses this to build a detailed user model based on default assumptions [8]. When the learner uses the system for the first time, an initial stereotype for the learner is activated by instantiating one of its triggers based on the response of the learner on a question-answer session. The system continues this process of querying the learner and assigning a stereotype to the learner until it concludes that it has enough information about the learner to construct a personalized learning path. Rich [9] introduced Stereotypes for a system for recommending books of interest to the user. The selection of books was done based on certain user characteristics such as age, gender, and profession etc. of the learner. Then, users of the system are categorized into stereotypes such as feminist, sports-person, religious- person etc. based on their choice of learning materials. This approach, though good and simple, has some limitations, as students are often incapable of providing an accurate measurement of their knowledge and may overestimate or underestimate their capabilities depending on their self-confidence. Considering this, Chin [10] made use of a double-stereotype for the user modelling. In similar works [11] [12], authors proposed a system for dynamic modelling of a student's progress in learning using a multi-dimensional stereotype approach. At the beginning, learners are classified into the stereotypes based on their initial values. Then after the individual student has interacted with the system sufficiently, the initial values provided by the stereotype are overwritten to reflect the individual student. The main advantage of stereotype modeling is its simplicity. It is relatively easier than other techniques to initialize the model and providing personalized learning path accordingly.

B. Overlay Model

Stereotype based learner model works by assigning learner to specific characteristics matching stereotype. As a result, this model often ignores learner's unique learning features by treating all learners under a specific stereotype in the same way by the adaptation mechanism. Overlay model provides an improvement to this situation. Overlay model presents learner's specific knowledge on the subject as an overlay of the domain model, which contains knowledge about the domain being taught. In an overlay model, a model of the student's knowledge is constructed evolutionary on a concept-by-concept basis and updated as the learner progresses through the system. This allows for a flexible model of the student's knowledge [13]. However, due to the inherent uncertainty involved in student's performance, many researchers tried to build overlay model using Bayesian Network.

- Overlay Model Using Bayesian Network

When a learner fails to answer a question correctly, we can assume that the learner might not know the concept, but we cannot conclude about the fact. This type of situation that deals with uncertain information leads to need of combining Bayesian Network with the existing overlay model. A Bayesian Network is a probabilistic model inspired by causality and provides a graphical model as an acyclic directed graph in which each node represents a variable and each link represents a causal influence (cause-effect) relationship [14].

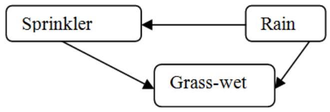

Figure 4. A simple bayesian network

In the figure above, a simple Bayesian network is shown. Rain influences whether the sprinkler is activated, and both rain and the sprinkler influence whether the grass is wet [15]. The use of Bayesian Network in adaptive web-based e-learning applications is useful to approximate the reasoning techniques in user modeling. Brusilovsky *et al*. (2007) [14] proposed a learner model using Bayesian Network using a two-step approach:

1) *Development of the qualitative model*: This step involves selecting variables for user modeling from a set of characteristics like learning styles, cognitive and meta-cognitive skills, competencies etc. Each of them is represented as a random variable and becomes node in the Bayesian Network. These variables could be selected through different interactions with the system such as questions-answers, or number of visits to certain contents. After selection of the variables, they are translated into a mathematical model. In the case of Bayesian Network, this means to structure this information in a causal relationship schema.
2) *Development of the quantitative model*: Once the qualitative part of the model has been defined or learned, the quantitative parameters are defined using knowledge engineering. This can be done by either having experts specify the probabilities or using pre-existent models to specify part of the needed probability distributions or by extracting the parameter values from available data set. For example, in the medical diagnosis domain, if D represents a disease and T a test used to diagnose it, the causal relationship is D $\rightarrow$ T, and the parameters are: the A Priori probability of the disease and the conditional probability distribution P (T/D). This means P (T=1/D=0) is the rate of *false positives* and P (T=0/D=1) is the rate of *false negatives* of test T.

There are two variants of overlay model available:

Differential Model – Expected knowledge is the domain knowledge that the learner is expected to excel. Differential model is an overlay on expected knowledge, which in turn is an overlay on expert's domain knowledge [16].

Perturbation model – Both overlay model and differential model do not consider the errors that the learners make due to their knowledge deficiency. These errors are also known as *mal-knowledge*, *buggy knowledge* or *incorrect beliefs*. The perturbation model represents learners as the subset of expert's knowledge (like overlay model) plus their mal-knowledge [17].

C. Combinational Model

The problem with stereotype model is that it is too simple for advanced adaptive e-learning software; on the other hand, it is also difficult to initialize all the variables of an overlay model from a short interaction with the system. Good results can be obtained by combining the stereotype model with overlay model. Conlan et.al [7] suggested that, the student may be initially categorized by stereotype and then this model is gradually modified as the overlay model from the information acquired from the student's interaction with the system.

D. Episodic Learner Model

Episodic Learner Model is a type of learner model that stores knowledge about the learner in terms of a collection of episodes of cases [18]. For example, in the domain of learning program languages, solutions to programming tasks represent episodes. Further, it comprises examples that the learners has studied in the learning materials as well as their own solutions produced when working at exercises [19]. Episodic Learner Model begins with its goal of producing individualized solutions of problem to learners by first analyzing the program code produced by the learner as a solution to a programming task. This step solely depends on the domain knowledge about the programming language. Then Episodic Learner Model is built dynamically by gradually collecting and storing cases that explains how problems are solved by the learner and which rules are preferred by the learner and applied successfully in problem solving. To sum up, Episodic Learner Model is based entirely on the cognitive diagnosis which helps to recognize which concepts and rules are used by the learner to solve problems, and which errors and misconceptions leads to erroneous solutions. Such information about learners' knowledge not only enables the system to individualize the learning style but also helps to predict individual problem solution in very small span of time.

E. Plan Model

A plan is a sequence of learners' actions to achieve desired or concrete goals. Plan recognition is commonly based on tracking user's performance [20].The system uses a library of different plans and consequently user's actions are regarded and matched to all available plans specified in the library. The plan, which is most similar to user's actions, is chosen as learner model. This process is known as plan recognition process. However, creating such library requires complex computation and large storage, and matching algorithm needs to be carefully implemented [17].

Different techniques of building learner model from learner-specific information serves one part of adaptive e-learning. In addition, we need to utilize this information to present adaptive contents to learners to suit her personal choices. Therefore, some adaptive presentation techniques are essential for a typical adaptive e-learning environment, which we discuss next.

V. Adaptive Presentation

The core idea behind various adaptive presentation techniques is to adapt the content of a page to current knowledge, goals, and other characteristics of the learner [21]. Some commonly used techniques for adaptive presentation are discussed below.

A. Variants Technique

Variants technique is the simplest form of adaptive presentation, which could be implemented by two approaches:

Page Variants Technique: Systems using page variant technique keep two or more varieties of the same page with different presentations of the same content. Each variant is prepared for one of the possible user stereotypes. Beaumont [22] showed a page variant technique to present different pages to different users as selected by the page variant according to the user's stereotype.

Fragment Variants Technique: In fragment variants technique, system stores several variants of explanations for each concept and each user gets the page, which includes variants corresponding to her knowledge level on the concept presented in the page [23]. This technique is also included in the work of Paris [24], who showed that users with different knowledge of a particular concept need structurally different explanations about the concept.

B. Conditional Text Technique

In this adaptive presentation technique, information about a concept is divided into chunks of texts, where each chunk is associated with a condition depending on learner knowledge. When information about a concept is presented to the learner, only those chunks whose condition is satisfied by the learner's concept depth are displayed. One example of conditional text technique is hiding irrelevant explanation based on learner's knowledge level of the current concepts. Such minimalist display of explanation has been used by Fishcher *et al.* [25]. The authors developed a system that uses knowledge about LISP programming and has a critiquing component that analyzes LISP source code and suggests improvements in terms of ease of interpretation by other programmers, efficiency of execution and memory use. The system has the following working principle:

Step 1. The learner asks the system to critique a section of code submitted by the learner. The system will then suggest transformations i.e. possible improvements to the code.

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Step 2. If the learner does not understand the suggestions, she can select the *explanation* menu to get a brief or minimalistic explanation of the functions and concepts on which the transformation is based.

Step 3. The learner who wants more information on a topic addressed in the minimal explanation can do so by clicking on the mouse selectable words to access the document text, which contains an extensive on-line resource regarding that topic.

Step 4. The learner can either accept or reject the improvements suggested by the system. To change the original code to the improved form, the learner can click on the *Accept* button and to retain the original code the *Reject* button.

Step 5. After all the transformations have been accepted or rejected, the resulting code replaces the original code in the buffer.

C. Stretch Text Technique

The idea of adaptive stretch text presentation was presented by Boyle et.al [26]. The goal is to present the requested page with all the stretch text extensions non-relevant to the learner being collapsed or unexpanded and all extensions relevant to the learner being un-collapsed or expanded form. In this technique, activation of a hot word leads to expansion of the clicked word with related text in the same page rather than opening up another page as prevalent in regular hypertext pages. After optional presentation of the stretch text page, the learner can further adjust the page by collapsing or expanding appropriate explanations and details according to her preference. Based on the preferences demonstrated by the learner, the system updates the learner model to ensure that the learner must always get a preferred blending of collapsed and expanded parts.

D. Frame Based Technique

In Frame Based technique, information about a concept is presented in the form of a frame, where each slot of frame contains several explanation variants of the concepts and links to other frames. Certain rules are specified to determine which slot should be presented to a particular user. Implementation of frame-based technique is found in different works like Hyper-adapter [27] and EPIAIM [18]. In EPIAIM, this technique has been extensively used to fetch appropriate content for a learner from a vast knowledge base by combining learner modeling, adaptive message generation and hypertext/hypermedia techniques. The Learner Model deals with the characteristics of the learner those are relevant for the functioning of EPIAIM. At any time, the user may ask for explanation of a concept mentioned in a message. The generation of messages is tailored to the learner's characteristics by a scheme-based approach. Rules are used to select one of the existing presentation schemes (each scheme is an ordered subset of slots of frames) and then used to present the concept. Production rules establish the relationship among the concept class, the learner characteristics and the schema to be selected for producing the message. The decision of selecting appropriate schema depends on the probability of a learner knowing or not knowing a concept. The major advantage of this method is that, explicit representation of message generation strategies and their linking with the user characteristics, which is typical for knowledge-based systems, makes the system very flexible.

VI. Adaptive Navigation Support

Adaptive navigation support is a specific group of technologies that support user's navigation in hyperspace, by adapting to the goals, preferences and knowledge-level of the individual user. Different techniques are used to implement adaptive navigation support, as discussed below.

A. Direct Guidance

Direct Guidance helps the learner to choose the best possible link among the list of links available on the current page based on the current knowledge and learning requirement of the learner. If a link to the next best page is not presented on the current page, the system can generate a dynamic link. The problem with direct guidance is that it provides no alternative for the users who would not like to follow the system's suggestion [28].

B. Adaptive Hiding

The purpose of adaptive hiding of links is to hide or disable links that are irrelevant to the learning requirement of the learner. Hiding protects users from the complexity of the exponentially large hyperspace by restricting the navigation space and thereby reduces their cognitive overload [6].

C. Adaptive Annotation

Adaptive Annotation of links *augment* the available links with some form of annotation so that the learner can understand more about the current state of the node behind the annotated links. These annotations can be in the form of different icons as presented by Passardiere *et al.* [29] or colors by Brusilovsky & Pesin [17] or font sizes by Hohl *et al.* [30]. The work [17] demonstrated use of different colored bullets, a green bullet in front of a link for recommended readings, while a red bullet indicates that the student may not be able to understand the information behind the link yet. Other colors, like yellow or white, indicate more educational states such as the lack of new knowledge behind the link.

D. Adaptive Sorting of Links

Adaptive sorting of links technique prioritizes the links available in a page based on the relevancy of links to the learner as per the learner model. Closer to the top means more relevancy of the link. One added advantage of this technique of adaptive navigation is that the links can be manually reordered by the user by dragging. Manual link reordering is considered by the system as a means of relevance feedback and is used to update the learner model [28].

VII. CONCLUSION

This paper attempts a brief review of the existing methodologies for supporting adaptation techniques within e-learning systems. The analysis, however cursory due to space limitations, has pointed out how different adaptive features could be incorporated within the existing setup of e-learning systems. Four major perspectives namely curriculum sequencing, user modeling, adaptive navigation and adaptive presentation are discussed in details. Implementation of adaptive curriculum sequencing with help of different advanced computing techniques like Genetic Algorithm, AND-OR graph and Ontology are discussed. Use of intelligent methodology like Bayesian network for learner modelling is also discussed. Some effective techniques of Adaptive presentation of contents are discussed in terms of conditional text technique, stretch text technique, and frame based technique. Finally some simple adaptive navigation techniques are discussed like adaptive hiding and sorting of links and adaptive annotations. During this review work we have observed that adaptive features in e-learning is a fast growing area for research with increasing number of contributions coming out every year. However, not to many commercial and open source e-learning tools are currently available that has implemented this ideas.

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