

## Chapter 7

# A New Approach of an Intelligent E-Learning System Based on Learners' Skill Level and Learners' Success Rate

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### **ABSTRACT**

*Learners usually meet cognitive overload and disorientation problems when using e-learning system. At present, most of the studies in e-learning either concentrate on the technological aspect or focus on adapting learner's interests or browsing behaviors, while, learner's skill level and learners' success rate is usually neglected. In this paper, the authors propose an online course generation based not only on the difficulty level of a learning unit, but also the changing learning performance of the individual learner during the learning process. Therefore, considering learner's skill level and learners' success rate can promote personalized learning performance. Learners' skill level is obtained from pre-test result analysis, while learners' success rate is acquired through specific tests after completing a learning unit. After computing success rate of a learning unit, the system then modifies the difficulty level of the corresponding learning unit to update courseware material sequencing. Experiment results indicate that applying the proposed intelligent e-learning system can generate high quality learning paths, and help learners to learn more effectively.*

### **INTRODUCTION**

Traditionally, the courses in e-learning systems consist of static hypertext pages with no student adaptability (Ghali et al., 2008). However, since the 1990s, researchers began to incorporate adaptability into their systems. Intelligent e-learning systems (IES) are distance educational systems based on the Internet.

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## ***A New Approach of an Intelligent E-Learning System***

One of the main problems in IES is to determine how to adapt the curriculum sequence to each student according to their learning characteristics (Kahraman, 2009) (Brusilovsky et al., 2003). At present, most of the studies on e-learning either concentrate on technological aspect or focus on adapting learner's interests or browsing behaviors, while, learner's skill level and learners' success rate is usually neglected. Generally, inappropriate courseware leads to learner cognitive overload or disorientation during learning processes, thus reducing learning performance (Cobos et al., 2013; Ghadirli et al., 2013). Besides, the learning paths problem of concept continuity also needs to be considered while implementing personalized courseware generation because smoother learning paths increase learning performance, avoiding unnecessary difficult concepts.

In this paper, learners' skill level and learners' success rate are used as valuable information to represent learner's current state and modify the difficulty level of each course material, in order to update the courseware material sequence. Courseware material sequencing aims to provide an optimal learning path to individual learner since every learner has different prior background knowledge.

The rest of the paper is organized as follows: section 2 provides the literature review on cognitive load theory and intelligent e-learning systems. In Section 3 we will give an overview on the overall architecture of the intelligent e-learning system. Section 4 will describe the scope of our approach. The experiments that have been conducted will be presented in Section 5. Section 6 will discuss the results of the experiment. We will conclude the paper in Section 7 along with the further works of the study.

## **Literature Review**

### **Cognitive Load Theory**

Cognitive load theory (CLT) is a framework of instructional design principles based on the characteristics and relations between the structures that constitute human cognitive architecture, particularly working memory and long-term memory (Wong et al., 2012).

Cognitive load is defined as a multidimensional construct representing the load that a particular task imposes on the performer (Paas et al., 1994). It can be assessed by measuring mental load, mental effort (Sweller et al., 1998; Paas et al., 2003). Mental effort is related to the strategies used in the learning activities, whereas mental load refers to the interactions between the learning tasks, subject characteristics and subject materials, which are highly related to the complexity of the learning content that the students need to face.

On the other hand (Paas et al., 2005) addressed that learners' motivation had a significant relation with cognitive load, especially on mental effort. They suggested that motivation could be identified as a dimension that determines learning success, especially in complex e-learning environments (Paas et al., 2005). The relationship between cognitive load and motivation is also stated by (Moos, 2009). The Motivated consists of 29 items covering six dimensions:

1. Goal orientation refers to student's general goals or orientation to the course as a whole.
2. Extrinsic goal orientation concerns the degree to which the student perceives herself to be participating in a learning unit for reasons such as skill levels, performance.
3. Task value differs from goal orientation in that task value refers to the student's evaluation of the how interesting, how important, and how useful the task is ("What do I think of this learning unit).

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