CHAPTER 2

LITERATURE REVIEW

This chapter presents a survey on learning content design and various adaptation levels to adapt to the learners’ needs in an e-learning environment. In general, the adaptation can be done based on the learners’ characteristics. In this thesis, we explore the adaptation that can be done, not only based on the learner context parameters, but also based on the learning content (Learning Object (LO)) and the configuration of e-learning environment. Before discussing the work carried out in this thesis, in this chapter, we provide a detailed review on the various levels of adaptation, learning objects design and process for learning content design, learner context parameters, and models/components of e-learning. Moreover, we analyze and portray the associations among the components necessary to achieve the adaptation in e-learning environment. This chapter also provides knowledge about how learner parameters can participate in the LOs optimization and sequencing process.

2.1 ADAPTIVE E-LEARNING ENVIRONMENT

Adaptive e-learning courses should be customizable to reflect the learners’ interests and needs. In adaptive e-learning, there is also a big challenge in the design of educational materials. In this literature review, we discuss about an e-learning system that should be adaptable, not only based on the learner’s requirements, but also based on the learning content, the goal, and the configuration of the learning environment.
In existing surveys, the general paradigms for implementing adaptive e-learning systems described about the concept of adaptivity, learning style models and components of e-learning (Kamceva & Mitrevski 2012). Moreover, the survey by Graf et al (2012) discussed how adaptivity and personalization could be achieved based on students’ characteristics such as learning styles, cognitive traits, affective states and motivational aspects. Another survey explained about how adaptive e-learning could be achieved through resource modeling based on domain ontology, learner ontology, instructional role ontology, structural ontology and instructional goal / level by using semantic web technology (Hammami et al 2012). One more survey discussed about the development of adaptive hypermedia systems based on adaptation models, adaptation levels and adaptation knowledge, ontology for content classification and user description (Souhaib et al 2010).

The above mentioned surveys provided the details about the modes/components, adaptation levels, learner profile information etc. However, they did not provide the details about the relationships between the e-learning models, adaptation levels, learner parameters etc. Furthermore, in our literature survey we mainly focus on learning object processes at each adaptation level and the associations of these learning object processes with the learner context parameters and e-learning models. Since, the learning objects play a major role in adaptive learning content design, we organize the taxonomy in our survey based on the classification of the levels of adaptations in e-learning scenario, incorporating the various learning object processes for learning content design and their relationships with learner characteristics, models/components of e-learning. In addition, this survey helps the researchers and practitioners to inculcate the knowledge in the design of e-learning practices, in order to accomplish the adaptation concepts in the different learning environments.
In particular, the adaptation levels are used to tailor a course (or, in some cases, a series of courses) according to the needs of the individual learner. The intention is to optimize the relationship between the course contents and the user characteristics / requirements, so that the optimal learning result is obtained, while the time and interactions expended on a course are reduced. The levels of adaptation in learning environments are based on a rather well-established set of models (content, learner, instructional and adaptive) and processes. The content/domain model is usually a representation of the course content being offered. The most important aspect of adaptive-course models is that they are usually based on the identification of relationships between course elements, which are subsequently used to decide upon the learner behaviors adaptation (Brusilovsky 2003). The learner model is used to refer to special cases of user models, tailored for the domain of learning. The specific approach to modeling may vary between adaptive learning environments. The learner model can be updated at interaction time, to incorporate elements or traces of the learner’s interaction history. In other words, the learner model in Adaptive Learning Environments (ALE), not only encapsulates general information about the learner (e.g., demographics, previous achievements, etc.), but also maintains a “live” account of the learner’s actions within the system (Froschl 2005). The instructional model is responsible for definition of the learner cognitive characteristics and preferences of the Learner Model, the structure of the educational resource description model, as well as, the content selection rules of the Adaptation Model (Karampiperis & Sampson 2005). The adaptation model incorporates the adaptive theory of ALE, at different levels of abstraction. Specifically, the (possibly implicit) adaptation model defines what can be adapted, as well as when and how it is to be adapted. The levels of abstraction at which adaptation may be defined, range from specific
programmatic rules that govern run-time behavior, all the way to general specifications of logical relationships between ALE entities that get enforced automatically at run-time. The most successful and widely known ALEs today use adaptation models that generically specify system behavior on the basis of properties of the content model (such as relationships between content entities) (Paramythis 2003).

Figure 2.1 shows the overall taxonomy of our literature review about adaptive e-learning. Here, we discuss about the levels of adaptation for learning content design through the learning object processes such as LO_design, LO_sequencing, LO_composition, LO_presentation and LO_evolution. In this taxonomy (Figure 2.1) we show the associations among the levels of adaptation, learning object processes, learner context parameters and e-learning models. The learning object sequencing will be discussed under link level adaptation; since the associations among the learning objects is based on learner context parameters. Subsequently, the learning object design and evolution should maintain the features of reusability and ability to edit. Accordingly, these processes are associated with the content level adaptation and models such as, content and instructional models. Moreover, the learning object processes could depend on the learner context parameters. In general, an adaptive e-learning system considers several parameters to define the learner’s learning context. Based on these context parameters, an e-learning system offers customized information to the learner. Most of the existing e-learning systems use only some of the context parameters, namely, learner’s preferences, learning styles, learner’s intentions etc.
In this chapter, we discuss about some additional learner context parameters such as learner personal profile, learner behaviors, cognitive traits and navigational patterns as shown in Figure 2.1. Furthermore, the e-learning models/components are used to represent the requirements for designing the system, analyze and design the learning content, manage the presentation of material, ascertain learner mastery by monitoring the learners’ knowledge and activities. The levels of adaptation integrate and use information obtained from the preceding models to drive presentation of adaptive learning content (Shute & Towle 2003). The levels of adaptation such as, content level, link level, presentation level, learner level and learning path adaptation will be discussed in the following sections.
2.2 LEVELS OF ADAPTATION IN E-LEARNING

Generally, the adaptive e-learning environment provides a framework to express the functionality of adaptation which specifies what should be adapted, according to what features it should be adapted to, and how it should be adapted. Here we consider two aspects. One is ‘what can we adapt to?’- Several learner characteristics, such as preferences, previous knowledge, goals, interests, background, experiences, learning styles, cognitive traits, context and environment. The next aspect is ‘what can be adapted?’- Presentation (adapting the actual learning content, the presentation of that content, or the media used) as well as the navigation (adapting the link anchors that are shown, the link destinations, and the overviews for orientation support). In general adaptivity has been implemented based on two adaptation technologies: adaptive presentation at the content level and adaptive navigation support at the link level (Brusilovsky 2001; Souhaib et al 2010). Based on these two classifications, we define five levels of adaptation such as Content level adaptation, Link level adaptation, Presentation level adaptation, Learner level adaptation, and Learning path adaptation. We integrate these adaptation levels in terms of learner context parameters, models of e-learning and learning objects processes (as we discussed earlier) such as LO_design, LO_sequencing, LO_composition, LO_presentation and LO_evolution. Content level adaptation is the most studied way of hypermedia adaptation (Beaumont 1994; Boyle & Encarnacion 1994). The idea of this level is to adapt the content of a page to the knowledge, goals, and other features of an individual user. With adaptive level of presentation, the content of a hypermedia page is individually generated or assembled from pieces, for each learner. Link level refers to adaptations that take place at the system’s interface and are intended to facilitate or support the user’s interaction with the system, without, however, modifying in any way (sequencing) the learning “content” itself. The most typical examples of
adaptations in this level are: dynamic course (re-)structuring; adaptive navigation support; and, adaptive selection of alternative (fragments of) course material (Brusilovsky 2001). Learner level refers to adapting to the learner context parameters. The idea of learning path adaptation techniques is to help the instructional designers to find the learners’ paths while learning in e-learning system by adapting the learner preferences, learning styles, and other characteristics of an individual user. The following sections describe about the various adaptation levels, which is used to provide the adaptive environments for e-learning systems.

2.2.1 Content Level Adaptation

The quality of an adaptive e-learning course is improved by learner-centered content, granularity, engaging content, interactivity and personalization (Ghirardini 2011). The main requisite while designing the e-learning content is, to adapt the learning objects in terms of reusability or ability to edit. In addition, there is a need to consider the learning objects life cycle such as obtaining, labeling, offering, selecting, using, and retaining, to adapt the LOs. In content level adaptation, content can be adapted while generating new LOs from existing ones, while deciding the complexity level of contents, and while creating the personalized learning content. This adaptation level can be applied in learning objects design and evolution processes, according to the learner personal profile which includes cognitive level and learner preferences, which will be discussed later.

2.2.1.1 Learning objects design

Learning object design is one of the main research topics in the e-learning community in recent years, and most of the researchers pay attention to the issue of learning object reusability while designing the adaptive learning objects. The main issue in learning objects design is metadata
generation and reusability (Noor et al. 2011). While generating LOs, creation of structured metadata is too difficult, complicated and time consuming for authors of LOs. In general, resource based and context based methods were used for automatic metadata generation (Bauer et al. 2010). The context is defined as, any information that can be used to describe the situation of an entity (Abowd et al. 1999). Normally, any systematic approach requires a sound architecture that gives rise to the overall success of creating, using and reusing the LOs (Koohang 2004).

There are two major technical issues to reusing LO: Editability and Granularity. Editability is important because any aspect of a learning object can be changed if it is available in a suitable form. If a LO is editable, its granularity can be modified. In addition, LO editability allows instructors to contextualize the LO, according to the learners’ needs. Before creating the LOs, one must consider the following issues: Granularity, Interoperability and Accessibility (Koohang 2004). Granularity (Wiley 1999) refers to how complex a learning object should be. Wiley (2000) discussed two different perspectives for expressing this: Efficiency and Instructional perspective. From the Efficiency perspective, the possible benefits of reusability are attained at the expense of classification. On the other hand, from the Instructional perspective, the major issues are the scope and sequence of the learning objects design. Granularity is the process of breaking down the digital learning content into small pieces or chunks. It deals directly with the size of the learning objects. The principle of granularity is to combine LOs to be shared and reused in a diversity of contexts (Currier & Campbell 2005). The authors argue that neither learning time, nor the physical size (in terms of bits and bytes) is a valid criterion for determining the size and granularity of a learning object. They also suggested that the logical size (in terms of instructional/learning time) rather than physical size (in terms of bits and bytes) is the appropriate manner for defining the size of a learning object.
Content models are used for defining the structure, that is, the level of aggregation or granularity of learning objects, and include the SCORM Reference Model, the aggregation levels defined by the IEEE Learning Technology Standards Committee (LTSC) LOM standard (Hodgins & Duval 2002).

Generally, Content model represents the various levels of organization and granularity involved in the creation of digital learning content in both e-learning and knowledge management. This content model also helps to visualize the relationship between granularity and reusability. The more granular the content, the more likely it is that the content will be reused. The more content is contextualized in learning objects, components and environments, the less likely it is that it will be reused without modification (Wagner 2002).

Interoperability refers to seamless transportation of LOs to different platforms. A digital tool for designing the learning object has been presented, which helps to shorten and strengthen the reusability and interoperability of learning content (Liu et al 2005). They developed a SCORM-compliant learning object authoring tool, which constructs the manifest and metadata. It can execute the instructor’s need, in order to edit the manifest. In the meantime, it can access the remote learning object repository, to utilize the reusable learning object and interoperable teaching materials, and thus reduced the developmental cost of the system.

A variety of learning objects repositories are vastly distributed over the internet, and leads to difficulty in accessing the desired learning object and hinders the concept of interoperability. One of the e- Learning features is to allow the accessibility of various forms of learning object through learning object repository. Learning object repository provides the essential activities that allow learning object accessibility, use and reuse (Lehman 2007). WBE
(Web-based Education) systems are centered in reusability, accessibility, durability and interoperability of didactic materials and environments of virtual education (Noor et al 2007). In order to easily access and reuse learning object, metadata is used particularly to describe the learning object. The author also determined important metadata for accessibility and reusability of learning object. Thus, while designing the LOs, the adaptation can be achieved by maintaining the granularity, interoperability and accessibility of learning objects.

2.2.1.2 Learning objects evolution

The evolution of learning objects is generally based on the similarity of the learning contents. To determine the similarity among the LOs, based on the information represented in their metadata, a metric has been proposed and integrated in to a learning objects management system, as part of the searching component (Menendez et al 2011). This method is based on a fuzzy approach to determine the semantic similarity of XML structures, where these structures are used to represent the LO Metadata. The author states that, the metric has been used to calculate the similarity between Learning Objects based on the IEEE LOM standard. Conversely, the components can be used to compare any XML structure, which is based on the Dublin Core standard metadata (NISO, 2012). A competency-based approach for comparing and combining the learning objects in a distributed system has been presented, based on the dynamic personalization and adaptation of the learning content according to the skills, competencies and knowledge of the learners using Skill Maps and Asset Structures (Albert et al 2003). A personalized course generation and evolution scheme has been presented using GA, which constructs the personalized courses according to the course difficulty level and learner’s changing performance in the learning process (Tan et al 2012). By comparing the learning objects, we can achieve
the evolution of learning resources based on content similarity of the learning object. Based on the literature analysis, we explain that the evolution process also incorporates personalization and adaptation techniques, according to the learners’ profile characteristics.

While designing Learning objects, instructional designer needs to consider several things by asking questions like, “What is a learning object?, What are the components of a learning object?, What is a learning object made of?, What goes into a learning object? and how much of that goes in?”. These questions actually relate to scope. Once these questions have been answered satisfactorily, the instructional designer would probably ask questions like, “So what do I do with these learning objects?, What can they be used for? How do I arrange them? In what order should the learner encounter them?” These questions refer to sequence (Wiley 2000). Accordingly, sequencing of learning objects process is required to arrange the learning contents based on some tactics, which will be discussed in the following sections.

2.2.2 Link Level Adaptation

In e-learning scenarios, content creators are usually required to arrange a set of learning resources (learning objects) and create some links among them, in order to present the organized learning materials to the learners in a comprehensive way. Hence, there is a need to apply link level adaptation, while creating learning objects. This level of adaptation is generally referred to as LO_sequencing, which considers pedagogical preferences, navigational patterns, instructional design, and learning path adaptation. Brusilovsky (2001) refers to link level adaptation with navigational link support, which is used to determine the learners’ behavior patterns, preferences and learning path (which will be discussed in the following sections, such as, learner level adaptation, and learning path
adaptation). Different LO’s have different navigation alternatives, depending on their type, role, content and structure.

2.2.2.1 Learning objects sequencing

The aim of sequencing learning content is to establish a certain order that will ensure link between the educational objectives and the learning activities of the students. To create an order among the set of LOs is called sequence, and hence the process is called LO sequencing (de-Marcos et al. 2008). Learning objects metadata and the curriculum information of the learning objects plays a major role in adaptive sequencing of the learning objects. The sequencing is not only based on the content of the learning object, but is also based on the metadata of managing the learning objects, which is developed in various representation formats (Seki et al 2005).

de-Marcos et al (2008) defined relations between LOs; so that the sequencing problem can be characterized as a Constraint Satisfaction Problem (CSP) and AI techniques can be used to resolve it. The author also discussed the process of creating e-learning contents using reusable learning objects and proposed an evolutionary approach for Learning Object Sequencing. Here, the author designed Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) agents that enabled automated curriculum sequencing, by means of interoperable competency records and LO metadata. Curriculum sequencing technology provides the learners with the most suitable individually planned sequence of knowledge units in order to learn and sequence learning tasks. These methods derived from adaptive hypermedia field (Brusilovsky 1996) and rely on complex conceptual models, usually driven by sequencing rules (De Bra et al 1999; Karampiperis & Sampson 2006). Generally, adaptation rules (concept and content selection rules) are required to adaptively select and sequence the learning resources. The problems of inconsistency and
insufficiency are considered in the defined rule sets of the Adaptation Model, used for sequencing the learning resources (Karampiperis & Sampson 2005).

The dependencies between educational characteristics of learning materials and learners characteristics are too difficult to understand, due to the availability of many possible permutations (De Bra et al 2004). The problems of the defined rules are, Inconsistency-when two or more rules are conflicting, Confluence-when two or more rules are equivalent, and Insufficiency-when one or more rules required have not been defined (Wu & De Bra 2001). The problems of inconsistency and insufficiency of the defined rule sets are responsible for generating conceptual “holes” in the production learning resource sequence (learning path). This is due to the reason that, though appropriate learning resources exist in the Media Space, the conflict between two or more rules (inconsistency) or the absence of a required rule (insufficiency), prevents the adaptive e-learning systems from selecting and using them in the learning resource sequence. As a result, either less appropriate resources are used from the Media Space, or required concepts are not covered at all by the resulting path (Karampiperis & Sampson 2005).

To overcome this problem, Karampiperis & Sampson (2005) proposed an alternative sequencing method instead of generating the learning path, by inhabiting the concept sequence with available learning resources; it first generates all possible sequences that match with the learning goal in hand and then adaptively selects the desired personalized learning path from the set of available paths. Automated sequencing of learning objects is a recurring problem in the e-learning field that could be handled by employing models and sequencing rules along with artificial intelligent techniques, which would ensure the reusability and interoperability of learning objects.
2.2.3 Presentation Level Adaptation

In e-learning, content can be presented to the learners in any format as they like to study. Each learner might have different individual characteristics for various learning types. Therefore all the characteristics of the learner are taken into consideration for composing and presenting the learning objects. Generally, adaptive composition and presentation of learning objects requires some models such as domain model, pedagogy model, user model, adaptation model and instructional model (Vassileva & Deters 1998). While composing learning objects, there is a need to consider the levels of adaptation such as content level, link level, learner level and presentation level. In addition, learner profile information for each learner is the most mandatory need for the presentation of the learning material (Li & Huang 2006).

2.2.3.1 Learning objects composition

The composition of learning objects generally begins by defining the instructional needs, then locating and selecting the best learning resources conformed. Finally, it is essential to convert them in to some e-learning standard (LOM), then sequencing and packing those learning resources, in order to present the learners. The composition of an adaptive course requires input from various modeled entities such as the learner, the teacher, the content, concept space/domain ontology, and pedagogical strategy(s). LO composition integrates learning activities of learners, adaptive mechanisms affect the composition process and comprehension of an adaptive course (Dagger et al 2005). When composing the courseware content, the instructor may break down the subject matter into varied formats, details and depth to achieve the instructional goals. Supporting this process, learning objects represent small and reusable chunks of instructional media (Atif et al 2003).
The author adopted object-based segmentation of knowledge (Bannan-Ritland et al. 2000) in order to provide a constructive approach to e-learning. Thus, the learning object is used as the building block, to compose the courseware content, in a process centered on the learner to “free learners from the drudgery of doing exactly similar tasks unadjusted and untailored to their individual needs” (Gibbons et al. 2001) which is the case, in traditional classroom instruction.

In general, e-learning curriculum is generated to cater for the different learning needs of the learners such as learning styles, preferences, etc. In addition, the learners may also specify some other constraints, such as, difficulty level, learning time, media type, etc. In this situation, the system could provide the facility to the learners to select and organize the learning materials in order to meet their own learning needs. Thus, an approach proposed (Li & Huang 2006) to dynamically compose an adaptive curriculum for e-learning based on a topic-centered resource space. Based on the semantic relationships, which characterize learning objects (LOs) and learner profile, the approach dynamically selects, sequences, and links learning resources into a coherent, individualized curriculum to address learners’ focused learning needs.

For composing the learning content, another model has been proposed (Atif et al. 2003) using learning object processes. Here, the system consists of three conceptual layers, such as, authoring layer, LO production layer and LO composition layer. LO production layer is crucial for adapting the LO content to targeted learners. LO composition layer, which is used to adjust the LO content is based on the LO metadata. In addition, they used the learner profiler and learning path generator to cater to learners’ preferences and skills.
The composition of LOs can also be defined as the necessary process for the construction of learning objects from a set of digital resources or other Learning Objects, eventually simpler resources such as assets or atoms and that in addition, satisfies certain specific aims of learning for a concrete context (Menendez 2008). In addition, the composed learning objects should have characteristics, such as, interoperability, reuse and adaptation, while presenting the learning content to learners.

2.2.3.2 Learning objects presentation

Learning objects are self-contained instructional units which accommodates heterogeneous learning sources (text, presentation, audio or video) or a combination of any of these media. In general, LO presentation is the way to present individualized learning materials (imbedded into the LOs) based on learners’ requisites and levels of the adaptation such as adaptive learning path, link level and learner level adaptation. Here, the multimedia technology contributes further to learning, when instructional designers use the most effective medium to present specific information. Hence, there is a need for instructional designers to map a learning content to an appropriate media. The content-to-media mapping is carried out through some experiments, so as to provide the best media allocation for learning content (Najjar 1996).

The models or components of e-learning play a major role, while presenting the learning objects of any course content. The content model expresses domain-related bits of knowledge and skills, and their associated structure or interdependencies. Basically a content model provides the basis for assessment, analysis, instruction, and remediation about the learning content. The learner model represents the individual’s knowledge and progress in relation to the knowledge map, and it may include other characteristics of the learner. In addition, it captures the important aspects of a
learner for purposes of individualizing instruction. This includes assessment measures that determine where a learner stands on those aspects (Esichaikul et al 2011; Froschl 2005). The instructional model manages the presentation of material and determines learner comprehension by monitoring the learner model in relation to the content model, and prescribing an optimal learning path for that particular learner. Information in this model provides the basis for deciding, how to present content to a given learner and when and how to intervene (Goyal et al 2012). Finally, the adaptation model integrates and uses information obtained from the preceding models to drive presentation of adaptive learning content (Shute & Towle 2003).

While composing and presenting the learning object to learners, an instructional designer should consider learner characteristics, adaptation levels, pedagogical preferences, and learning path of all learners. In addition, they need to consider all e-learning models (content, learner, instructional and adaptive), while composing and presenting the learning objects. In addition, educational materials could be of any format as the learners’ ideas differ from one individual to the other. Therefore all learner characteristics and preferences are taken into consideration for composing and presenting the learning objects.

2.2.4 Learner Level Adaptation

An adaptive e-learning system considers many parameters that contribute to describing learner’s contexts. By using these learner context parameters, the system will give customized learning content to the learner. Context is defined as “any information that can be used to describe the circumstances of an entity.” Context sensitive e-learning systems choose or filter the learning materials, so as to make the e-learning content more relevant and suitable for the learners in their situation. The selection or filtering of the e-learning materials is done by considering the learner’s
profile information, learning styles, preferences, learner’s situation, etc. Many researchers have worked in the area of context sensitive e-learning systems, and all of them have considered learner context parameters, while designing the learning the content. The customization of learning content is generally carried out by considering various learner context parameters, such as, learning style, learner’s preferences, learner’s intention, level of expertise, learner’s situation etc. (Das et al 2010).

2.2.4.1 Learner personal profile

Learner personal profiles are generally used to create instructional/learning content automatically, according to the pedagogical preference and cognitive ability of learners. The profile can be formed based on the learner’s behavior, learning styles, learner goals, performance etc. Based on the learner profile formation the adaptive concept can be defined as, Adapted systems, Adaptable systems and Adaptive systems (Edmonds 1981).

- Adapted systems: in which adaptation is hard-wired by the instructional designer; in this case, the system is customized to a particular learner profile, which is defined earlier, at design time.

- Adaptable system: in which adaptation is explicitly required by the learner. More precisely, the learner can specify her/his own preferences, by manually creating her/his profile; thus the system is dealing with a fixed profile, which can only be modified by learners’ intervention.

- Adaptive systems: in which adaptation initiative belongs to the system itself, based on continuous observation of learner preferences and needs. The learner’s profile is no longer
static; it is dynamically updated by the system, after tracking and analyzing learner behavior (Souhaib et al. 2010).

One of the technical issues in the e-learning system is the handling of learners in a personalized manner, by building different profiles according to their behaviors, knowledge and expertise. Generally, the profile-based frameworks of e-learning, matches the content to the context of interaction, so that the learning content can be adapted to the learner’s needs and capabilities (Tzouveli 2008). Moreover, continuous monitoring of behaviors is essential in assessing the progress of learners during the learning process and used to present adaptive learning content which is more suitable to learners. Thus, there is a need to integrate the static and the dynamic learner models in adaptive e-learning systems.

For adaptive e-learning, a personalized semantic retrieval system has been presented, that uses domain ontology based matching of static profile information, to obtain the learning objects from the database (Ibrahim 2012). However, using typical static profiles for adapting to the needs of the users will not give accurate results. Generally, the learner might not like the same way of approaching learning every time. Therefore, every time the learner logs on to the system, he/she needs to be evaluated automatically, and his/her profile needs to be updated dynamically. Learning styles and preferences are identified, by using different types of learning contents preferred by the learner. The correct identification of the learning style and dynamic updating of learner profile is a key factor to appropriate learning content presentation to each individual learner in the web based learning system, according to their behaviors such as time spent on particular learning content, preference of learning content etc. In the following section, we discuss about these learner behaviors clearly.
2.2.4.2 Learner behavior analysis

The behavior of the learner might not always be the same. Therefore, learner behavior should be logged every time he/she enters e-learning system. Hence, learner behaviors have been observed dynamically (Dharani & Geetha 2013) based on the various browsing actions like time spent on materials, time spent on tests, type of learning objects preferred, learning objects skipped, count of various learning objects used, Performance in tests, Navigational patterns etc..

The navigational behavior of the students of a e-learning virtual environment are described at three levels of behavior analysis of students, such as, session level, where students perform a few actions in a single session logged to the virtual campus; course level, where all single sessions are joined to form a course navigational pattern; and lifelong learning level, to analyze how students evolve from the beginning of a degree until they successfully finish it each academic semester (Carbo et al 2005). Based on web browsing semantics, users’ behaviors are classified (Bousbia et al 2010) and adapted navigation typology (Canter et al 1985). Using the navigation type indicator learners’ navigation behavior is evaluated through educational hypermedia resources. This indicator with qualitative value classified the learner’s navigation behavior in four types (Bousbia et al 2009) i.e. (i) Overviewing- this value is close to the Canter “scanning” value. It implies that the learner is covering a large proportion of pages constituting the course. Through this fast reading, the user seeks to acquire an overall “panoramic” view of the course. (ii) Studying- corresponds to a partial or complete reading of the course pages, with a span of time on each pages. (iii) Deepening- is rather close to the preceding value. It describes a learner who remains for a relatively longer time on a course, careful with details, and seeking web documents, related to the course topics. (iv) Flitting- close to the Canter
“wandering” value. It is a journey without a strategy or a particular goal. The main difference with the overviewing type is the lack of focusing on the course.

Navigational behavior denotes, how learners navigate through the course and in which order they visit different kinds of learning objects and activities. The order in which learners prefer to take in and learn from specific kinds of learning material and activities, as well as in which order and priority these different kinds of learning material and activities, should be presented for supporting learners with different learning styles is a key aspect of most learning style theories. In addition, adaptive navigation support, in terms of recommending learners a suitable way through the learning material and activities, is one of the main way for adding adaptive functionality to learning systems (Brusilovsky 2001).

Based on the analysis of the learners’ behavior through the collection and the interpretation of traces on the learner’s activities, we can find the learner preferences and learning styles, in a web-based learning. Learner preferences refer to the kind of materials the learner wants to study. The learner prefers learning materials, which meet their exact needs in the simplest way possible.

2.2.4.3 Learner preferences

In general, the enormous and different kinds of learning materials clatter users mind and de-motivates them from achieving their learning goals. To overcome such aversion towards the learning materials, learner is provided with the preferred learning objects. Here, the kind of material we mean whether the learner prefers concept, detailed concept, examples, flow diagram, case study, exercise etc. Preferences can be identified from the learners’ behavior patterns. Few learners prefer the overview of concepts
rather than detailed contents. Others may like to learn facts according to the context, while others like to read in a sequential manner. Some might also like to understand the concept using the flow diagram of the entire content, while others might like to learn practically like working out examples or doing activities. Moreover, each learner has a preference for a teaching style that allows him to learn better. Few like to listen and talk, while others prefer to analyze a text, or simply using a visual medium. Therefore, all types of contexts are considered before forming the learning objects (El Bachari et al 2011).

Due to the differences in background knowledge, learning styles and preferences, students may take different approaches towards learning (Watson et al 2010). The author proposed a pedagogical interface for authoring adaptive e-learning courses to provide a graphical illustration on the pedagogical meanings of different course settings, such as, how each part of a course should be delivered to a student without certain academic background, and how much content details are distributed across different parts of the course when a particular student learning preference is applied. The author considered student learning preferences, as well as teacher’s teaching preferences.

Though some significant steps have been made towards the direction of providing enhanced, personalized educational services, there is still a great volume of research that needs to be further conducted with a view to render these services fully personalized and adaptable. In this context, the learner preferences should play a primary role and should dictate the structure and functionality of the entire educational system. This implies that either the learner is in a position to explicitly specify these preferences or the system has the ability to infer them through a monitoring process. Hence, one of the issues that must be addressed, is the prediction of these learner preferences.
and the modeling of the learner’s profile, in terms of educational level, familiarity with a particular course, overall performance etc. The learner model and the learner preferences can be predicted effectively using Bayesian network probabilistic relationships (Kritikou et al 2008). To learn effectively and manage their way of learning, learners have to be aware of their preferences. This information enables the learners to improve the effectiveness of the learning so as to exploit their own resources and also to find their learning styles.

2.2.4.4 Learning styles

Adaptive e-learning offers adaptive learning resources, learning policies and adaptive e-courses according to a learner’s learning style. The learning style of the learner can be identified by using the behavior pattern of each individual’s natural processing capability. Learning style may be defined as “the attitudes and behaviors which determine an individual’s preferred way of learning” (Honey & Mumford 1992). The performance of the learners can be enhanced by providing the suitable learning contents to the learners based on their learning styles. Hence, the initial step for creating adaptive learning environments is to identify learners’ learning styles. Learning style identification facilitates an instructor to effectively teach by using the personalized learning content (Gregorc & Ward 1977; Keefe 1987; Tseng et al 2008).

Every description of learning style involves various behavioral features that can be composed and studied from the learning behavior of a learner. There have been some models for describing and measuring learning. Kolb (1999) proposed that learners can be classified into convergent learners, divergent learners, assimilators, and accommodators. Based on this classification, these four styles of learning are assessed by two dimensions (abstract/concrete and active/reflective), which describe four abilities required
to be an effective learner. A number of researchers have applied Kolb’s learning style theory to study the effects of e-learning and hypermedia learning, and most of them indicate that learning styles are a key factor in improving the effectiveness of learning (Kolb et al 2001).

Learning style can be described as, both a student characteristic and an instructional strategy (Keefe 1991). As a student characteristic, learning style is an indicator of how a student learns and likes to learn. As an instructional strategy, it informs the cognition, context and content of learning. Learning style is a consistent way of functioning that reflects the underlying causes of learning behavior (Keefe 1987). Keefe’s learning style test, can be used to identify, Sequential Processing Skill, Discrimination Skill, Analytic Skill and Spatial Skill of the students, might be the most suitable model to be used in an e-learning or web-based environment, because in such learning context, where rich information sources and various ways of presentations are used, students’ processing, Discrimination, Analytic and Spatial Skills are quite important for dealing with the learning materials (Tseng et al 2008).

Felder & Silverman’s learning style (FSLSM) model described the category of intuitive/sensitive, global/sequential, visual/verbal, inductive/deductive and active/reflective, which can be used to discriminate 32 learning styles. For example, the sensitive/sequential/verbal/deductive/active is a learning style (Felder & Silverman 1988). Stangl (2002) distinguished learners into four styles, i.e., acting, hearing, reading and seeing. Instructor feedback and student learning styles significantly affect the perceived learning outcomes of e-learning students (Marcovic & Jovanovic 2011). The author also states that, quality of education will significantly be enhanced if instructors modify their teaching styles to accommodate the learning styles of all students in their class. Deborah et al (2012) identified
Felder–Silverman learning style model as the suitable model for E-learning and suggested the use of Fuzzy rules to handle uncertainty in learning style prediction so that it can enhance the performance of the E-learning system. Graf (2013) considers learning styles and introduces a dynamic student modeling approach that monitors students’ behavior over time and builds an accurate student model by frequently refining the information in the student model as well as by responding to changes in students’ learning styles overtime using Felder-Silverman learning style model. Learning problems are frequently not related to the difficulty of the subject matter but are associated with the type and level of cognitive process required to learn the material (Keefe 1987). In the next section, we discuss about this cognitive ability of the learners, to satisfy the various needs of the learners.

2.2.4.5 Learner cognitive traits

In general, students have a number of cognitive abilities. Some of these capabilities are crucial for learning. The capabilities such as working memory capacity, inductive reasoning ability, information processing speed, associative learning skills, meta-cognitive skills, observation ability, analysis ability, abstraction ability, etc. (Graf et al. 2012) Adaptation of the E-learning system according to cognitive characteristics of the students is a relatively new direction of research, where there is a conjunction of technical and pedagogical aspects (Goyal et al. 2012). It is particularly important that the E-learning systems are able to integrate different types of learning content and navigation in order to respond to diverse needs of the students. Learner Cognitive Traits is used to describe whether the learner is a beginner or the learner has some pre-knowledge about a particular topic or the learner is an expert in that topic. The relationship among cognitive processes (remembering, understanding, applying, analyzing, evaluating, and creating) and knowledge outcomes (factual, conceptual, procedural, and meta-cognitive
knowledge) has been described (Hench & Whitelock 2010). Accordingly, the
author defined knowledge as acquisition, comprehension, or manipulation of
information and the awareness of the cognitive processes used and knowledge
level is the measure of the degree to which knowledge has been achieved.

Wenger (1987) proposed a learner model which includes the
performance and knowledge of the user which can affect the learning and
progress of the students. In some reviews (Carver et al 1999; Kinshuk 2004)
researchers express the opinion that the way of thinking, goals, interests and
knowledge levels are the main attributes that determine the definition of
different types of learners. It is confirmed that these four types of data are
highly correlated with the cognitive style of each learner (Messick 1970). An
Intelligent Tutoring System (ITS) which monitored the performance of a
learner, and provided adaptation to learner’s learning style, current knowledge
level and appropriate teaching strategies in e-learning systems has been
presented (Phobun & Vicheanpanya 2010). The system assessed each
learner’s action within this interactive environment and developed a model of
their knowledge, skills and expertise. It composes these three types of
knowledge (domain expert’s subject matter knowledge, learners’ knowledge,
and instructional knowledge) and organized into four separate models, such
as, expert model, learner model, instructional model and interface model.

The above sections discussed the four levels of adaptations, such
as, content, link, presentation, and learner level. In addition, we explained
about learning object processes, learner context parameters, and e-learning
models, as well as illustrated the links among them along with adaptation
levels. In the next section, we discuss about the learning path adaptation,
issues, various approaches and techniques used for generating learning path.
2.2.5 Learning Path Adaptation

As we discussed earlier, one of the new major directions in research on web-based educational systems is the concept of adaptability. Typically the educational system adapts itself to the learning profile, preferences, styles and ability of the learner. In this section, we look into the issues of providing adaptability with respect to the learning paths of learners. Providing an adaptive learning path according to the context of the learners’ is a key issue. An optimal adaptive learning path will help the learners in reducing the cognitive surplus and incomprehension, and thus improving the efficiency of the adaptive e-learning systems.

In reality, the majority of learners are not able to find the most suitable Learning Objects (e.g. learning materials, learning resources) from the web. Consequently, a lot of researchers have focused on developing e-learning systems with tailored learning mechanisms to aid on-line web-based learning and to adaptively provide learning paths. However, most personalized learning mechanism systems ignore the relationship between learner attributes (e.g. learning style, domain knowledge) and LO’s attributes. Therefore, it is not easy for a learner to find an adaptive learning object that reflects his own attributes in relationship to learning object attributes. Hence there is a need to create attributes-based system to help the learners find an adaptive learning object more effectively.

In a web based learning environment the enormous amount of available learning objects will increase the cognitive overload for the learner and will lead to disorientation (Van Merrienboer & Ayres 2005). These problems can be overcome using an adaptive learning path based on the learner context (Lin & Wu 2007). Using an optimal learning path the learning objects can be provided in an effective way to the learner. That is each learner
can be provided with individualized learning contents depending upon their needs and contexts.

There are various approaches found in the literature for learning path adaptation that are classified here based on the techniques used for learning path generation. In Artificial intelligence the usage of Swarm Intelligence techniques in adaptive e-learning scenarios offers a way to combine simple interactions of individual learners to resolve more complex problems. Several approaches, for finding the optimal learning path in an adaptive manner, are based on Evolutionary Computation (EC) methods. Genetic algorithm (GA) and Ant Colony Optimization (ACO) are two normally used EC approaches.

The EC methods used for adaptive learning path are categorized as social sequencing and individual sequencing tactics. In the social sequencing, the choice of the optimal learning path is based on the collective path and performance of the complete learners’ society. The individual sequencing is based on the individual learner rather than a group’s characteristics (Pushpa 2012). GA is the leading technique used in social sequencing is (Romero et al 2002; Guo & Zhang 2009). Furthermore, GA (da Silva Lopes & Fernandes 2009; Chen 2008; Huang et al 2007) and Particle Swarm Optimization (Chu et al 2011; de-Marcos et al 2007) are also used for individual sequencing. Other EC methods such as Memetic Algorithm are mainly used for individual sequencing (Acampora et al 2011).

In general, the learning scenario is constructed by sequencing the learning objects based on the learning necessity, the learning history information, and the curriculum information of the object of learning, according to the characteristics of the learning object (Seki et al 2005). Moreover, the problem of concept continuity of learning paths also needs to be considered, while implementing personalized curriculum sequencing.
because smooth learning paths enhance the linked strength between learning concepts. Generally, inappropriate courseware leads to learner cognitive overload or disorientation during learning processes, thus reducing learning performance (Chen 2008). Therefore, compared to the freely browsing learning mode without any personalized learning path guidance used in most web-based learning systems, the author proposed genetic-based personalized e-learning system, which can generate appropriate learning paths according to the incorrect testing responses of an individual learner in a pre-test, provides benefits in terms of learning performance promotion while learning.

ACO provides more adaptive and robust solution among all these approaches, in the direction of social sequencing (Pushpa 2012). ACO based inductive planning for recommending learning paths (social sequencing) is a heuristic method that has been successfully used to deal with complex problems. Here, the probabilistic rule is biased by pheromone values and heuristic information: the higher the pheromone and the heuristic value associated to an edge, the higher the probability of an ant to choose that particular edge. Once all the ants have completed their tour, the pheromone on the edges is updated. Each edge then receives an amount of additional pheromone proportional to the quality of the solutions to which it belongs. A Learning path is constructed by applying this constructive procedure to each ant (Sengupta et al 2011).

Learning Path Graph is also used to find out learning path where an acyclic graph defines the structure of domain knowledge and the associated learning objectives (Karampiperis & Sampson 2005). Adapted learning path is selected from this graph and contains all the available learning paths based on learner’s attributes in the learner model. Learner model consist of learners’ knowledge level and characteristics like learning styles and preferences. The author used suitability function for weighting each connection of the Learning
path graph for providing suitability factor for learning resources. From the weighted graph, the most appropriate learning path is selected for a specific learner by using shortest path algorithm. Learning activity graph (Zhu & Cao 2008) is used to organize learning resources in a learning task.

By using the clustering technique, instead of generating single path for every individual learner, the learners are grouped into clusters (social sequencing) of different learning styles and a learning path corresponding to the cluster can be generated. Concept Map is the graphical representation of ontology which reveals the entire courseware structure and core knowledge about a subject domain (Bai & Chen 2008). For grouping courseware with high correlation into the same clusters, fuzzy clustering analysis schemes are also used. Moreover, a Self Organizing Map (SOM) neural network (Kwasnicka et al 2008) is used for grouping the learners and providing suitable path fit for the cluster in which the learner belongs.

The statistical approach Bayesian probability theory is used for finding the adaptive learning path (individual sequencing) (Anh et al 2008). Here, firstly a node probability table (prior) based on Bayesian probability theory is created. The probability value is assigned based on the learner level of expertise, learning style and learning pace, which are called candidate learning paths. Next, a Bayesian network is constructed to calculate probability value which represents each knowledge unit in the learning path. From this, the shortest path is selected to provide the appropriate learning path for a learner (Marquez et al 2008).

Petri Net based approaches (Gao et al 2005; Lin et al 2004) are also used to create adaptive learning path for each individuals. For adaptive learning path, learner’s behavior should also be considered to provide an adaptive environment for learners (Dharani & Geetha 2013). The author used Colored Petri Nets (CPN) to track the learners’ behavior dynamically in the
e-learning system. Finally, Adaptive Learning Path is generated using the learner’s behavior patterns which are modeled as learner’s characteristics like learning styles, goals and performance. Petri Nets based approaches are also used for controlling the learning path between learning activities and has brought a lot of improvements to the paradigm of adaptive e-learning systems, based on similarity between learning objects graph and the formalism of Petri Nets (Kamceva & Mitrevski 2012).

In this chapter, we discussed different adaptation levels, including, learning object processes, learner context parameters and e-learning components/models, necessary to create an adaptive e-learning environment for learners by offering appropriate learning content to all individuals.

2.3 SUMMARY

Providing an adaptive and interactive environment tailored to the learner’s needs is one of the most important areas of research in e-learning environments. In this chapter, we reviewed the different aspects of adaptive e-learning environment, along with various learning object processes, levels of adaptation and e-learning models. Here, we studied that the adaptation can be provided to an e-learning system, not only based on the learner’s requirements, but also based on the learning content (learning objects), and the configuration of the learning environment. The existing surveys provided the description about e-learning models, adaptation concepts and learner profile information separately. However, in this survey, we described the adaptation levels, learning object processes, learner parameters, e-learning models and also portrayed the relationships among them. Hence, this chapter offers a clear picture of how to create adaptive e-learning environment, based on the learning object processes at each of the adaptation levels. Here, the processes of the learning objects such as LO_design, LO_sequencing, LO_composition, LO_presentation and LO_evolution are described, through
the various levels of adaptation. The learning objects process for learning content design, involves not only the collection, systemization and conversion of learning materials; but also include various design models, in order to meet different learning styles, desires and capabilities. In addition, the conversion from general curriculum path to individual learning path, contains the learning objects that satisfies the learning objective of the courses, which could be used in various learning environments. Thus, this chapter provides detailed information about the learning object processes for e-learning content design, which is necessary to offer the appropriate and customized learning content to learners. This survey motivated us to consider the learner parameters in the process of learning objects optimizing and sequencing. In addition, this chapter leads us to incorporate instructional design strategies in dynamic course composition module and provided a good guidance of applying adaptation levels in learning object processes and dynamic learner modeling.