

DYNAMIC ADAPTIVE E-LEARNING MECHANISM BASED ON LEARNING STYLES

**A THESIS SUBMITTED TO THE UNIVERSITY OF MANCHESTER
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY
IN THE FACULTY OF ENGINEERING AND PHYSICAL SCIENCES**

2016

By
Samar M. Alkhuraiji
School of Computer Science

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Word count: 43285

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Abstract

Dynamic Adaptive E-learning Mechanism Based on Learning Styles

Samar M. Alkhuraiji

A thesis submitted to the University of Manchester

For the degree of Doctor of Philosophy, 2016

Learning management systems are widely used in educational organizations and universities to deliver self-paced online courses. Furthermore, educational theories have suggested that providing learners with learning material suitable for their learning styles may affect their learning performance. Learners with different individual traits, levels of knowledge, backgrounds, and characteristics are using these learning systems to enhance their learning understanding. This study is concerned with personalizing learning environments based on each learner's individual needs by designing and developing intelligent adaptive e-learning management systems. These systems behave according to the data collected in a 'learner model' from the learner to provide accurate learning material that adapts to learners' needs by changing the learning environment rapidly based on the learners' learning requirements and their learning styles.

A dynamic adaptive e-learning system (DAELS) is proposed. The idea is to build an algorithm that can quickly understand an individual learner's learning styles. We propose the Similarity algorithm, which aims to adapt to the student's learning styles by taking advantage of the experience of previous students that used the same system and studied the same course. This algorithm presents the content to each student according to predictions of his/her preferred learning styles. These predictions can change during a student's progress and response to the presentation. The ID3 machine learning method was used and integrated into our Similarity algorithm. Such a method can search learners' databases efficiently and quickly by classifying learners based on their attributes. Methods and associated techniques that address these issues by use of Felder and Silverman Learning Styles Model (FSLSM) have been developed and can be built into Moodle, the learning management system, as an integral component. We then conducted experiments on students to evaluate the flexibility of the DAELS and its effect on students' learning performance.

An experiment was designed and implemented to validate the proposed approach's reliability and performance on learners' scores. The proposed DAELS was compared with a static adaptive e-learning system (SAELS) and a non-adaptive e-learning system (non-AELS). The results of the empirical experiment demonstrate the effectiveness of using DAELS on student performance. On average, the dynamic adaptive group had an average increase of 60% in the post-test from pre-test, whereas the average score of the static group increased 32%, and the control group had an average increase of 8%. The results reveal that the dynamic group had the highest average scores in the post-test, and the control group had the lowest average increase in scores. The findings indicate that the developed Similarity algorithm, implemented in our DAELS for personalising learning content presentation according to students' learning styles, is appropriate in e-learning systems and can enhance learning quality.

Declaration

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Acknowledgements

I would like to thank my supervisors, Dr. Barry Cheetham, Dr. Omaima Bamasak and Dr. Mohammad Abdel Razek, for their continued inspiration, understanding, guidance and moral support from the beginning of my research journey.

I would like to thank all my colleagues at King Abdulaziz University's Department of Statistics who supported my study by helping me to correct and evaluate my experiment's procedures and case study content. Also, I would like to extend my thanks and gratitude to the students at the University of King Abdulaziz for being so collaborative and for accepting of my invitation to participate in my experiments.

I am also grateful to all my friends for their thoughtful insight and kind and friendly words of encouragement.

Special acknowledgements belong to my family, who has been very supportive throughout all the stages of my work.

Chapter 1

Introduction

Stockley (2006) stated that “E-learning is the delivery of a learning, training or education program by electronic means”. The electronic means referred to are computers or telephones linked by communication networks, broadcast radio and television. E-Learning technology is broadening the range of available educational opportunities and overcoming many traditional learning barriers. It is providing unprecedented access to learning methodologies as well as knowledge and factual information. The use of text, diagrams and images is being augmented with streamed and real-time audio-visual communication to improve the effectiveness of the learning approach. Virtual reality technologies are also being used effectively for real-time teaching and as a tool for students to interact with one another (Monahan et al., 2008) indicated that the registration rate of online students has been growing significantly faster than higher education enrolments in general. The report states that during the 2007 autumn term, more than 3.9 million students in the United States were studying at least one online course. This number had increased by 12% from the year 2006. The number of online enrolments had increased by 12.9% of the overall higher education student population, which had increased only by 1.2%. Over 20% of all U.S. higher education students were taking at least one online course in the fall of 2007.

Currently, most e-learning environments are built around the Internet and communication tools such as e-mail. They present mainly pre-designed fixed-course material and directed study procedures backed up by limited student-tutor interaction. In practice, the same course is taken by learners whose concepts of learning, expectations, cultures, backgrounds and learning styles may be different (Blanchard et al., 2005, R-Moreno et al., 2008). This “one style fits all” approach means that all learners are expected to adopt the same learning style as dictated by the e-learning environment. The student-tutor interaction moderates the inflexibility of this approach to a degree, but the electronic means of communication and inevitable resource constraints limit the scope of the interaction.

Existing E-Learning systems efficiently employ the facilities of available communication technologies to deliver course content to learners, but they are less efficient in exploiting the same facilities to be responsive to the perceived needs and reactions of learners (Ab Hamid et al., 2006). For example, e-learning management systems such as WebCT, Moodle and Blackboard are frequently and very successfully used in E-education. They provide many features for administrators and teachers, including software facilities and support for the

creation of manageable online courses. But they do not cater for the individual differences of learners (Graf and List, 2005, Graf, 2005, Popescu et al., 2007a, Cristea and Stash, 2006). Personalization in e-learning implies modifying the material and its presentation according to individual student learning styles behaviour and needs. The required modifications may be determined by examining the responses to questionnaires and to a student's success or failure with previous material (Esposito et al., 2004a, Chen et al., 2005).

The term 'adaptive' in the context of e-learning systems means that different ways of learning, i.e., learning styles, can be accommodated by the same system. An adaptive e-learning system will try to match the choice and presentation of educational material to the needs and characteristics of individual learners. According to Brusilovsky (1996), "Adaptive Hypermedia (AH) systems build a model of the goals, preferences, and knowledge of each individual user, and use this model throughout the interaction with the user, in order to adapt to the needs of that user". It is already well known that such adaptivity can improve the progress and success of learners (Felder and Silverman, 1988b, Cristea and Stash, 2006).

An adaptive e-learning system must have a means of determining the user's preferred learning style, either in advance of the course delivery, for example using an online questionnaire, or during the course delivery by continually monitoring student reactions. This determination can be done according to proven educational theories that have been studied over many years and have already proved their reliability and validity to be of practical use (DeCapua and Wintergerst, 2005). Among these proven theories are Kolb's learning style theory (Kolb, 1984), the Dunn and Dunn learning style model (Dunn and Dunn, 1999), and the Fielder-Silverman theory (Felder and Silverman, 1988b). The Fielder-Silverman theory introduced a learning style assessment instrument that was specifically designed for classroom use and was first applied in the context of engineering education (Felder and Silverman, 1988b). The instrument is now available as an on-line questionnaire allowing learners to take an online test to obtain an assessment of their learners' learning style preference.

To discover the potential for adaptive e-learning, traditional theories of education and proven theories of learning and learning styles must be studied along with the current state-of-the-art technologies in adaptive hypermedia. To investigate the benefits of adaptivity in e-learning systems, automated methods of identifying learning styles from questionnaires and by monitoring the behaviours and actions of learners should be implemented and evaluated.

The research goal for this thesis is to propose and evaluate a proposed DAELS that can adapt e-content to the learner's learning styles within the learning environment and improve

learners' performance during learning to guide them to complete learning activities in an intelligent way. The system aims to help learners by applying educational psychology theory and adopting different learning styles in online courses. The research goal of evaluating the effectiveness and the validity of matching instructional methods to learners' styles and preferences in e-learning has value in the field of educational psychology, and in the field of adaptive educational hypermedia.

1.1 Problem Statement

In current online educational systems, teaching has traditionally followed a “one style fits all” approach, which means that all learners are expected to adopt the same learning procedures. This type of learning does not take into account the different learning styles, learning strategies, and preferences of students. Currently, the development of e-learning systems has accommodated personalized learning, in which instruction is tailored to a students' individual needs. Some personalized approaches let students choose content that matches their personality. Other approaches build systems based on fixed learning styles that cannot be changed during the student's progress and learning strategy. These systems provide a somewhat inflexible form of adaptation that adapts to a student's individual needs at the beginning of the course but does not change after that. The delivery of course content material is an important part of personalized learning. Graf (2007) showed that adaptivity is introduced in the way common features available in e-learning management systems are used. Information may be emphasized, de-emphasised, repeated and re-ordered, but the delivery mechanism remains the same (static-adaptivity) during the entire course. The inefficiency of the current adaptive e-learning systems represents a significant lack in the learning process. In addition, designing a well-designed, effective, adaptive e-learning system represents a challenge due to the complexity of adapting to the different needs of learners (Alshammari et al., 2015).

To improve the adaptivity of e-learning software, we need to develop a dynamically adaptive mechanism. This mechanism adapts e-content intelligently and is customizable with the pedagogy most appropriate for particular learners. The goal is to formulate a working framework and architecture of an integrated DAELS by proposing an adaptive algorithm to effectively update learners' models.

This goal can be achieved by solving several sub-problems:

- Implement an online learning system based on educational theory that determines the learning styles and characteristics of learners and then models them as a means of predicting the learner's likely reaction to particular learning material.
- Design and implement an adaptive algorithm as a series of mathematical equations.
- Integrate the adaptive algorithm in a currently available learning management system.
- Evaluate our proposed DAELS to determine its effectiveness.

1.2 Research Hypotheses

It is hypothesized that the proposed intelligent DAELS can be made better for learners and more time efficient. The framework for the proposed intelligent system is to integrate the current learning management system, Moodle, with our proposed dynamic adaptive algorithm, named Similarity, which uses our proposed techniques. To evaluate performance of the DAELS, the work presented here attempts to investigate two forms of assessment: one-time (static) and dynamic assessment. One-time assessment is carried out before the start of the presentation, which determines how the material will be presented for the whole of the session. Dynamic assessment continually updates the presentation style according to how the student responds to the material. This work regards student learning styles behaviour and learning content structures.

A comprehensive hypothesis is as follows:

- a) The proposed Similarity algorithm for dynamic adaptivity combined with a learning management system will perform better than non-adaptive and other published adaptive systems.
- b) The proposed DAELS for adapting learners' models by the proposed approach will allow learners to adapt effectively.
- c) Using a machine-learning decision-tree algorithm as a lightweight approach to adaptation will increase adaptive system performance for online courses and increase computational

1.3 Research Approach

This thesis formulates, implements and evaluates a novel adaptive e-learning system. We promote an approach for achieving useful adaptivity in the context of dynamically adaptive e-learning system DAELS.

To define the term *adaptivity*, we surveyed the published research literature in e-learning management systems, focusing on recent publications concerned with adaptive e-learning and the automatic detection of learning style. We also surveyed and studied the most established pedagogy concerned with educational learning-style theories and considered their relevance to e-learning.

To understand the properties of adaptive e-learning systems for learner model classification, an analytical model was developed using the proposed adaptive approach. The proposed model was developed using our Similarity algorithm. The proposed approach was implemented in a current learning-management system, Moodle, for performance evaluation. Useful context information about learning style characteristics was extracted from learning styles results and incorporated into the proposed Similarity approach.

Finally, subjective testing of an implementation of the research idea mentioned above within an existing integrated e-learning environment, Moodle, was planned and carried out. The results were evaluated according to established statistical criteria.

The following sub-problems were addressed as objectives:

- 1) Defining a suitable learner characteristics model required a survey of existing learning-style models and consideration of how they could be implemented in our adaptive system. It was also necessary to devise a new identifier format to implement the learning style characteristics in a way that was applicable to our system.
- 2) Developing a dynamic adaptive algorithm involved modelling the learner by applying an adaptive mechanism that could personalize learner characteristics, needs, and learning styles.
- 3) Integrating the adaptive mechanism in a learning management system required the Moodle learning management system to be investigated and integrated with our proposed algorithm.
- 4) Functionally testing the adaptive system showed whether it worked and affected learners.
- 5) Evaluating the integrated adaptive system experimentally on undergrad students demonstrated its effectiveness.

1.4 Research Contribution

Dynamically adaptive e-learning systems that continuously monitor and adapt to the learners' performance during on-line sessions are becoming popular in the research community and are leading to the invention of a wide range of personalized applications in learning environments. Such systems must process large amounts of data yet respond quickly

to the learning styles behaviour of each online learner. This sets new challenges beyond just making the systems work. This thesis considers how we can personalize learning environments in an effective way.

Although this field of research has generated much interest over the past few years, there are still many questions that need to be addressed. In this thesis, a number of research gaps are identified and filled in by introducing novel dynamic adaptive e-learning methods that are shown to be lightweight and effective. These methods will be among the first published to apply techniques such as ID3 machine learning to adaptive e-learning. Our proposed Similarity algorithm will be implemented in real-time and used to adapt the learner models that will ultimately determine how the content material will be presented to the student.

Accordingly, the contributions of the research are as follows:

- 1) Identifying the common limitations shared by most adaptive e-learning systems.

This issue marks an essential aspect of the project. It requires us to identify the gaps and limitation between web education and adaptive systems According to Ravenscroft (2001), the use of technology in education has tended to be "technology-led rather than theory-led". Despite the rapid development of e-learning technology and the Internet, the provision of personalized learning mechanisms for individual learners in the e-learning environment is still an unsolved problem (Dolog et al., 2004). Finding the right courses to match the students' interests, learning styles and needs and adapting their delivery during the learning progression is hardly catered to in current e-learning platforms. Several adaptive web-based educational systems have been proposed in the literature, but few of them incorporate dynamically adaptive learning systems (Graf, 2005). A review study by Akbulut and Cardak (2012) revealed that learning styles may be affected by learners' past experiences, so we need to have dynamic student modelling that is frequently updated with new students' behaviour such as learning styles. In order to identify these limitations, we have investigated the current research on adaptive web education.

- 2) Integrating the concept of dynamic adaptive content in online learning management systems.

To address this issue, we first surveyed the problems experienced by researchers when empirical experiments were conducted. Many of these experiments were simply conducted to investigate if adaptive web education improves students learning. Conclusions from this survey will be summarized in the thesis. The next step was to investigate whether it is possible to design an algorithm to dynamically

adapt to a student's learning style by taking advantage of the experience of previous students who used the system and studied the same course. The algorithm must take advantage of information taken from the data records of previous students to identify similar learning styles behaviour among students. A similarity measure may be defined based on student learning styles, GPA scores and time spent learning the course content. Based on this measure of similarity, the adaptive algorithm can determine how best to modify the way information is presented to each given student as he or she progresses through the course. The DAELS was developed and implemented to extend the current learning management system, Moodle. We then conducted experiments on students to evaluate the flexibility of the DAELS and its effect on students' learning performance.

3) Capturing and identifying student's learning styles.

In our adaptive e-learning system, we used the learning-styles theory of the Felder-Silverman model. The model depicts learning styles in four dimensions. The information for this model is often obtained from a standardized and well-known questionnaire. In this thesis, we use a different approach, which allows us to capture information about the learning styles from online student behaviour. Rather than the discrete representation of each learning style dimension proposed by Felder and Silverman (Felder and Silverman, 1988a), we use a continuous representation of styles as a set of points in two-dimensional space. This is more suitable for our situation when we need to find the relationship between two learning styles according to our similarity algorithm. The relationship between these learning styles is used as a distance measure (Redden, 2012) to show us how close or far apart these two learning styles are. The advanced classification methods used in this thesis will improve the accuracy and efficiency of learning styles classification.

4) Proving that the proposed dynamically adaptive learning approach has a greater benefit to students' learning performance than static adaptive methods and conventional e-learning systems.

To fulfil the above contribution, an experiment was conducted, based on the learning activity of the 'mathematical statistics' course delivered by the Statistics Department at King Abdulaziz University. We aimed to find out whether the proposed approach could improve students' learning performance and reduce their time spent learning the content. First, we developed our DAELS using the current learning management system, Moodle. An experiment was then conducted to evaluate the performance of the proposed approach statistically. Participants were randomly assigned to three groups: static, control, and dynamic.

- The static group used a SAELS with personalized presentation based on the learning style of each participant.
- The control group learned with a conventional non-AELS without personalized presentation.
- The dynamic group learned with a dynamically adaptive system DAELS based on our proposed Similarity algorithm. This algorithm presents the content to each student according to predictions of his or her preferred learning style. These predictions can change during a student's progress and response to the presentation. As the number of learners increases and the data generated by their previous learning history also increases, an implementation of our proposed algorithm could become unscalably complex, causing it to become too slow to be usable without huge computing resources. To address this problem, a decision-tree machine learning method ID3 will be used and integrated into our adaptive system. Such a method can make searching learners' history databases efficient and fast by classifying learners based on their attributes. Among these attributes are GPA, time spent learning and learning styles. Consequently, searching the database for a particular learner's adaptable model will be less time-consuming.

The value of our approach will also be in the data that are collected experimentally. Our dynamically adaptive system will be evaluated experimentally and compared with other adaptive and non-adaptive systems. These comparisons will establish whether we have truly established a useful relationship between the adaptivity of learning content and learning outcomes. Such a relationship can clearly be exploited to contribute significantly to helping students excel in their study. Furthermore, the findings can also work as guidelines for and contribute to future e-learning research.

1.5 Publications

- 1) ALKHURAIJI, S., CHEETHAM, B. & BAMASAK, O. *Toward Adaptive E-learning Based on Proven Educational Theories*. The Eighth IASTED. International Conference, Web-based Education, 2010 Sharm El Sheik, Egypt. ACTA Press, 210-218.

This paper suggests ways of enhancing the capability of existing e-learning management systems by introducing adaptivity in the way the information is presented to the on-line learner. Adaptivity means that the course content can be presented in various ways according to the results of an assessment of the preferred

learning style patterns of each individual learner. Assessments may be made on the basis of proven educational theories, by employing questionnaires and/or observing learning styles behaviour and progress with on-line learning tasks. The success of existing studies is surveyed, and a new approach is proposed with experiments devised for its evaluation.

- 2) ALKHURAIJI, S., CHEETHAM, B. & BAMASAK, O. *Dynamic Adaptive Mechanism in Learning Management System Based on Learning Styles*. 11th IEEE International Conference on Advanced Learning Technologies 2011 Athens, Georgia, USA.

This is a short paper that is concerned with enhancing the capability of such systems by introducing adaptivity in the way the information is presented to the on-line learner. Adaptivity means that the presentation style is personalized to the preferred learning style of each student, as may be modeled by a Bayesian Network technique. The modeling is based on learning theories that have been proven by much experience, and provide appropriate assessment procedures. Techniques for introducing two forms of adaptivity, static and dynamic are considered, and two experiments, based on case-studies are devised for evaluating their potential.

- 3) ALKHURAIJI, S., CHEETHAM, B., RAZEK, M. A. & BAMASAK, O. *Emerging Web 2.0 for Adaptive Learning Management System Based on Student's Learning Styles*. *Web 2.0 Tools, Methodology and Services For Enhancing Intelligent Tutoring Systems Workshop*, Supplementary Proceedings of the Eleventh International Conference on Intelligent Tutoring Systems, 2012, Chania, Greece., 15-31.

We have presented the analysis of the first results of the pilot study of adaptive Moodle system based on students' learning styles. The obtained results demonstrated the potential and the necessity of further experimental on a larger number of participants in order to come up with truly convincing results. In this work, we proposed the idea of static adaptation system. We designed and implemented the proposed static adaptive system by extended Moodle version 2.2 features. In this paper, we suggested completing the design and the implementation of the dynamic adaptive algorithm using machine learning algorithms.

- 4) ALKHURAIJI, S., CHEETHAM, B., RAZEK, M. A. & BAMASAK, O. *A flexible approach for providing adaptivity in learning management system based on learning styles*. 12th International Conference on Intelligent Systems Design and Applications (ISDA), 27-29 Nov. 2012. 718-722.

This paper describes our approach to build a dynamic adaptive course in learning management systems based on students' learning styles. Our method aims to adapt the student's learning style by taking the advantage of the previous students taught the same course. To achieve this goal, we present an approach for adaptivity by taking the advantage of information that can be taken from previous students' data record to find similarity between the students. Based on this similarity we can find the next suitable learning style for the current students.

Two posters are submitted to *Research Student Symposium POSTER Presentation. Manchester University, UK.*

1.6 Thesis Structure

The following paragraphs provide an outline of the rest of the thesis with a brief description of each of the individual chapters.

Chapter 2: Background and Related Work

This chapter presents a literature review, covering aspects related to adaptive hypermedia, adaptivity in e-learning, and learner modeling. A critical exploration of the existing literature reveals that adaptive web education systems still have much room for improvement from the dynamic adaptive content perspective. The review focuses on presenting the importance of e-learning systems in education, the learning theories concerned with detecting learning styles, and a survey of adaptive educational hypermedia systems, along with their methods and techniques. The review answers the first research question by analyzing current systems and presenting their limitations.

Chapter 3: Designing an Adaptive Learning Mechanism

Selecting a good learning styles model is an important step towards providing adaptivity. Most of the educational systems already developed rely on a single learning style model, such as the Felder-Silverman model (FSLSM). In this chapter, we start with a discussion of the selected learning styles model FSLSM, which is employed in our adaptive system. We explain the model specifications and its assessment tool. Investigating common problems that arise in adaptive systems helps us when we are designing the architecture for our proposed dynamic and static adaptive systems. This chapter also includes a discussion of the components and technical architectures of static and dynamic systems. The proposed algorithm that uses the 'similarity' equation is explained in full detail in this chapter.

Chapter 4: Experimental Design

This chapter presents the plan and the design of the experiments which we used to evaluate our proposed dynamic adaptive e-learning system and the static adaptive e-learning adaptive system. Experiments, our hypothesis, and the methodology and procedures that should be used to evaluate the effectiveness and flexibility of our adaptive systems are explained in full detail in this chapter.

Chapter 5: Development of Dynamic Adaptive E-learning System

To answer the third research question, we developed and implemented static and dynamic adaptive systems. The developed systems are based on our proposed dynamic algorithm using the learning management system ‘Moodle’. The Moodle system is described in this chapter first. Then we describe how it is extended to include our proposed algorithm.

Chapter 6: Evaluation of the Experiments

This chapter starts with a critical review of the hypotheses against which the performance of our dynamically adaptive system was evaluated. To evaluate our proposed system, we designed an experiment to test the hypotheses. We discuss in this chapter the criteria upon which the experiment's participants were selected. In addition, we explain how these participants were divided into three independent groups. Two groups were assigned to test a static adaptive system and the dynamic adaptive system, whereas the third group was used as a control group. To evaluate the effectiveness of the proposed approach, a pre-test, a post-test, and the time spent in learning a concept was taken into account to test our hypotheses. Methods for statistical data analysis, such as ANOVA and t-test, are used to analyze the experimental results. The findings of the experiments are discussed in more detail in this chapter.

Chapter 7: Conclusion and Future Work

This chapter concludes the thesis by presenting a summary of results obtained throughout the PhD work and discusses the possible route for future work. The focus of the work in this research is to propose a means of demonstrating and ultimately investigating different styles of presentation and adaptation mechanisms to extend adaptability to make it dynamic. We introduced a similarity algorithm to produce a dynamic adaptivity mechanism. We have provided experiments as evidence relevant to our thesis hypotheses. The experimental findings show significant positive

influence for a dynamically adaptive e-learning system based on learning styles and students learning performance. The significance of this research offers ground for further investigations into the value of using dynamically adaptive systems in the previously researched area of comparing the positive effects of incorporating learning style theories within the learning process.

In future work, there is much still to be learned about how the use of assessments of learning styles, based on learning theory principles, may affect learners' performances in adaptive e-learning systems. Research in this area needs a better knowledge and understanding of learning styles to explore the correlation between learners' learning style and course content presentation.

Chapter 2

Background and Related Work

This Chapter presents a review and analysis of current e-learning management systems and adaptive hypermedia systems for E-learning.

2.1 Adaptivity in Education

Using a computer with Internet and World Wide Web (WWW) access, learners can have access to various educational resources around the world, including library catalogs, campus information systems, databases and archives. The rapid growth of information and knowledge resources on the Internet may cause confusion to learners who may experience difficulty in focusing their purpose and goals in their search for knowledge. Learners need to self-direct their learning processes to suit their learning level and personality. Much research effort is being targeted towards adapting learning in such a way that it fits each individual. The following sections explore the field of adaptive learning in E-education.

2.1.1 Adaptive Learning

Adaptation in learning means personalizing the learning environment or learning process to facilitate or accelerate individual learning performance in a dynamic way. Adaptivity means the ability of the learning system to detect differences in individual learning approaches, in terms of knowledge level, preference of learning styles, cognitive ability, goals etc. (Graf, 2007, AHMAD, 2016) Another definition of adaptive learning is that it is a form of on-line learning where the presentation of the content material can be varied according to an individual's preferred learning style. The material may be available in different formats such as text, graphics, audio or video, and an adaptive learning system would then be able to automatically select the most appropriate style for a given learner. The potential of adaptive learning is to accelerate learners' performance in achieving their goals, reduce time spent in learning, facilitate instructions, or improve learners' scores or knowledge.

2.1.2 Adaptivity in E-learning System

Originally, e-learning meant learning using computers which mainly provided the electronic delivery of lecture notes and other text, audio-visual material, solved problems, assessment exercises and other largely non-interactive media, as may be read from a CD-ROM or non-interactive web sites (Monahan et al., 2008, AHMAD, 2016). Provision of feedback from human tutors and on-line discussions was the main mechanism for interaction. As illustrated by Figure 2.1, reproduced from (Peretto et al., 2008), early approaches to e-Learning were

generally based on providing web-based teaching aids presented as text files or graphic presentation notes for online self-study. As the bandwidth available to Internet users increased, online courses with material presented using audio and video in more sophisticated forms became possible. (Peretto et al., 2008). The use of e-mail, text-based instant messaging, 'chat' and whiteboard facilities has always been part of e-learning, but with the enhanced Internet access, on-line real time voice telephony, audio visual conferencing and interactive live classes have been increasingly used. Simulating the interaction between real teachers and typical students under different conditions may be used in many contexts, from simple text-based interactions to the use of full interactive multimedia and 3D graphics to allow learners to interact in an online virtual reality environment (Dron, 2007).

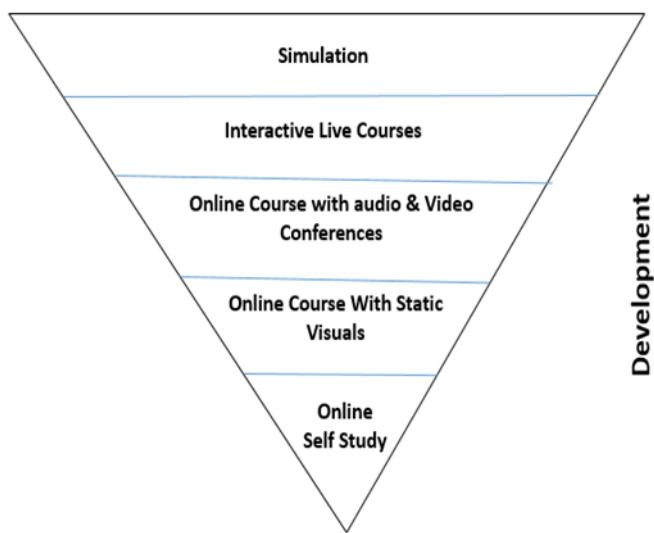


Figure 2.1 E-Learning Stages

Within the field of e-learning, a 'learning platform' is commonly referred to as an 'e-learning platform', a 'Learning Management System' (LMS), a 'Course Management System' (CMS) or a 'Virtual Learning Environment' (VLE). Ardito et al (2006) defined an e-learning platform as "a more or less complex environment with a number of integrated tools and services for teaching, learning, communicating, and managing learning material".

As the Internet and network based technologies have developed, e-learning platforms are now able to support more advanced collaborative environments and educational material. These advanced platforms can better support the process of learning and enable educators to better provide for the needs of online students and hence to improve their teaching (Peretto et al., 2008, Rego et al., 2005). Now, e-learning platforms provide greater authoring tools for teachers to design online courses and better manage the distribution of online courses

materials and assignments. These platforms provide learners with ready access to course material and encourage them to use the available communication tools. A course designer has facilities for creating assignments quizzes, discussion forums, video conferencing sessions, chat and many other online teaching aids. Administrative functions are provided for managing and allocating learning resources, dealing with student registrations and monitoring and keeping track of their progress and performance.

Most LMSs are used for distance learning or to enhance learning within institutions. Currently, universities are adopting LMSs to deliver traditional courses as part of daily communication with their students. There are a number of commercial LMSs that can be used as e-learning platforms such as WebCT, BlackBoard (Godwin-Jones, 2003), Lotus LearningSpace, and Moodle (Dobrza ski et al., 2006). These platforms are widely and successfully used to manage the delivery of self-paced online courses, but they are not built on a specific pedagogical strategy (Rego et al., 2005). The applied pedagogical strategies in LMSs focus on how to teach learners from a general point of view, without considering the individual needs of learners and their preferred learning styles (Bartlett-Bragg, 2008, Graf, 2007).

2.1.3 Adaptivity in Intelligent Tutoring System

The term intelligent tutoring system (ITS), widely used in the educational domain, is an example of adaptive system. Intelligent tutoring systems focus on the use of techniques from the field of artificial intelligence to provide the learner with better support in solving problems, hence, improved learning experience. For example, when an ITS program detects that a learner has a weakness in solving a particular problem, the program repeatedly asks him/her to solve similar problems until he/she achieves the passing score.

Brusilovsky (1994) proposed four modules that he believed are essential to provide personalized content for learners in ITS:

- The *student module*, which is responsible for finding out the current intellectual level of the student for building and updating a student model.
- The *expertise module*, which is responsible for the domain knowledge and selecting the required knowledge according to the current level of the student module.
- The *tutoring module*, which operates according to the student module to provide information about how the learning material, available from the expertise model, can be presented in an appropriate way considering the individual needs as identified by the student module.

- The *Interface module*, which controls the ways in which the ITS and the learner can exchange information and mutually interact

2.2 Adaptive Educational Hypermedia System

In a hypermedia educational system, learners can be motivated to explore many different navigational paths through the domains of knowledge. Adaptive hypermedia systems offer an alternative approach to the traditional "one-size-fits-all" approach. The aim of adaptive hypermedia systems is to provide hypermedia content that fits the individual needs of each user. Towards this aim, a new generation of educational hypermedia systems has been proposed, called Adaptive Educational Hypermedia Systems (AEHSs) (Brusilovsky, 1996). According to Brusilovsky's definition (1996), an adaptive hypermedia system is a system that adapt to each learner's individual personality. It constructs a model of the goals, needs, objectives and prior knowledge of each individual learner, and uses this model to control the interaction with this user. The aim of an AEHS is therefore to deliver personalized learning support. The adaptive dimension of these systems is about modifying the content and appearance of the hypermedia according to the knowledge level, goals and other characteristics of each learner.

Adaptive educational systems behave differently for different learners or groups of learners according to information accumulated in the student models (Brusilovsky and Peylo, 2003). With AEHS, the learners can be given the freedom, themselves, to dynamically construct or adapt the presentation of material according to their needs, whereas in ITSs the presentations are typically pre-determined (Hatzilygeroudis and Prentzas, 2005).

2.2.1 Adaptive Hypermedia Core Elements

In most adaptive educational hypermedia applications, a learner model is the basis for the adaptation of the previously given parameters of the learning process. The first stage in the adaptation is to extract the most important characteristics that were collected in each learner profile to determine a learner model. Thus, the adaptation system presents learning instructions based on the learner model constructed in the first stage. Figure 2.2 illustrates the adaptation process in an adaptive educational system.

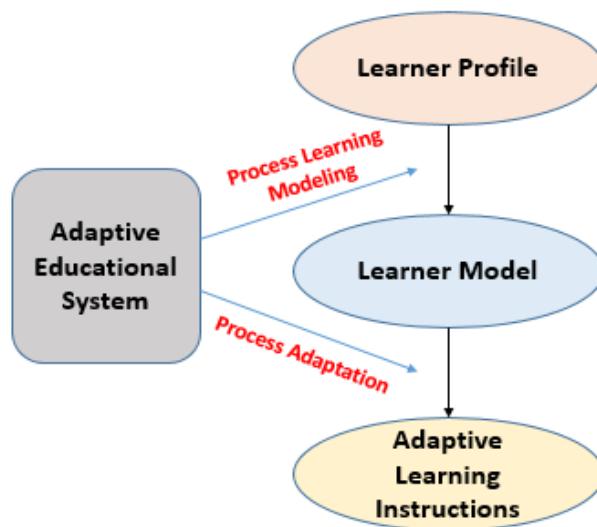


Figure 2.2 Adaptation Process in Adaptive Educational System

Oxman et al. (2014), Martins et al. (2008), and Nguyen et al (2008) identified three important adaptive components: Learner Model, Domain Model, and Instructional Model, described in the following.

2.2.1.1 Learner Model

A Learner Model is a high level representation of a learner's profile.. A learner's profile consists of personal information about the learner, such as his or age, sex, preferences, and goals. It does not try to infer or predict any other information about the learner. Learner models are key factors in determining how to adapt the learning instructions and content to the needs of an individual learner. The learner model describes the learner in such a way that the domain model and instructional model have the information needed to allow them to present content learning to learners according to their needs. Some adaptive systems make statistically estimated inferences about the learner's knowledge, based on their information in the personal profile. Other adaptive systems track the learners' performance and knowledge in the system and update the learner model with the new information continuously. Brusilovsky (1996) identified two ways of building student models: collaborative and automatic. In collaborative learner modeling, the data are collected explicitly from the user via forms or questionnaires, or the learner provides clear feedback about his or her preferences. In automatic learner modeling, the data are collected implicitly by the system via monitoring the users' actions and learning styles behaviour when they are using the system for learning. The modeling may be 'static' or 'dynamic'. In static learner modeling, the data are usually collected only once when the learner registers for an online course. In dynamic learner modeling, the student model is updated regularly according to the learners' actions and responses during their progress in taking the course. A study by

Chrysafiadi and Virvou (2013) surveyed a literature of student modeling in the last decade to identify and present the most common approaches available. They presented nine approaches and techniques for predicting and diagnosing student models. One of these is the ‘overlay model’, which identifies the student’s knowledge level for each element in the domain model. The ‘stereotype model’ clusters students into groups according to their shared common characteristics. The ‘machine learning model’ is for characterizing students’ behavior and actions in the system using automated induction. Other models are as follows:

2.2.1.2 Domain or Content Model

This model defines the content material and the way it is structured. Some systems represent the ‘domain’ or ‘content’ as a set of concepts expressed in the form of different definitions and tasks. Each concept represents an element of knowledge and associated consequences and outcomes. Other systems represent the domain or content as pre-arranged sequences of learning objects. The system should determine which part of the content is appropriate to a specific student, based on the student learner model. A domain or content model is usually represented in the form of a graph (Triantafillou et al., 2003, Brusilovsky and Millán, 2007)

2.2.1.3 Instructional or Interaction Model

This model contains the selection rules for the concepts or objects in the domain model. It has the ability to select an appropriate concept for a given student at each stage of his or her study session. It defines the interaction between the user model and the domain model. According to (Oxman et al., 2014), there are two essential types of instructional models for selecting the rules for adaptive learning systems:

- ***Rule based selection*** using conditional ‘if-then’ logical decisions. This approach builds its system as a branching architecture. This approach is clear and simple, however, it becomes more and more difficult to process the branches as the number of components of the domain model increases.
- ***Algorithm based selection*** using mathematical functions to analyze students’ actions in the domain model. This approach is considerably more complex than the Rule Based technique. Algorithm based selection often uses machine learning techniques to learn more about the contents and the students’ behaviour. These techniques employ highly complex algorithms for predicting which choice of content is likely to be most successful in terms of learning outcomes.

The following subsections will discuss popular existing techniques for providing adaptive content in adaptive hypermedia. Several AEHS systems are then introduced which adaptively provide content based on assessments of learning styles.

2.2.2 Adaptive Educational Systems Incorporating Learning Styles

This section presents a number of the adaptive educational hypermedia systems that employ learning styles for adaptivity. The overview of the selected systems highlights the differences between these systems focusing on how the systems collect data about the learners and which features they are using to provide adaptivity.

CS383 (Carver et al., 1999b) is one of the first adaptive educational hypermedia systems that incorporated the Felder-Silverman learning style model. The system is based on three of the four dimensions of the FSLSM model (sensing/intuitive, visual/verbal, sequential/global) to provide adaptivity. At the beginning of the course, the students are assessed explicitly by applying the Felder-Solomon Index of Learning Styles (ILS) questionnaire for identifying preferred learning styles. The result of the questionnaire is stored in the student profile. The developed Hypermedia of CS383 (Carver et al., 1999c) provides a comprehensive collection of media objects to support the transfer of information such as, slide shows, hypertext, lesson objectives, a response system, a digital library, digital movies, and audio. In the CS383 system, each media type was rated on a range level from 0 to 100 to determine the degree of support to each learning style. For example, the digital movie supports the visual person by 100, verbal by 80, sequential by 40 and global by 30. This rating number is stored in the student profile to produce an HTML page containing an ordered list of the lesson media elements. The lesson is presented to each student in a sorted list ranked from most to least conducive based on the identified learning styles as stored in the student profile. The system offers the student the option to re-order these objects in an arrangement that they consider suitable to their individual learning styles. The student then sequentially selects the lesson media element links to explore the course material in the determined order (Carver et al., 1999c). The adaptation is therefore done at the presentation level by sorting media elements according to suitable learning styles (Popescu et al., 2007b).

Task-based Adaptive learner Guidance On the Web (TANGOW) (Paredes and Rodriguez, 2004), is a system based on two dimensions of the FSLSM: sensing/intuitive and sequential/global. The system is designed for building web-based courses on the basis of teaching tasks and rules. Tasks are represented by teaching knowledge that needs to be achieved. Tasks such as examples and practical work can be accomplished by the students. Tasks are arranged by rules which determine how the tasks are combined together. The rules

are used to facilitate the description of a course. When a learner logs into the system for the first time, he/she is asked to fill in an ILS questionnaire. The result of the questionnaire that identifies learning styles is stored in the learner model. The learner model is automatically updated by monitoring the students' actions in the course. The content of a course is defined as a list of media elements related to a teaching task. In order to provide adaptivity, the system orders the task and orders the elements within the tasks. According to the task selected by the learner, the system generates the corresponding web page (Alfonseca et al., 2005).

AHA! (Adaptive Hypermedia Architecture) is an open source adaptive hypermedia Web-based adaptive engine for maintaining a user-model which is based on knowledge about concepts (De Bra and Calvi, 1998). AHA!, does not provide any questionnaires. The student models are constructed manually by asking students to state their preferences in learning styles. The students' knowledge is generated either by reading a page in a hypermedia system or by taking a test. Adaptive navigation is implemented by providing links with three possible states: desired, undesired and uninteresting. Links may be uninteresting because the information has been visited and does not represent new information to be learned. Undesired links may provide information for which prerequisites have not been covered. Adaptive presentation is implemented through inserting and removing fragments or altering fragments. In the AHA system, the authors have much flexibility in choosing their instructional strategies for identifying how learning style preferences can be inferred from students' browsing behaviour. If the student model information does not match their browsing behaviour, the learner is asked to change the instructional strategy (Stash et al., 2004).

A study by (Graf, 2007) provides adaptive support with respect to learning styles in LMS. The study extends the 'Moodle' learning management system (Moodle, 2009) with the capability of identifying student learning style. The study involved 235 students who studied a course on 'object oriented modeling' using the Moodle system with extended adaptation capabilities. The learners completed the online ILS questionnaire and were then classified according to three of the four FSLSM dimensions, active/reflective, sensing/intuitive and sequential/global. Next, they were randomly divided into three groups: 'matched', 'mismatched' and 'standard'. The time spent in the system, the number of logins and the number of visited learning requests for additional learning objects were recorded and analyzed. An automated approach is used to construct the student model. The proposed approach identifies the student learning styles according to the student learning styles and actions with Moodle considering the commonly used features in Moodle such as content

objects, outlines, examples, self-assessment tests, exercises, and discussion forum. Student actions are recorded and then analyzed using two approaches for inferring learning styles: a data-driven approach using Bayesian networks and a literature-based approach using a simple rule-based method for inferring learning styles. Each learning style dimension is mapped to a relevant pattern. The adaptation is done based on ordering the learning resources i.e. examples, exercises, self-assessment tests, content objects according to the students' preferences. The study found significant differences in the learning time between the matched group and the mismatched group and also between the matched group and the standard group. Furthermore, the study found a significant difference in the number of requests for additional learning objects between the matched group and the mismatched group.

2.2.3 Methods and Techniques of Adaptive Hypermedia

Brusilovsky (1996, Brusilovsky, 1999, Brusilovsky and Peylo, 2003) distinguishes two major technologies in AHS: adaptive presentation and adaptive navigation support. The aim of adaptive presentation technology is to adapt features based on content, such as adaptive multimedia presentation, adaptive text presentation, and other information stored in the student model. Pages of educational material are adaptively generated or gathered from different sections according to the needs of each learner (Papanikolaou et al., 2002). In a system with adaptive presentation, the adaptivity is at content level, with selections dynamically based on the learner model (Eklund and Brusilovsky, 1999).

The aim of adaptive navigation support technology is to support the student to find the most relevant path in hyperspace. Adaptive navigation is based on links and includes features such as map adaptation, as well as adaptive sorting, hiding, annotating and generating of links. In a system with adaptive navigation, the page-link level adaptivity is static in content but alters the appearance of the links (Eklund and Brusilovsky, 1999).

A study by Bajraktarevic et al (2003) suggested an experiment on sequential/global adaptation based on Felder-Silverman, to show that students can benefit from learning material being adapted to suit their learning preferences. The authors applied two adaptation techniques i.e. adaptive presentation and adaptive navigation, in designing hypermedia courseware to accommodate preferred learning styles.

Figure 2.3 reproduced from (Bajraktarevic et al, 2003), illustrates an example of the global and sequential page layouts. For students with a global learning style preference, pages contain elements such as a table of contents, summary, diagrams as an overview of

information. For sequential students, the pages contain small chunks of information and text-only pages with ‘forward’ and ‘back’ buttons.

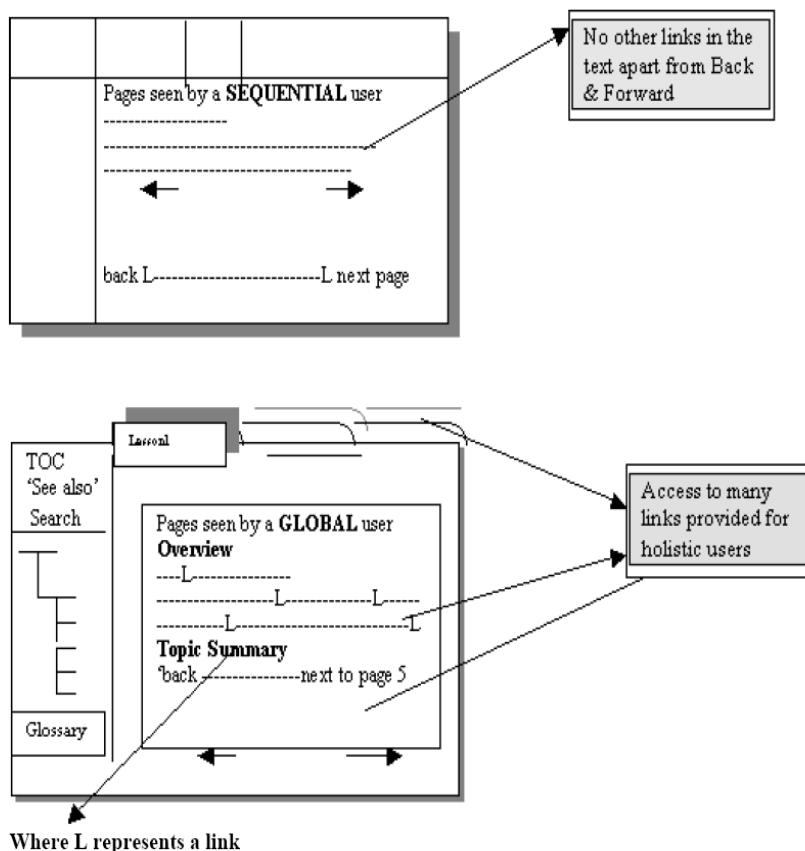


Figure 2.3 User Interface Templates (Sequential and Global)

2.3 Learning Theories

Learning theories try to explain how people think and what features control their learning behavior. ‘Socratic’ learning dictates that the instructor and student should engage in an active dialog as a guide to encourage learners to construct their own understanding. The role of the instructor is to translate and transform information to be learned into a format suitable to the learner’s current state of understanding (Laurillard, 2002, Tweed et al., 2002). In the literature, learning theories have evolved from ‘constructivism’, which is concerned with how the learner creates his/her own meanings, to ‘behaviorism’, where the learner is considered as an empty vessel to be filled with knowledge, and later to ‘cognitivism’, which studies how processing occurs within the brain based on the inputs of knowledge. The different learning theories can be used to guide the development of a teaching and learning process taking into account different phenomena such as learning styles.

Constructivism, one of the big ideas in education, is a philosophy of learning as a process in which the learner's knowledge is constructed through her or his own experience. The learners in constructivism theory are active learners who build new ideas or concepts upon their own knowledge and performance (Jonassen et al., 1995).

The theory of 'behaviorism' was mostly developed by B. F. Skinner (Skinner, 1974) and is concerned with the study of human behaviour rather than mental behaviour in which no concrete knowledge is possible. Behavioral theorists view the learning process as correlation between stimuli producing the correct responses and behaviour change (Downs-Lombardi et al., 2004). In the classroom, the teacher roles is to guide the student to the correct learning behaviour (Downs-Lombardi et al., 2004). Implementing behavioral theory in e-learning systems involves the creation of learning systems, which present appropriate learner stimuli, observe and measure the behavioral responses and try to ensure that the stimuli encourage behaviour patterns that are known to associate with successful learning.

In the early 1950s, learning theory trends started to shift from focusing on behaviour to taking the 'cognitive' approach (Ertmer and Newby, 1993). Cognitivism theory focuses on the student mind as an active organized processor of how information is received, stored, structured, and retrieved (Ertmer and Newby, 1993). In addition, it is concerned with how learners process information in the mind and tries to discover and model the learners' mental processes during the learning process. Comparing cognitive behavioral learning theories, cognitivists prefer to concentrate on how the learner receives information, whereas behaviorists focus more on the design of the environment in which the learner exists (Ertmer and Newby, 1993).

Many learning style models have been published in the literature. The following section discusses the most common used learning styles models in e-learning systems and their features.

2.3.1 Learning Styles

Once a course syllabus has been finalized, teachers must decide how best to teach the material. There will usually be many ways of explaining a given topic and the best method will be different for different learners. In traditional classrooms, educators have always needed to employ a variety of teaching styles and adapt the chosen style to the apparent needs of the majority of the class. Reactions are often hard to judge with large classes, though trends are often observed by teachers who teach the same material from year to year. One year, a particular approach may work well and the following year, with a different group of students, the same approach with the same material may not work quite so well. There may,

of course, be many different reasons for this difference. In one-to-one teaching, a teacher can be more receptive to the student's needs as judged by his or her reactions and apparent understanding. Disregarding the personal preferences of the teacher, there will likely be identifiably different learning styles from student to student. The differences may be due to the nature of the material, the style of the teacher, the time of day (i.e. state of freshness or tiredness) and many other factors. However, there are believed to be characteristics within the personalities of most students that predispose them to particular ways of learning. According to many theories of learning, there are considered to be identified by different learning styles that are adopted by people when they approach new ideas.

Educational researchers have recently started to focus on how to personalize e-learning environments using aspects of personal characteristics such as the preferred learning style of the student. Adaptive educational systems address personal learning issues by providing learners with courses that fit their individual needs and characteristics such as their normally adapted learning styles. Messick (1976) defines learning styles as "characteristic modes of perceiving, remembering, thinking, problem solving and decision making".

The study of learning styles has many features that have led to different concepts and views. The most common learning style theories cover three main features of how people study: how the learner perceives information, how the learner processes information, and how the learner reacts to the way the information is presented.

In the literature, many learning style models have been published, many proposing different scales and classifications of learning styles. Learning styles and their influence on learning have been examined carefully by Coffield et al (2004b). They identified seventy-one models of learning styles and classified thirteen of them as the most famous models in view of how commonly they are used, their theoretical significance in the field and their influence on other learning style models. The selection of these models was based on Coffield's review (Coffield et al., 2004b, Coffield et al., 2004a), the fact that they are among the most cited theories and the fact that many researchers in e-learning have referred to and used these theories in recent publications. The selected theories are those of Kolb (1984), Honey and Mumford (1982), and the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988a). The following subsections review the above mentioned learning style models and the methods that may be used to characterize each learner's preferred styles of learning.

2.3.1.1 Kolb's Learning Styles Model

The learning style theory by Kolb (1984) is based on Experiential Learning Theory, i.e. learner's knowledge is created during the change of experience through the learning process. Kolb identified learning cycles as four stages:

- Concrete experiencing
- Reflective observing
- Abstract conceptualizing
- Active experimenting

As illustrated in Figure 2.4 Kolb's learning style model categorizes learners in two dimensions: the concrete-abstract dimension and the active-reflective dimension. The four poles of this diagram are considered to represent four different types of learning styles: diverging, converging, assimilating and accommodating.

Diverger learners are concrete experiencers and reflective observers. They look at things from various scenes. Diverger learners are sensitive and prefer to watch rather than to do, prefer to gather information first and then use imagination to solve problems. They are best at viewing real situations from several different points of view. Learners with this style tend to be more creative and like to work in groups.

Converger learners are abstract conceptualizers and active experimenters. Learners with a converging learning style are best at finding practical uses for ideas and theories. They prefer technical tasks. Learner prefer to work by themselves, thinking carefully and acting independently.

Assimilator learners are abstract conceptualizers and reflective observers. Their greatest strength lies in the cognitive approach, preferring to think rather than to act. Learners with this style prefer readings, lectures, exploring analytical models, and having time to think things through.

Accommodator learners are concrete experiencers and active experimenters. They are opposite to assimilators in that they prefer the 'hands-on' approach, and learn best from 'doing' rather than just 'thinking'. They tend not to like lectures and routine and do like becoming involved in new experiences.

Kolb's learning style model is associated with the Learning Style Inventory (LSI) which was developed by Kolb (1976) for identifying learning styles. Learners are asked to complete 12 sentences about their preferred way of learning. Each sentence has a choice of four points and the learners are asked to rank the points according to what best describes how they learn

(4 = most descriptive of you; 1 = least descriptive of you) (Cassidy, 2004). The Kolb learning cycle 'Experiential learning' can be applied to any kind of learning through experience approach.

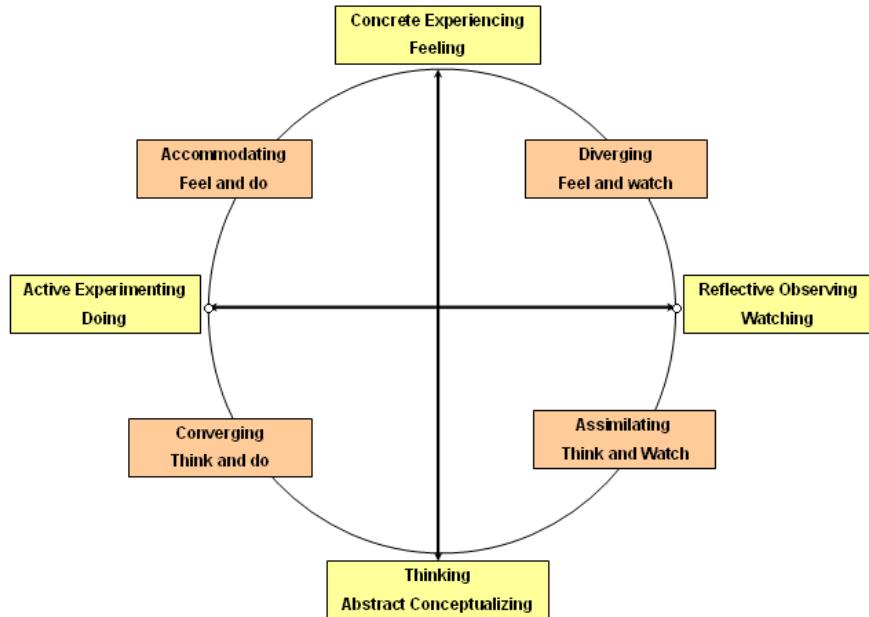


Figure 2.4 Kolb's Learning Style

2.3.1.2 Honey and Mumford's Learning Style Model

The learning style model by Honey and Mumford (1982) is based on Kolb's Experiential Learning Theory idea. The model distinguishes between four types of learner:

- Activists
- Reflectors
- Theorists
- Pragmatists

Activists prefer the challenges of new experiences, involvement with others, and learn best by doing something actively. Active learners like new things, problem solving, and discuss things with a small group. *Reflectors* learn best from activities where they have time to think before acting.

Reflectors like to watch other people and gain their experiences from many different perspectives to establish and maintain a 'big picture' perspective.

Theorists prefer to think problems through in a step-by-step manner. They like attending lectures, studying analogies, analyzing systems, considering case-studies, understanding models, and reading published papers. They like to explore the deepest relationships between

ideas, events and situations. They need models, concepts, and facts in order to engage in the learning process.

Pragmatists are interested in putting ideas, theories and techniques into practice quickly, and are efficient and innovative in searching for new ideas and experiments. They act quickly and confidently on ideas, and prefer to get straight to the point.

For identifying learning styles according to Honey and Mumford's model, a Learning Style Questionnaire (LSQ) is available. It is directly derived from Kolb's theory. The LSQ was initially developed in 1982 (Honey and Mumford, 1982) and has been revised several times (Honey and Mumford, 2006). Has two versions of the LSQ exist, one with eighty items and one with forty items. Each version has particular advantages, depending on the learners' needs and situation.

2.3.1.3 Felder-Silverman Learning Styles Model

The Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988a) classifies an individual's preferred learning style according to the ways he or she receives, processes, perceives and understands information. These are the four dimensions of the FSLSM model. For each dimension, there is a sliding scale, which quantifies the extent to which: perception is sensing as opposed to intuitive, reception is visual as opposed to verbal, processing is active as opposed to reflective, and understanding is sequential as opposed to global. Figure 2.5 illustrates how learning styles are classified according to the four dimensions of the FSLSM model. This should be seen as a four-dimensional rather than a two-dimensional graph. A sliding scale quantifies each dimension by a 'score' in the range -11 to +11.

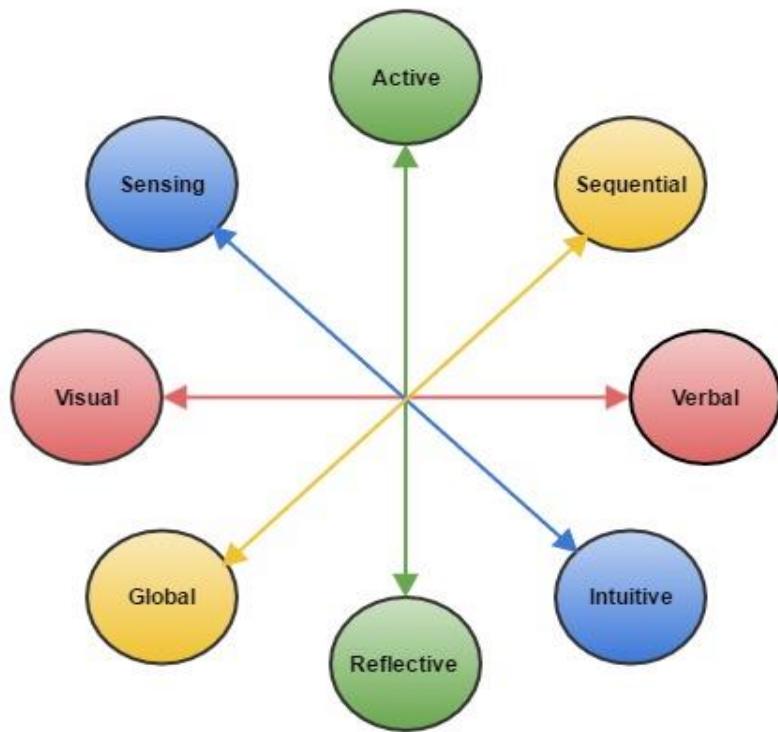


Figure 2.5 Felder-Silverman's Learning Style Model

The Index of Learning Style (ILS) is an on-line instrument designed for assessing preferences in the four dimensions of the FSLSM model. Felder and Silverman characterize a person's learning style using a scale from +11 to -11 for each of the four dimensions. Each learner is assumed to have a personal preference, to some degree, in each dimension, though the scales allow 'zero preference' indicating that a learner does not have a specific preference in one or more dimensions. Using the active-reflective dimension as an example, the value +11 would represent a strong preference for active learning and the value -11 would indicate a strong preference for reflective learning (Felder and Spurlin, 2005). Each learner's style is therefore characterized by four integers each between +11 and -11. Felder and Silverman consider the resulting preferences as tendencies rather than fixed predictions of behaviour, meaning that even if a learner is modeled with a strong preference for a certain way of receiving, processing, perceiving or understanding learning material, he/she must be expected to react differently on some occasions for a host of different reasons (Graf et al., 2007).

Table 2.1 shows the preferred learning way according to Felder and Silverman learning styles model (1988b) explanation for the four dimension:

Table 2.1 Felder Silverman Learning Styles Model

| Learning Styles | Preferred learning |
|-------------------|---|
| Active | Learn by doing things or experimentation and work in group |
| Reflect | Learn by thinking and reflect on the issue |
| Sensorial | Learn by fact and given a detail method |
| Intuitive | Theoretical, find possibility and relations |
| Visual | Picture, graph, video, flowchart |
| Verbal | Text and audio |
| Sequential | Logic step- by-step |
| Global | Given big picture and jumping from one topic to another in a nonlinear path |

The *active-reflective dimension* (related to information processing): Active learners like to learn and understand information best by doing active things, such as discussing work with group or practicing it or trying to explain it to other people. Reflective people prefer to reflect on the issue before assuming any practical posture. Active learners tend to like group work more than reflective learners, who prefer working alone.

The *sensorial-intuitive dimension* (associated with information perception): Sensing learners tend to like to be presented with facts, and details of well-behaved methods, while intuitive learners often prefer to discover possibilities and relationships between ideas themselves. Sensing learners are fond of details and are very good memorizers of facts and practical applications. Conversely, intuitive students like working with abstractions and formulae, which allow them to understand new concepts quickly and perform new tasks.

The *visual-verbal dimension* (referring to information retaining): Visual learners remember best what they see such as pictures, diagrams, flow-charts, films, and demonstrations. Verbal learners' personal learning processes are driven by written or spoken explanations.

The *sequential-global dimension* (referring to information organization): Sequential learners prefer to construct their learning process step by step following logically from the previous one and focus on a final goal. In contrast, the learning processes of global students are characterized by discrete steps or jumps, sometimes in apparently random directions. Global learners have the ability to solve complex problems quickly or put things together in novel ways once they have understood the big picture, but they may have difficulty explaining how they did it.

In our proposed adaptive learning system, we used Felder-Silverman learning styles model (FSLM) because it identifies the learning styles characteristics elaborately and can be easily applied in our adaptive framework. The current version of ILS questionnaire is considered valid, reliable, and suitable (Felder and Spurlin, 2005, Zywno, 2003). FSLSM is more applicable for technology education. Furthermore, the ILS questionnaire is most suitable and feasible to be implemented in adaptive hypermedia system (Zywno, 2003)

2.4 Dynamic Adaptive Educational Systems

Recently, several research projects have focused on creating dynamically adaptive educational systems that automatically generate learning instructions or content based on the learner model which is updated frequently. Research by Anh Nguyen and Dam Ho (2006a, 2006b) developed an Adaptive Course Generation system (ACGs) for adaptive course delivery, which was designed and implemented at the Faculty of Information Technology, College of Technology, Vietnam National University, Hanoi. It is a simple adaptive e-learning system presenting material according to an adaptive web-based curriculum sequencing process. The adaptive course is created based on the student's ability and background. An 'intelligent agent' is used for each student to assess his/her background and generate an adaptive content sequence based on the assessment outcome. Each student using the ACGs should be registered in the system, and will be required to answer some questions and do some tests designed for evaluating their background and knowledge and thus providing information for a Learner model. Then, for each student, ACGs generate an adaptive course based on his/her learner model. ACGs has a Learner Agent (LA) devoted to each learner to the update learner model information of the student during the course. During the student progress in the adaptive course, testing and evaluating students is implemented by an Evaluate Learner Package (ELP). Results of the student evaluation are stored in the learner model. The evaluation task is carried after each unit of knowledge is completed. Results of evaluations are updated in the learner model by the LA. The authors built ACGs in a web-based application and experimentally evaluated it by means of a survey of opinions on ACGs's properties, involving 70 students. The students were asked about the structure, interface, adaptive ability, and ability to meet the demands of typical learners. The conducted survey indicated that 85% of students considered that the ACGs application provided them with excellent adaptive ability. Anh Nguyen (Anh Nguyen, 2012) improved the ACGs system to ACGs-II . ACGs-II the second phase of ACGs applied a new approach to learner modeling by using two modeling approaches, an overlay model and a Bayesian network (BN). The BN is used to statistically evaluate the learner's knowledge level. The selected adaptive course content is generated based on probabilistic evaluations of the levels of

knowledge and understanding achieved by each student for each concept and their success in completing the tasks. Empirical testing of ACGS-II indicated that the proposed model is helpful in providing guidelines for the development of future adaptive e-learning systems based on probabilistic evaluations of understanding and measures of task completion.

Another study by Anthony et al (2013) developed MyC; an adaptive hypermedia system used by students as a tool to help them in learning C programming. They built MyC to help the University of Malaysia, Sabah, to overcome the problem of big classes for teaching the C programming language. The aim of this study was to determine whether students using an adaptive system based on their level of knowledge and assessments of their preferred learning styles could help them to understand the programming language. In addition, they examined the use of the Honey and Mumford learning style Model to help students in their technology education.

The framework for MyC was derived from the ‘Adaptive Hypermedia Architecture Model’. It consists of a user interface in the form of a web browser, a web server and a database to store the information for learning models which include ‘adaptive profiles’ and ‘user profiles’. Each student using MyC is asked to fill in a two-part questionnaire. Part 1 consists of 10 questions for identifying the student's level of knowledge. Part 2 consists of 80 questions based on the Learning Style Questionnaire (LSQ) for the Honey and Mumford Model (Honey and Mumford, 1982). Based on the outcome of these questionnaires, students are divided into three levels (excellent, average, and poor) and four learning styles ('theorist', 'reflector', 'activist' and 'pragmatist'). According to these two classifications, the students are grouped into 12 categories such as 'theorist-Average', 'theorist-Advanced', 'theorist-Poor'. They identified four learning models based on the four learning styles of Honey and Mumford: Activists, Reflectors, Theorists, and Pragmatists. The experiment was conducted over a period of five months during a normal semester for students taking an introductory course in the C language.

They divided the students into two groups: control group and experimental group. For the experimental group, the MyC system was based on their preferred learning style. For the control group, the MyC system was based on a fixed learning model. The experiment was used to assess the adaptive educational system, MyC, by using the Honey and Mumford learning style model. The findings of this study were that the experimental group performed better than the control group. The study suggests that presenting the students with learning content according to their learning styles can lead to a more successful and accelerated learning process.

A recent study by Dominic et al (2015) presented a design for an adaptive e-learning system framework which personalizes the learner's learning experience in an efficient way. The aim of this work was to present an adaptive system that can adapt learning contents and learning sequences based on the student's characteristics obtained from a series of tests. The proposed framework realizes adaptivity by using four models:

- Learner Preference Model
- Case Based Reasoning Model
- Simplex Model
- Learning Object Repository Model

The learner preference model infers student' characteristics from the series of test conducted on the student to identify student's preferred learning styles, Learners' Subject competency level , personal profile, and the Perpetual ability and reasoning skills. This model also indicates whether the student requires to be presented with a new set of paths based on his/her preferences or whether the student is low-level subject competent. When a new student accesses the system, the learner preference model identifies his/her level of subject competency. If this level is low or if the student prefers to use the 'author selected path', the adaptable system uses a 'Static Learning Path' model to present the learning content sequences. The 'case based reasoning model' searches the system repository which contains a set of learning paths which students have went through. The Simplex Model generates the new 'dynamic learning path'. All the new generated learning paths are stored in the case based repository and presented to the new student. Each learning path is read and rated by the student, the rating being returned to the repository. The simplex model generates a collection of feasible learning paths and presents all to the student who can choose any of them or use them all and rate them, subsequently. The system accumulates characteristics of different kinds of learners and their feedback on all the generated optimal learning paths. Then, the system retrieves the highest feedback rate by most students for a suitable learner preference once the system matures.

2.5 Analysis of the Surveyed Adaptive Systems

The goals of the surveyed studies focus on the effectiveness and/or efficiency of adaptation, which are measured through learners' performance, learning time, navigation patterns, and learners' subjective estimation. So far, we have discussed the adaptation methods and techniques used in related work, as well as their adaptation approaches. Different factors are considered in these studies such as the relationship between matching and mismatching

instructional approaches with learners' learning style (Siadaty and Taghiyareh, 2007, Graf, 2007).

Any adaptive system can be decomposed into two relatively distinct parts: the modeling component and the adaptation component. These processes are strongly interconnected, since adaptation decision making is based on the results provided by the student modeling components. Each of the surveyed systems employs varying degrees of an overlay model, which illustrates the student's knowledge of a subject which is a subset of the system knowledge. As the student progresses in the course, the student knowledge subset should grow. The developer of the learner model should keep track of this subset, estimate student knowledge level, and specify whether it is acquired from the system or by other means initiated by the student. It should also record whether the concept is generally well known or relatively unknown (Triantafillou et al., 2003). AHA (De Bra and Calvi, 1998) employs an overlay model where concept-linked attributes are used to represent the learner's current knowledge state. Page visits containing different fragments fire rules that dynamically change these attributes as the learner browses content presented by AHA!. The adaptive approach of CS383 is based on initial assessment of the learning style profiles which then remain stable (Wolf, 2003).

The surveyed AH systems utilize different adaptive mechanisms that operate on student models to produce personalized learning environments. Student models are initialized and estimated manually by students (De Bra et al., 2006). AHA! employs both adaptive navigation and presentation techniques. It uses link annotation to indicate the suitability of a linked page (Bhosale, 2006). This is associated with the concepts in that page and whether the learner model indicates that the learner has met the pre-requisite concepts for that page (De Bra and Ruiter, 2001). Adaptive presentation is achieved through conditional fragments being added or removed from the page. Again, the inclusion or exclusion of fragments is based on comparing the learner model with the domain model (Bhosale, 2006). The disadvantage of this approach to adaptive presentation is that pages a learner has already visited may change without their knowing. For example, if the learner has gained knowledge of a concept that was a pre-requisite to the inclusion of a fragment from a page they have already visited, then they may miss that fragment if they do not revisit that page. AHA! systems use link annotation to denote the suitability of certain learning content. This approach seems to have student acceptance as it does not hide content from them; it simply advises which hyperlink is the most suitable to follow. This form of student guidance introduces no restrictions on what the student can access. This procedure, however, may guide to certain degrees of cognitive overload especially when the student at the beginning

of the course, the learner is introduced with more links that are ill-advised than are advised (Conlan, 2005). Giving the students the freedom to select their learning paths are important, but cognitive overload must be avoided and reduced where possible.

The CS383 study (Carver et al., 1999c) is based on two ideas: developing of the hypermedia courseware and the development of an interface that provides dynamic tailoring of the presentation of course material based on the each student's learning style. The hypermedia course could provide lesson media elements in different formats such as audio, graphics, digital movies, slideshows, and others. The lesson media is presented in a sorted list ranked from the most to least conducive based on the learners' learning style. They use the ILS questionnaire to determine each student's learning style. The CS338 system offers a student the option to order these media objects in accordance with how well they fit her or his learning style. The student is also given the option of exploring the course material either according to his or her learning style or without considering his or her learning style. The key to this approach is the determination of what type of media is appropriate for the different learning styles. No empirical assessment has been carried out to evaluate their efficiency on student performance (Brown et al., 2009).

Graf's (2007) study found no significant difference in the average scores between matched and mismatched groups. CS383 system (Carver et al., 1999c) showed no significant changes in students cumulative GPA but the performance of the best student significantly increased.

The systems TANGOW (Paredes and Rodriguez, 2004) and (Graf, 2007) offered different sequences of alternative contents for the same concepts. In Graf's system, learners with a reflective preference indicated that they preferred to visit examples first and then perform exercises. In the TANGOW system (Ruiz et al., 2008) for Sensitive users, the instruction strategy is led by "example", which means that students are presented first with an example and after that they presented with the other representations of the concept. This is mainly due to the fact that each style has both common and specific content for every concept, and may be different in the way of these contents are presented. The TANGOW system did not show an empirical evaluation of the effectiveness of its adaptation mechanism for students' performance (Brown et al., 2009).

According to (Ruiz et al., 2008), current adaptation systems may be classified into two types. The first type offers each learner a different sequence of materials according to the individual's specific learning style as determined by previous responses to similar concepts. This type is exemplified by the TANGOW system (Ruiz et al., 2008). The second type of adaptation adapts the content's presentation as well as the sequence of concepts via the

navigation process, based on preferred learning style. Both types of system, according to (Carver et al., 1999a), are based mainly on a ‘one-dimensional’ learner model which means that according to the learner’ category style, the course is generated completely before it is presented to the learner i.e. the course structures and sequences are not changed during the learning session. According to (Carver et al., 1999a) the learner models of AH systems should be multidimensional and adaptive as well. The adaptation techniques in all the surveyed adaptive hypermedia systems are focused on content presentation or navigation support, or both. CS383 is the only system with its adaptation focused on the media types such as sound, graphics, or video (Carver et al., 1999a).

The surveyed studies that provide dynamic adaptive educational systems based on the student’s learner model use different techniques and approaches to present adaptivity. In the ACGs system (Anh Nguyen and Dam Ho, 2006a, Anh Nguyen and Dam Ho, 2006b) the adaptation is done based on students’ level of knowledge by using intelligent agents. It is implemented as a simple web-based system and they evaluated its flexibility to the students. Students have a choice to learn using their self-chosen manner of learning or to follow their adaptive system. Specifying the student's level of knowledge is not an easy task. For that, Anh Nguyen and Dam Ho improved their ACGs to ACGs-II. They used a probabilistic Bayesian Network model to quantify the student's level of knowledge with the related concepts and tasks. Our proposed DAELS will be implemented in Moodle, a current learning management system using our proposed ‘similarity’ algorithm to do adaptivity.

The surveyed ‘MyC’ system (Anthony et al., 2013) presents an adaptive hypermedia system that is based on the Honey and Mumford Learning Model. The effectiveness of the system on the student's performance is evaluated by comparing the performances of two groups: a control group and an experimental group, using the Honey and Mumford Learning Model. The adaptation is done statically and does not change during the student progress in the system. Our proposed work, however, presents dynamic adaptation that continuously changes the content presentation based on previous student similarity as it will be explained in Chapter 3.

A recent study by (Dominic et al., 2015) presented a framework for an adaptive educational system that personalizes student learning content based on student learning styles (Felder-Silverman learning model) and other factors such as the Learners’ Subject competency level. Their framework allows students to follow their adaptive learning content paths or follow the author’s static learning content. The low-level rated learning content paths by students will be remove from the system database to accelerate the domain model to generate the

learning content paths. The study did not present an experimental evaluation of its effectiveness on students' performance in learning or the flexibility of the adaption process.

In contrast, our proposed adaptive system will employ machine learning algorithms to accelerate the search for suitable learning content paths to present to our learner in a timely manner. Moodle will be extended to implement our proposed DAELS. Moreover, the effectiveness of our adaptive system will be evaluated using three groups of students:

- 1) Control group that is presented with non-personalized learning content,
- 2) Static group that is presented with personalized learning content,
- 3) Dynamic group that is presented with personalized learning content which may be changed based on the updated learner model.

More details will be presented in the next chapters.

As is clear from the systems introduced above, a variety of learning styles strategies exist and may be incorporated in many different ways in adaptive educational hypermedia systems.

Table 2.2 summarises the adaptive systems mentioned in this Chapter with respect to their applied learner styles, the student modelling methods used, the way they provide adaptive learning content, and the empirical statistical evaluation used to assess system feasibility and its effectiveness on student's performance.

Table 2.2 Summary of the Survey Adaptive Hypermedia Systems

| Adaptive System | Learning Styles | Learner Modeling | Adaptivity methods | Empirical Evaluation |
|---|------------------------|---|--|---|
| AHA! (De Bra et al., 2003, De Bra et al., 2006) | Specified by teacher | Initialized and estimated manually by student and update by adaptive model strategies and rules | Adaptation is performed by creating different adaptive navigation paths, ordering items, and selecting information to present. | No an empirical evaluation has been conducted to evaluate students' performance |
| CS383 (Carver et al., 1999c) | FSLSM | Student Fill in ILS questionnaire of FSLSM | Adaptivity is done by ordering the multimedia content based on student's learning styles | No a formal assessment has been conducted |
| Graf (Graf, 2007) | FSLSM | Automatic approach by Using a rule-based approach | Adaptivity is performed by ordering the course content in different sequences based on student's learning styles | An empirical evaluation has been conducted between three groups: match, mismatch and regular class students |
| TANGOW (Paredes and Rodriguez, 2004) | FSLSM | Students fill in ILS questionnaire to initialize their model and update by an automatic student modelling approach for revising the information in the student model according students behaviour | Adaptivity is performed by altering the order of course tasks and the order of components within the tasks | No empirical evaluation has been conducted |

| | | | | |
|---|---|--|---|---|
| ACGs (Anh Nguyen and Dam Ho, 2006a) | x | Students fill in some questions to evaluate their level of knowledge and update by Evaluate Learner Package (ELP) | Adaptivity is performed by presenting learning contents according to learner model; students can follow the suggested content order or follow their own way for learning | A survey evaluate ACGs in structure, Interface, Adaptive ability, and Meet learner demand ability |
| MyC (Anthony et al., 2013) | Honey and Mumford Learning style Model | Student is asked to fill in a questionnaire of 10 questions to assess the students' level of knowledge in mathematics and programming. And then, the student fill in Learning Style Questionnaire (LSQ) based on Honey and Mumford model | Adaptivity is performed based on students' categorization of learning style and level of knowledge; each student will be presented with their learning modules and the proposed learning path that they should follow | An empirical evaluation has been conducted between two groups: control group and experimental group to show its effectiveness on students learning out comes in individual quiz, midterm and final exam |
| A study by (Dominic et al., 2015) | FSLSM | Student fill in ILS questionnaire first time uses the adaptive system, and then asked to select its competency level from 1 to 4 | Adaptivity is performed based on students' learning styles and students' subject competency level. Student can follow their adaptive learning content paths or follow the author static learning content. Students rate all the suggested learning paths and the low-level rated learning path by all students will be removed from the system database to accelerate the domain model to generate the learning content paths | The study did not show experimental evaluation for its effectiveness on students' performance in learning and its flexibility in adaption process |

2.6 Limitations of Current Adaptive Educational Systems

Despite the success of e-learning platforms in teaching people through the Internet, current e-learning platforms have some limitations. Most of the current e-learning platforms contain fixed pre-designed courses stored in different databases and storage technologies. These courses are accessed by different learners with different background knowledge and learning styles to achieve the same goals (Camacho et al., 2007). According to Weller's (2006) discussion on the future direction of e-learning environments, the characteristics of current commercial e-learning environments have no strong pedagogy. A study by Britain and Liber (2004) investigated a pedagogical framework for the evaluation of e-learning platforms. This study drew the conclusion that their design was not strongly enough based on pedagogical learning models. According to Ravenscroft (2001), the use of technology in education has tended to be "technology-led rather than theory-led". Despite the rapid development of e-learning technology and the Internet, the provision of personalized learning mechanisms for individual learners in e-learning environment is still an unsolved problem in e-learning research (Dolog et al., 2004). Finding the right courses to match the student's interest, learning styles and needs and adapting their delivery during the learning progression is hardly catered for in current e-learning platforms. Several adaptive web-based educational systems have been proposed in the literature but few of them incorporate adaptive learning systems (Graf, 2005).

A study by Chatti et al (2010) asserts that all adaptive intelligent educational systems present knowledge as a static predefined representation. However, student knowledge is dynamic and changes with experience. In addition, the content material is usually generated and organized by instructors as fixed prepackaged content which is not updated while the learner is studying the course. Moreover, in adaptive navigation systems navigation through the course content is linear. That means that each navigated page leads to another pre-specified page and so on. However, learning is a non-linear process. It should be designed to controlled by pre-programmed adaptive teaching engines.

Chatti et al (2010) also specified that adaptive educational systems based on learner models will require a very large number of parameters to be taken into account as important characteristics for the learner. They identified three problems that may affect the building of a robust adaptive educational system.

First, to build a dynamic learner model that can be updated frequently based on changeable characteristics such as knowledge level, cognitive capability, goals, styles, etc. is a complex task.

Second, a student's knowledge level is complex and has many aspects, which should be considered and assessed in an appropriate way to be incorporated in student model.

Third, there is not a unique learner model or style for each student. However, learning modeling approaches and techniques assume that a student uses a single procedure to solve a task. In fact, learners use the most suitable procedures for themselves and these procedures differ based on the task they are undertaking.

A review study by (Akbulut and Cardak, 2012) revealed that adaptive educational systems need a robust diagnostic technique to extract accurate learner characteristics to build an effective learner model. Analyzed studies showed that the majority of current adaptive systems ask the learners about their preferences or ask them to fill in questionnaires to predict their needs and learning styles. These questionnaires can be long and boring, and learners may then not be strongly motivated to respond. Other systems use automatic modeling by tracking learner actions and behaviour. This kind of technique needs more information to build a robust learner model.

A paper by (Dominic et al., 2015) points out that designing and integrating adaptive systems are complex and expensive tasks, and that creating and using learning content is difficult and time-consuming. Learners should have some pre-knowledge to use such systems effectively. The main drawback of many adaptive hypermedia systems, including the ones surveyed in this thesis, is that they do not explicitly consider the reusability of the components used for adaptivity such as CS338 system.

In this thesis, we aim to overcome the above-mentioned limitations by introducing a dynamic and adaptive educational system based on a Similarity algorithm that allows student's models to be dynamically updated. The models are then used for performing content adaptations according to the students' learning styles. In addition, we improve the adaptive system domain model by using a machine learning algorithm to select the appropriate content. More explanation and details about this technique will be presented in Chapter 3.

Chapter 3

Design an Adaptive Learning Mechanism

As we pointed out in Chapter 2, the first step to developing an adaptive system is building the learner model. Therefore, we need a way to accurately capture the personalized characteristics, needs, and learning styles of a student. We start this chapter with a brief overview of the methods that have been proposed in the literature for this purpose. This is followed by our proposed Similarity algorithm and the architectures for our DAELS.

3.1 Review of Learner Model Approaches

Based on the literature review presented in Chapter 2, we can classify the methods being used in modeling learner in adaptive educational systems into two categories: explicit and implicit methods. Some systems use questionnaires for determining the preferred learning style as an explicit method. Other systems use the observed behavior of students as an implicit method.

3.1.1 Explicit Modeling Method

Explicit modeling represents the learning characteristics and needs of each student based on data obtained by requiring each student to answer a series of questions or, alternatively, to enter the model parameters themselves. Most adaptive learning systems use the explicit approach by requiring students to fill out a learning style questionnaire. The main advantage of this approach is its simplicity and the availability of well known standardized questionnaires. However, its disadvantage is the extra amount of work required at the beginning of the course. Some of the questionnaires are quite long and include more than 100 questions. This can decrease the student's motivation to answer the questions accurately, as is clearly necessary to gain a true impression of their preferred learning styles. Some students may not recognize the significance of thinking carefully in answering these questions. They may select their answers by guessing. If the resulting model, as created at the beginning of the session, is not updated further during the student's interaction with the system, it remains a 'static' model. Among the adaptive systems that used 'static' explicit models are those published by (Kinshuk, 2004, Surjono, 2014).

3.1.2 Implicit Modeling Method

Implicit or dynamic learner modeling means that an adaptive system continuously updates the learner model based on the initial preferences of the learner and also his or her subsequent interactions with the system. Adaptive systems use different approaches to update learner

models implicitly. In some systems, explicit feedback is obtained from the learner in the form of a ‘rating’ of their experience and success with the course as it progresses. In other systems, implicit learner feedback and performance measures are obtained automatically by monitoring interactions with the system. The time spent on each learned item, the way the pages are browsed, the frequency of accessing some of the resources and other factors are monitored continuously to provide information for updating the model. The main advantage of this approach is that it removes the need for explicit feedback. The disadvantage is the difficulty of interpreting learner behaviour appropriately to produce a meaningful and useful model. In the literature, many different techniques and approaches have been proposed for modeling learner's behavior implicitly. Bayesian Networks have been used to detect the learning styles of a learner in a web-based educational system (Garcia et al., 2005). Another approach by (Esposito et al., 2004b), they used machine learning techniques to detect students' behaviour and predict their applicable learner profiles to deliver personalized content learning materials that fitting their personal choices.

To devise a static adaptive system, we used an explicit learner model employing the Felder-Silverman Index of Learning Styles (ILS), with its dedicated questionnaire, in order to assess students and determine their preferred learning styles at the beginning of the course. Course content is then presented according to the predicted learning styles for each student's model. In our DAELS we use explicit learner modeling, employing the ILS questionnaire as a first step. This first step initializes the learner model. As a student progress in the system the learner model is updated automatically according to the interactions with the system. This is achieved by means of our proposed implicit learner model which is explained in the next section.

3.2 Proposed Dynamic Adaptive Algorithm

This section describes our automatic approach for updating student models and adjusting the coursework delivery according to their preferred learning styles. The model specifications and assessment tools will be explained in Section 3.2.1. Then, Section 3.2.2 will show how this model is incorporated in our adaptive algorithm.

3.2.1 Learning Styles Model

We focus on the Felder-Silverman learning style model (FSLSM). The model describes the preferred learning style of a learner, distinguishing between preferences in four dimensions (‘process’, ‘receive’, ‘perceive’, and ‘understand’).

In the ‘process’ dimension, the preferred style of a learner may be quantified according to a scale ranging between ‘strongly active’ (11a) and ‘strongly reflective (11b) as indicated in Figure 3.1. It is sometimes convenient to represent the scale as integers between -11 (for strongly active) and +11 (for strongly reflective), though Felder-Silverman prefer an integer in the range 1 to 11 followed by ‘active’ or ‘reflective’. We use ‘a’ for ‘active’ and ‘b’ for ‘reflective’ in this dimension.

In the ‘receive’ dimension, the preferred style of a learner may be quantified according to a scale ranging between ‘strongly visual’ (11a) and ‘strongly verbal (11b) as indicated in Figure 3.1.

In the ‘perceive’ dimension, the preferred style of a learner may be quantified according to a scale ranging between ‘strongly intuitive’ (11a) and ‘strongly sensing’ (11b) as indicated in Figure 3.1.

In the ‘understand’ dimension, the preferred style of a learner may be quantified according to a scale ranging between ‘strongly sequential’ (11a) and ‘strongly global’ (11b) as indicated in Figure 3.1.

There is a strong argument for removing the bipolarity of this model, and instead having 8 dimensions rather than four. However, we have chosen to use the original model as it is widely accepted and well justified in the original paper (Felder and Silverman, 1988a). ‘Active’ and ‘reflective’ are in many senses opposites, and it is considered that a person will not be both strongly active and strongly reflective. Similarly for the other dimensions.

FSLSM provides a well-established ‘Index of Learning Style’ (ILS) instrument with an on-line questionnaire comprising a set of 44 questions. There are 11 questions for each of the four dimensions. Each question requires a choice between two possible answers: (a and b). After processing the answers to the questionnaire, the instrument provides a score (11a, 9a, 7a, 5a, 3a, 1a, 1b, 3b, 5b, 7b, 9b, or 11b) for each of the four dimensions. The letters “a” and “b” refer to the two poles of each dimension. Figure 3.1 shows the output from the ‘ILS instrument’ after the learner has answered the 44 questions. The ILS results provide an indication of a learner’s preferred learning styles in the form of four scores.

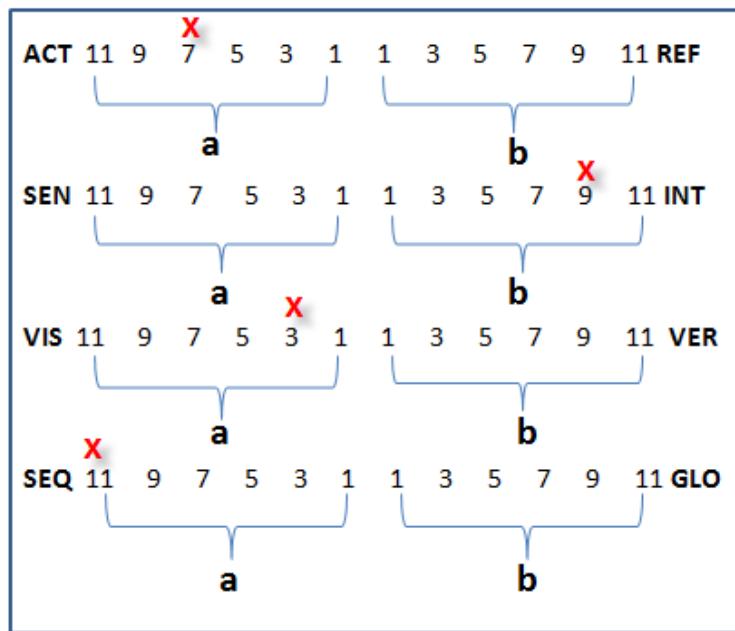


Figure 3.1 ILS Results

The learner has a personal preference in each dimension. Each preference may be expressed by a value between -11 to +11. The learner represented in Figure 3.1 has scores of 7a, 9b, 3a and 11a which may also be expressed as -7, +9, -3, and -11. Scores in the range 3a to 3b (i.e. -3 to +3) for one of the dimensions indicate fairly well-balanced preference on the two dimensions of that dimension. Scores in the range 7a to 5a or 5b to 7b indicate a moderate preference for one style of delivery in the given dimension and scores in the range 11a to 9a or 9b to 11b indicate a strong preference for a style of delivery at one of the poles of the dimension. Table 3.1 shows all the ILS questioner scores results for FSLSM.

Table 3.1 ILS Questionnaire Score Results Categorize

| Dimension | a | | | b | | |
|-------------------|-------------|----------|--------------|-------------|----------|--------------|
| | Very Strong | Moderate | Fair Balance | Very Strong | Moderate | Fair Balance |
| Active/Reflect | 9 - 11 | 5 - 7 | 1 - 3 | 9 - 11 | 5 - 7 | 1 - 3 |
| Sensing/Intuitive | 9 - 11 | 5 - 7 | 1 - 3 | 9 - 11 | 5 - 7 | 1 - 3 |
| Visual/Verbal | 9 - 11 | 5 - 7 | 1 - 3 | 9 - 11 | 5 - 7 | 1 - 3 |
| Sequential/Global | 9 - 11 | 5 - 7 | 1 - 3 | 9 - 11 | 5 - 7 | 1 - 3 |

Richard M. Felder and Barbara A. Solomon provided an ILS scoring sheet as shown in Figure 3.2 and a procedure for calculating the learner ILS scores. The procedure is as follows:

1. Place “1”s in the suitable spaces in the table below such as, if a learner answered “a” to question 1, place a “1” under column “a” by question 1, but if he/she answered “b” for question 1, but a “1” under column b. Each question answered should be “a” or “b”.
2. Sum all the ones under each columns and write the totals in the indicated spaces.
3. Subtract the smaller total number from the larger one for each of the four scales.
4. Write the difference result which will be a number between 1 to 11, and then write the letter “a” or “b” for which the total was larger on the lowest line.

For example, under “ACT/REF” column if a learner answered 4 questions “a” and 7 questions “b”, the answer would be the difference between 7 and 4, which is “3” and ”b” because we have more “b” than “a”. Then, we would write on the lowest line under the “ACT/REF” column “3b”. This means that the learner has fair balance Reflect learning style for “ACT/REF” dimension.

| Act/REF | | | SNS/INT | | | VIS/VER | | | SEQ/GLO | | |
|--|----------|----------|----------------|----------|----------|----------------|----------|----------|----------------|----------|----------|
| Q | a | b | Q | a | b | Q | a | b | Q | a | b |
| 1 | - | - | 2 | - | - | 3 | - | - | 4 | - | - |
| 5 | - | - | 6 | - | - | 7 | - | - | 8 | - | - |
| 9 | - | - | 10 | - | - | 11 | - | - | 12 | - | - |
| 13 | - | - | 14 | - | - | 15 | - | - | 16 | - | - |
| 17 | - | - | 18 | - | - | 19 | - | - | 20 | - | - |
| 21 | - | - | 22 | - | - | 23 | - | - | 24 | - | - |
| 25 | - | - | 26 | - | - | 27 | - | - | 28 | - | - |
| 29 | - | - | 30 | - | - | 31 | - | - | 32 | - | - |
| 33 | - | - | 34 | - | - | 35 | - | - | 36 | - | - |
| 37 | - | - | 38 | - | - | 39 | - | - | 40 | - | - |
| 41 | - | - | 42 | - | - | 43 | - | - | 44 | - | - |
| Total (SumX's in each column) | | | | | | | | | | | |
| Act/REF | | | SNS/INT | | | VIS/VER | | | SEQ/GLO | | |
| a | b | | a | b | | a | b | | a | b | |
| - | - | | - | - | | - | - | | - | - | |
| (Larger - Smaller) + Letter of Larger | | | | | | | | | | | |
| ----- | | | ----- | | | ----- | | | | | |

Figure 3.2 ILS Scoring Sheet

The result of evaluating an ILS questionnaire is a set of four points or scores, one for each dimension. The overall learning style may be expressed as a vector:

$$\text{LS} = [\text{LS1}, \text{LS2}, \text{LS3}, \text{LS4}] \quad (3.1)$$

Each dimension LS1 to LS4 may be represented as value between -11 and 11. Alternatively, each dimension LSi for i = 1 to 4 may be represented as a vector (Pi , Qi) where Pi is an integer between 1 and 11 and Qi is ‘a’ or ‘b’

According to FSLSM, each LSi takes 4 points [p₁, p₂, p₃, p₄]

Where, P₁ is a point on the processing dimension, and -11 <= P₁ <= 11

P₂ is a point on the understanding dimension, and -11 <= P₂ <= 11

P₃ is a point on the reception dimension, and -11 <= P₃ <= 11

P₄ is a point on the perception dimension, and -11 <= P₄ <= 11

So each learner’s learning styles can be represented as a set of 4 points ((a₁ , b₁) , (a₂ , b₂) , (a₃ , b₃) , (a₄ , b₄)).

3.2.2 Similarity Algorithm

The course content for our adaptive system is divided into ‘concepts’ referred to as ‘learning objects’. Each learning object is divided into a number of ‘atoms’, each of which concentrates on one particular issue. Each atom presents a piece of information and incorporates one assessment question. Each learning object can be presented in different learning styles. The dynamic adaptive algorithm proposed in this thesis is based on a concept of ‘similarity’.

To find the similarity between two students, we compare their data records which catalogue their previous interaction with the system. Normally we compare the incomplete record of a ‘new student’ who is currently studying a learning object with the complete record of a previous student who has completed the learning object successfully. There may be many previous students who have completed the learning object. The identities of these previous students are stored in a ‘similarity-queue’ which is ordered according to the similarity of the records with the incomplete record of the new student up to the point the new student has reached. The queue is sorted from the most similar to the least similar. The adaptation algorithm then searches this queue to find the highest similarity score between a previous student and the new student in order to decide how to present the course content to the new student.

Table 3.2 Symbols Description for Similarity Algorithm

| Symbol | Description |
|-----------|--|
| S | All students studied in the adaptive system |
| C_k | A concept from the content learning materials |
| S_i | Failed student studied concept C_k and not passed |
| S_j | Previous student studied concept C_k and passed |
| G_i | GPA for failed student failed to pass concept C_k |
| G_j | GPA for previous student passed concept C_k |
| T_{ik} | Time spent by a failed student during studying concept C_k |
| T_{jk} | Time spent by a previous student during studying concept C_k |
| LS_{ik} | Learning styles for failed student during studied concept C_k |
| LS_{jk} | Learning styles for previous student when he/she studied concept C_k |
| m | Group of students studied concept C_k |
| h | One student from group m studied concept C_k |

Table 3.2 summarizes notation we used in our proposed algorithm. Suppose we have had n previous students using our adaptive system. Then the list of previous students is $\mathbf{S} = \{S_1, S_2, \dots, S_n\}$. A new student will be referred to as S_{n+1} and will have an initial learning style vector $LS_{n+1}(\text{initial})$ assigned by the ILS assessment of FSLSM, obtained when the new student starts to use the adaptive system. If the new student does not pass with his/her initial learning style assessment, the algorithm looks for the most similar previous students who have studied and passed the same learning object.

The similarity between two students S_i and S_j who have studied concept C_k where S_i has failed to answer the assessment questions for C_k and S_j has passed it, is defined by the following ‘similarity equation’ :

$$Sim(i, j, k) = \frac{1}{3} [\Gamma_g(G_i, G_j) + \Gamma_t(T_{ik}, T_{jk}) + \Gamma_{ls}(LS_{ik}, LS_{jk})] \quad (3.2)$$

G_i and G_j are the grade point averages (GPA) for S_i and S_j respectively, and $\Gamma_g(G_i, G_j)$ is a ‘GPA distance’ function measuring the difference between G_i and G_j .

T_{ik} and T_{jk} are the time-durations (in seconds) taken by S_i and S_j respectively to study the material for concept C_k , and $\Gamma_t(T_{ik}, T_{jk})$ is a ‘time-distance’ function measuring the difference between T_{ik} and T_{jk}

LS_{ik} and LS_{jk} denote the student learning style vectors for S_i and S_j respectively while studying concept C_k . These do not change with k for static adaptation, but they may change when the adaptation is made dynamic. $\Gamma_{ls}(LS_{ik}, LS_{jk})$ is a ‘learning style-distance’ function measuring the difference between LS_{ik} and LS_{jk}

All the three distance functions $\Gamma_g(G_i, G_j)$, $\Gamma_t(T_{ik}, T_{jk})$ and $\Gamma_{ls}(LS_{ik}, LS_{jk})$ are normalized to lie between 0 and 1. Therefore, $0 \leq Sim(i,j,k) \leq 1$ for all values of i, j , and k .

3.2.2.1 GPA Similarity

Based on the similarity equation mentioned above (3.2), a similarity value can be obtained between 0 and 1. The function $\Gamma_g(G_i, G_j)$ should be normalized to weighting between 0 and 1.

The possible definition of distance measure probability for the GPA

$$\Gamma_g(G_i, G_j) = \begin{cases} \varphi(G_i, G_j) & \text{if } \varphi > 0 \\ 0 & \text{if } \varphi \leq 0 \end{cases}$$

$$\text{Where } \varphi(G_i, G_j) = 1 - \frac{1}{\ln(2)} - \left| \ln\left(\frac{G_i}{G_j}\right) \right|$$

We adopt the definition of the GPA as defined in King Abdul-Aziz University, Kingdom of Saudi Arabia where the experiment is conducted, where the maximum GPA is equal to 5. The GPA is calculated by taking the number of grade points a student earned in a semester.

Then, $\xi \leq G \leq 5$ and $0.000001 \leq \xi \leq 5$

The ‘GPA distance’ function is defined as follows:

$$\Gamma_g(G_i, G_j) = \begin{cases} 1 - \frac{1}{\ln(M)} \left| \ln\left(\frac{G_i}{G_j}\right) \right| & : 1/M \leq G_i / G_j \leq M \\ 0 & : \text{otherwise} \end{cases} \quad (3.3)$$

Where it is assumed that the ratio G_i/G_j most likely lies between $1/M$ and M . Typically we take $M=5$. We accumulate the **GPA** of the students from the student’s information system

and then feed them in our learning management system. Figure 3.3 shows this distance measure when $M=5$. The graph is drawn using MATLAB software.

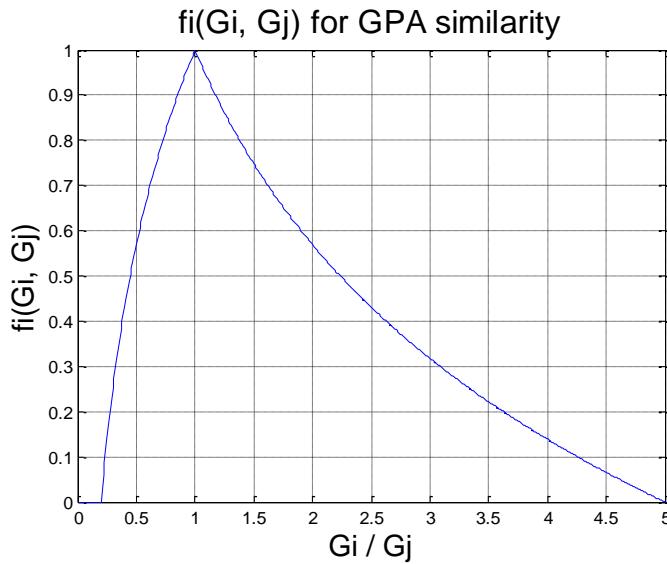


Figure 3.3 Distance Measure for GPA when $M=5$.

3.2.2.2 Time Similarity

Based on the similarity equation mentioned above (3.2), a similarity value can be obtained between 0 and 1. The function $\Gamma_t(T_{ik}, T_{jk})$ should be normalized to weighting between 0 and 1.

$$\Gamma_t(T_{ik}, T_{jk}) = \begin{cases} \psi(T_{ik}, T_{jk}) & \text{if } \psi > 0 \\ 0 & \text{if } \psi \leq 0 \end{cases}$$

$$\text{Where } \psi(T_{ik}, T_{jk}) = 1 - \frac{1}{\ln(\Delta_k)} + \ln\left(\frac{T_{ik}}{T_{jk}}\right)$$

Where Δ_k is a predefined constant that stands for the difference between T_{ik} and T_{jk} . The predefined parameter b can be calculated by computing the average time between all the concepts as follow:

Suppose we have a group of students S studied concept C_k

S^m Students studied the concept C_k and passed

$$\text{Let } S^m = \{S_j\}_{j=1}^m$$

Let ϕ_i a student studied the concept C_k and passed

Where $\phi_i \in S_k^m = \{\phi_{ik}\}_{i=1}^m$

Then, we will compute the average time for all students spent studying concept C_k and passed

$$\begin{aligned} \text{Average Time} &= \{t(\phi_{1k}) + t(\phi_{2k}) + t(\phi_{3k}) + \dots + t(\phi_{mk})\} \\ &\quad \frac{\{|t(\phi_{1k}) - t(\phi_{2k})| + |t(\phi_{1k}) - t(\phi_{3k})| + \dots + |t(\phi_{1k}) - t(\phi_{mk})|\}}{(m-1)} + \\ &\quad \frac{\{|t(\phi_{2k}) - t(\phi_{3k})| + |t(\phi_{2k}) - t(\phi_{4k})| + \dots + |t(\phi_{2k}) - t(\phi_{mk})|\}}{(m-2)} + \\ &\quad \frac{\{|t(\phi_{3k}) - t(\phi_{4k})| + |t(\phi_{3k}) - t(\phi_{5k})| + \dots + |t(\phi_{3k}) - t(\phi_{mk})|\}}{(m-3)} + \dots + \dots \\ &= \frac{\{|t(\phi_{ik}) - t(\phi_{(i+1)k})| + |t(\phi_{ik}) - t(\phi_{(i+2)k})| + \dots + |t(\phi_{ik}) - t(\phi_{mk})|\}}{(m-(m-1))} \\ &= \sum_{i=1}^{(m-1)} \frac{1}{(m-i)} \sum_{j=1}^{(m-i)} |\phi_{ik} - \phi_{(i+j)k}| \end{aligned}$$

Then Δ_k = Average Time

Then, the time-difference function between T_{ik} and T_{jk} can be defined by the following equation:

$$\Gamma_g(T_{ik}, T_{jk}) = \begin{cases} 1 - \frac{1}{\ln(\Delta_k)} \left| \ln \left(\frac{T_{ik}}{T_{jk}} \right) \right| & \text{if } 1/\Delta_k \leq \frac{T_{ik}}{T_{jk}} \leq \Delta_k \\ 0 & \text{otherwise} \end{cases} \quad (3.4)$$

Δ_k is a predefined constant that determines the range of values we expect for the ratio T_{ik}/T_{jk} . It can be defined by the following method:

$$\Delta_k = \sum_{i=1}^{(m-1)} \frac{1}{(m-i)} \sum_{j=1}^{(m-i)} |\phi_{ik} - \phi_{(i+j)k}| \quad (3.5)$$

3.2.2.3 Learning Styles Similarity

Felder and Silverman (Felder and Silverman, 1988a) proposed the ILS, which is a 44-item questionnaire for diagnosis of the learning style based on FSLSM. Each learning style is identified by answering 11 questions, and each question has two multiple choice answers (*a* or *b*). Also, they provided a procedure to calculate the learning styles' scores by recording the total number of *a*'s student selected and the total number of *b*'s student selected, which will be between 1 to 11. For more detail about Felder and Silverman's method, see Section 3.2.

To define similarity between two learning styles, we use a Euclidean distance measure equation between two points in two-dimensions (Redden, 2012). A point's location on the scale is given by two numbers: one that tells where it is on the x-axis and another which tells where it is on the y-axis. Together, they define a single position on the scale.

Given two points (a_1, b_1) and (a_2, b_2), the Euclidean distance between them is

$$D = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \quad (3.6)$$

The distance D is a positive value that tells how far the two points are from each other.

To define the learning style distance function $\Gamma_{ls}(LS_{ik}, LS_{jk})$ between two learning style vectors LS_{ik} and LS_{jk} obtained from the ILS questionnaire, these learning styles are represented as follows:

$$LS_{ik} = ((a_{i1}, b_{i1}), (a_{i2}, b_{i2}), (a_{i3}, b_{i3}), (a_{i4}, b_{i4}))$$

$$LS_{jk} = ((a_{j1}, b_{j1}), (a_{j2}, b_{j2}), (a_{j3}, b_{j3}), (a_{j4}, b_{j4}))$$

where a_i and b_i are the scoring integer numbers between 1 and 11 obtained from ILS scoring sheet.

Then we compute the Euclidean distance between each of the four dimensions. The distance for each dimension is divided by $\frac{1}{11\sqrt{2}}$ to normalize it to a number between 0 and 1.

$$R1 = \frac{1}{11\sqrt{2}} \sqrt{(a_{i1} - a_{j1})^2 + (b_{i1} - b_{j1})^2}$$

$$R2 = \frac{1}{11\sqrt{2}} \sqrt{(a_{i2} - a_{j2})^2 + (b_{i2} - b_{j2})^2}$$

$$R3 = \frac{1}{11\sqrt{2}} \sqrt{(a_{i3} - a_{j3})^2 + (b_{i3} - b_{j3})^2}$$

$$R4 = \frac{1}{11\sqrt{2}} \sqrt{(a_{i4} - a_{j4})^2 + (b_{i4} - b_{j4})^2}$$

The learning style distance function can then be calculated as follows:

$$\Gamma_3(LS_{ik}, LS_{jk}) = D = \frac{1}{4}(R1 + R2 + R3 + R4) \quad (3.7)$$

If the learning style distance between two students is equal to 0, then the two students have the same learning styles. If it is equal to 1, the two learning styles are maximally different; i.e. the ILS vectors are as different as they can possibly be.

It is useful to present an example to illustrate the idea of learning styles similarity:

Assume we wish to find the distance between the learning styles LS1 and LS2 of two students S₁ and S₂ where:

$$LS_1 = ((10, 1), (10, 1), (7, 4), (9, 2)) \text{ and } LS_2 = ((9, 2), (7, 4), (4, 7), (3, 8))$$

We obtain:

$$R1 = \frac{1}{11\sqrt{2}} \sqrt{(10 - 9)^2 + (1 - 2)^2} = 0.09$$

$$R2 = \frac{1}{11\sqrt{2}} \sqrt{(10 - 7)^2 + (1 - 4)^2} = 0.27$$

$$R3 = \frac{1}{11\sqrt{2}} \sqrt{(7 - 4)^2 + (4 - 7)^2} = 0.27$$

$$R4 = \frac{1}{11\sqrt{2}} \sqrt{(9 - 2)^2 + (3 - 8)^2} = 0.55$$

$$\text{Giving } \Gamma_3(LS_{ik}, LS_{jk}) = \frac{1}{4}(0.09 + 0.27 + 0.27 + 0.55) = 0.295 \quad (3.8)$$

In this example, the distance between the learning styles of the two students is quite small.

The following chart Figure 3.4 shows us the distance between the scores of the two leaning styles for S₁ and S₂ for each dimension.

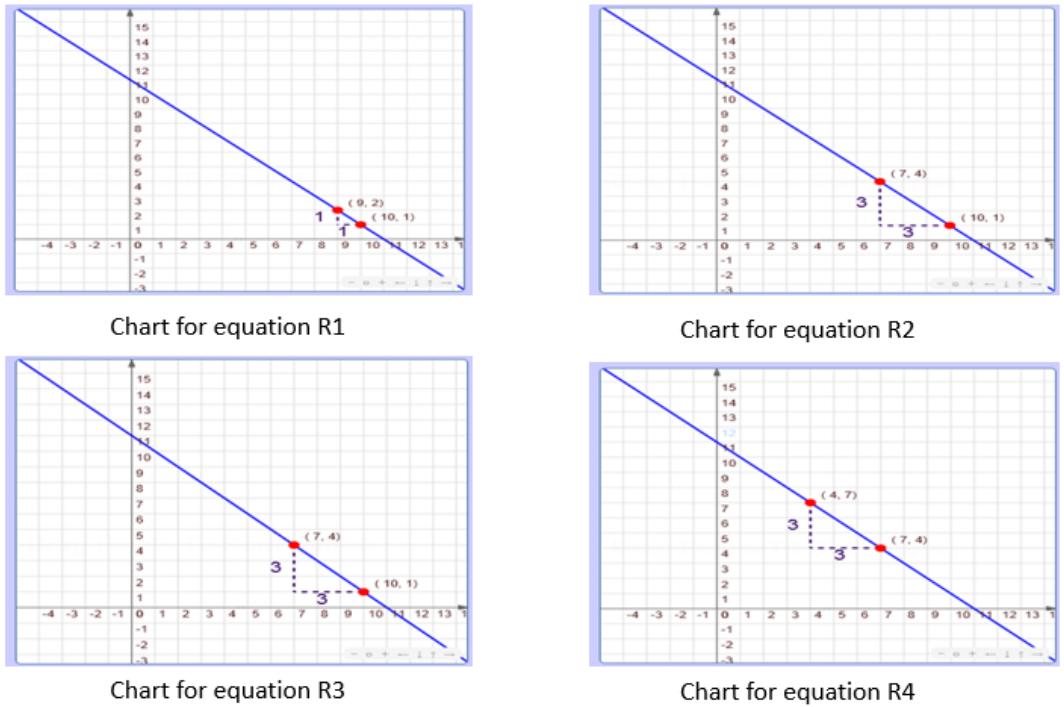


Figure 3.4 Charts for Equation R1, R2, R3, and R4

3.3 Adaptive Learning System Architectures

In order to validate the modelling and adaptation mechanisms proposed in the previous sections, we implemented them in an experimental adaptive educational environment that extends, Moodle, the learning management system. In order to validate the proposed approach in terms of reliability and performance, we will compare it with a static adaptive system and a regular online learning management system. In the next sections, we will present the proposed architectures for the three systems.

3.3.1 Non-AELS Architecture

The diagram in Figure 3.5 illustrates the system architecture of the regular non-adaptive online e-learning system. The student may fill in an ILS questionnaire, but it is not used to affect course delivery. The learner model is usually very simple, compared to that needed for SAELS or DAELS. It contains basic learner information, such as name, age, GPA and level of knowledge. The course content model accesses the database of course material through SQL queries to retrieve the required learning content without any access to the learner model. The system then presents the learner with the concepts as prepared by course authors. At the end of each concept, the system evaluates the student's understanding. If the student passes, then he or she will be presented with the next concept. If the student does not pass, he or she can repeat the concept up to two times with the same presentation. The student continues learning in the same way until the end of the course learning content.

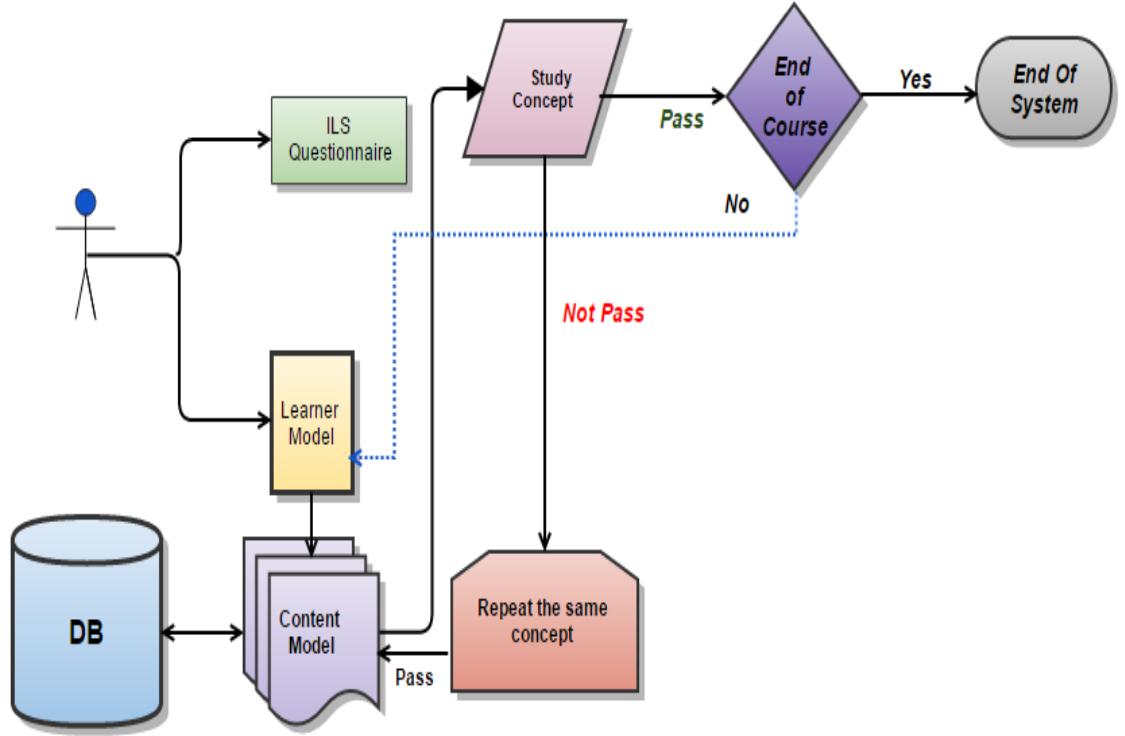


Figure 3.5 Non-AELS Architecture

3.3.2 SAELS Architecture

The diagram in Figure 3.6 illustrates the static adaptive learning system architecture. When a student logs in via Moodle, a learner model that stores all the student-specific data is initialized. The student fills in an ILS questionnaire and the ILS scores are stored in the learner model. The course content model accesses the database of course material through SQL queries to extract the learning content. It presents the material to the student in a form that matches the student's preferred learning styles, as currently stored in the learner model. The static adaptive system presents the concepts in turn to the student, and at the end of each concept, the system evaluates the student's understanding of the concept. If the student passes, then he/she moves on to the next concept. If the student passes, then he or she moves on to the next concept. If the student does not pass, he or she can repeat the concept up to two times with the same presentation. The student continues learning in the same way until the end of course. The learner model is not updated throughout the course; the learning content adaptation is performed at the beginning of the course and does not change.

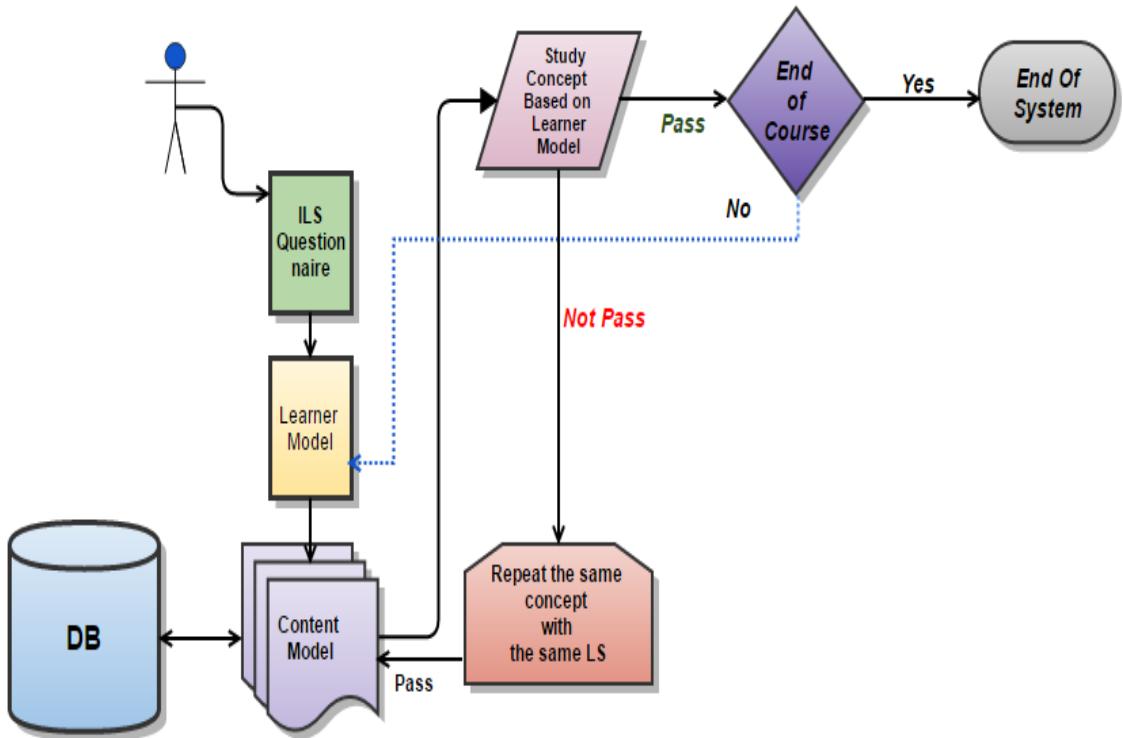


Figure 3.6 SAELS Architecture

3.3.3 DAELS Architecture

The main goal of this research is to provide dynamic adaptivity of the learning content based on identification of the learner's characteristics and learning styles combined with the results of a series of tests conducted at the end of each concept. As shown in Figure 3.7 adaptivity is realized using four components: a learner model, a content model, a similarity algorithm, and a machine-learning algorithm. When a student logs in via a Moodle LMS, an ILS questionnaire is initiated to be filled in by the student to predict his or her learning style. All learner-specific data, learning styles scores, current learning content stage, student GPA, and interaction with the system are recorded in the learner model.

The content model accesses the learning content and presents it to the new student according to the preferred learning style dimensions. The learning contents are adapted to the student's preferred learning style, as will be explained in Section 4.2.4.2. After studying each concept, the student is required to answer a series of assessment questions to assess his or her understanding of the concept. If the assessment results are not satisfactory and the student does not pass the evaluation, the Similarity algorithm searches the system database for previous learning patterns that are similar to that of this new student. The measure of similarity is based on the similarity equation (3.2) defined in Section 3.2. Then, the algorithm forms a list of previous students and re-orders it, according to similarity, from highest to lowest. The similarity is not only in the student learning style; it covers the

characteristics of the student, his time spent in the concept, his GPA, and his learning style. Accordingly, the algorithm selects the most similar student and presents the concept's learning contents adapted to their preferred learning style, which may not be the same as the previous student. This is followed by an assessment of the new student's understanding of the newly adapted concept presentation. If the new student passes the evaluation with the new learning style, the algorithm updates the learner model with these changes. These changes will be fed back to the learner content model to be used to present the next concept with an updated learner model.

If the student does not do well the second time with the adapted new learning styles, the algorithm selects the next student from the similarity list. The system then presents the concept to the new student with the preferred learning style of this second previous student. We allow the new student to repeat the same concept up to three times. This limits the time taken by participants taking part in the experiments to be described in Section 4.2.4.5. If the new student does not do well in any of the three repetitions, the system selects the best of the three outcomes to decide which learning style is to be used for presenting the next concept.

Our adaptive system is implemented on a LMS used by students taking online courses. The adaptivity algorithm must be able to produce the ordered list of previous students rapidly in order to respond to student action and learning styles in a reasonable amount of time. To achieve this, the algorithm is associated with a machine-learning scheme capable of handling students' data records efficiently as the number of records gets large. As the number of records of previous students increases, the efficiency of the implementation of the similarity algorithm becomes more and more important. It needs to be able to process the records fast to identify similar learning styles behaviour between students. To achieve this efficiency, a classification algorithm is used to identify and parameterize similar patterns in the records. This is one of the merits of the proposed system, i.e., increasing system performance and accuracy compared to similar adaptive systems, which are complex and expensive (Dominic et al., 2015).

An advantage of the proposed system over other adaptive systems is that it does not involve any extra work for the learners, apart from filling in the ILS questionnaire at the start. The learners need have no role in choosing their preferred learning path and are not required to give opinions or ratings that may confuse and distract them. Our proposed adaptive system adjusts the student's learning styles according to their actions throughout the course and updates the learner model periodically.

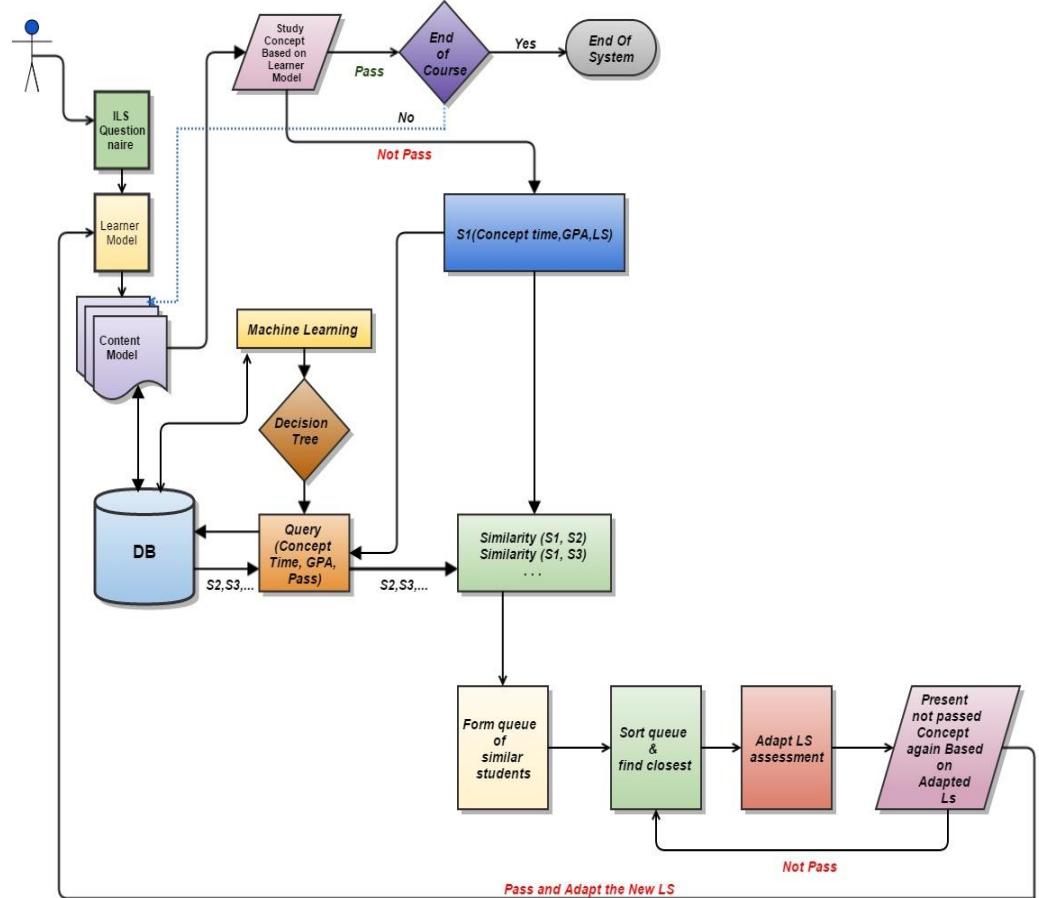


Figure 3.7 DAELS Architecture

3.4 Machine Learning in Adaptive Learning Systems

A large volume of data will result from back-tracking the records of previous students. Computing the similarity between these student records will be challenging and could take a long time. Machine learning algorithms can make this process more efficient by grouping the students' records into classes labelled with common features. Then the adaptive system can look for the class for which the labels indicate that its members are close to the current student. It then performs the similarity algorithm among the smaller number of students who belong in this class.

3.4.1 Machine Learning Algorithm

Machine learning can build models of complex data structures that can be trained to make predictions about their likely distribution. Computer programs can thus be programmed to effectively identify patterns in data and make automatic decisions about it. Decisions can take many different forms, including classification, clustering and prediction. In classification, we may have a huge amount of data and want to divide it into labelled subsets

containing data with similar characteristics. The labels parameterize the characteristics. Clustering assigns data to classes according to appropriate measures of distance, and prediction anticipates the behaviour of data in a particular class according to its parameterized characteristics. New instances of data can be mapped to an appropriate class.

The process of applying classification by machine learning to a real world problem is illustrated by Figure 3.8, reproduced from a report by (Kotsiantis et al., 2007). The first step is collecting the dataset for a problem and finding its important features and attributes. In some cases, the dataset needs to be pre-processed to remove noise and missing feature values. An appropriate machine learning algorithm must then be chosen and trained with representative examples of data. After that, preliminary testing is carried out to evaluate how well the algorithm maps instances to classes.

Machine learning algorithms are organized based on the preferred outcome of the algorithm. Logic-based algorithms are focused on two groups of logical learning methods: decision trees and rule-based classifiers. In our adaptive learning system, we use ID3, a decision tree learning algorithm. The reason for choosing this algorithm is that it is readily implemented in PHP and MySQL, which are the same tools used to implement Moodle. ID3 is easily implemented, and the time to build the model increases only linearly with dataset size. It is therefore faster than many other machine learning algorithms such as Bayes' machine learning algorithm (Kotsiantis et al., 2007). Bayes' classification algorithm compute a product operation to estimate the probabilities that label each class and that could take quite long time to construct the tree. In contrast, the ID3 tree is constructed according to the attribute's value. Each class is assigned to one leaf that representing the most appropriate target value. Searching the tree will be based on these attribute's value, which makes the ID3 is the best suitable algorithm for our Similarity algorithm.

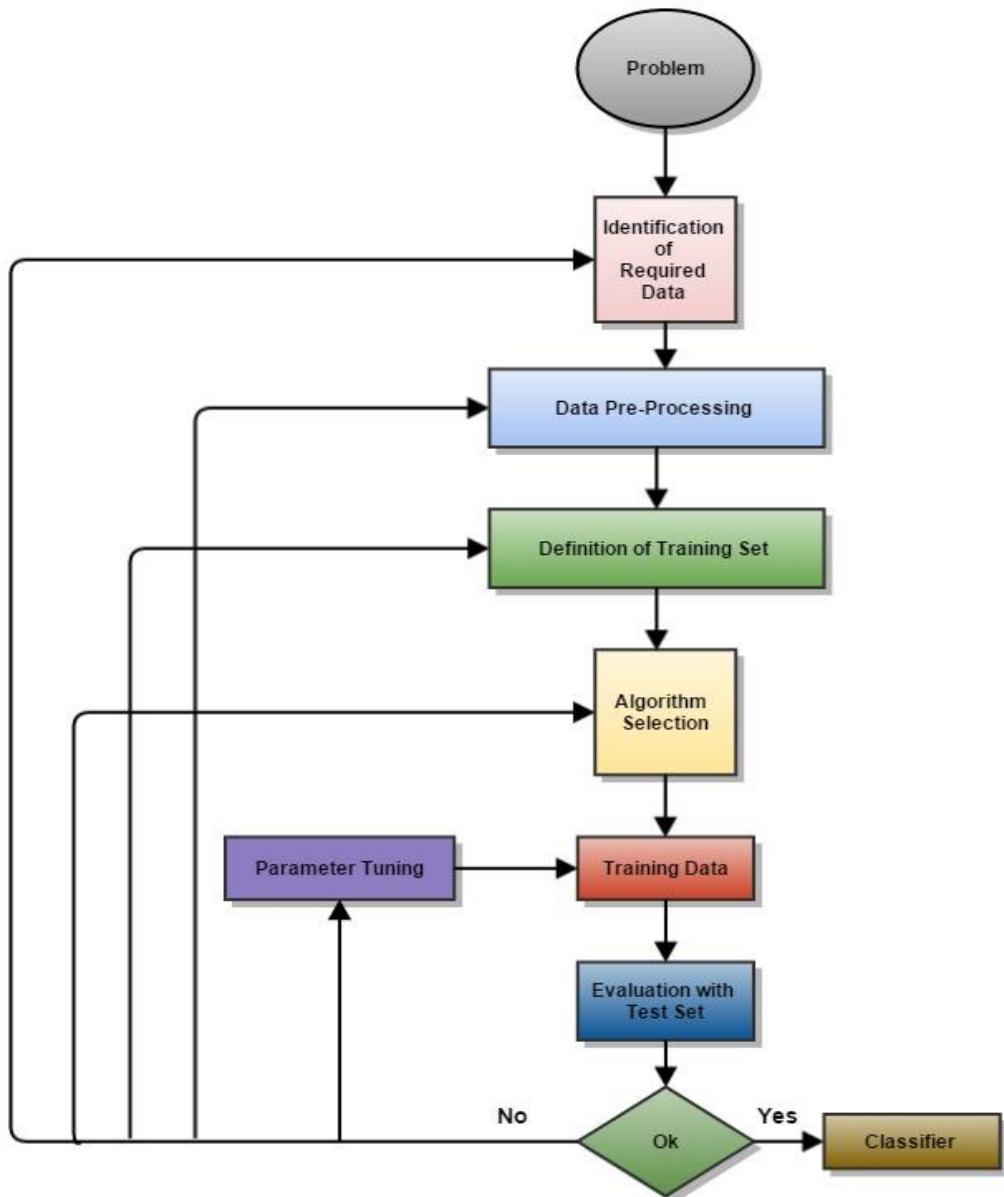


Figure 3.8 Process of Machine Learning Classification

3.4.2 Decision Trees Algorithm

Decision tree learning is one of the most widely used algorithms for inductive instances. It classifies instances by sorting them top-down tree from the root to leaf nodes that classified instances based on features value. We starts at the root node, and asks questions to determine which edge to follow, until we reaches a leaf node and the decision is made. Each non-leaf node of a decision tree matches to an input attribute, and each arc to a possible value of that attribute. Leaf nodes represent classes which correspond to the expected value of the output attribute when the input attributes are described by the path from the root node to that leaf node.

One of the widely used algorithms for decision trees learning is ID3 (Mitchell, 1997). ID3 classifies a new example to a suitable class. The tree has some leafs. Each leaf represents a target (class). The model is built by around 30 to 40 % of the dataset. The ID3 algorithm aims to find the target variable based on several input variables. The algorithm is built based on a function called the Information gain, as defined by equation (3.10). This function determines the node that has to go through based on the probability between this current node and the child node. It is a statistical property that measures how well a given attribute splits the training examples according to their target classification.

$$Gain(S, A) = Entropy(S) - \sum_{set\ value\ (A)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (3.10)$$

Where, the *Entropy* is a mathematical function that measures information content of a random process.

$$Entropy(S) = \sum_{i=1}^c -P_i \log_2 P_i \quad (3.11)$$

Values (A) is the set of all possible value for attribute A, and S_v is the subset of S for which attribute A has value v.

ID3 uses the information gain measure to select among the candidate attributes at each step while the tree is growing. Based on these iterations, the algorithm works until it reaches the leaf.

Figure 3.9 shows the modeled ID3 algorithm for students' data as a tree in which the root and the nodes are machine learning attributes such as student pass or fail ,course concepts ,or the GPA attributes. The tree leafs would be the course concepts. The tree structures can be used to infer the attributes that will be used to improve query performance in retrieving the data from the database in a timely manner.

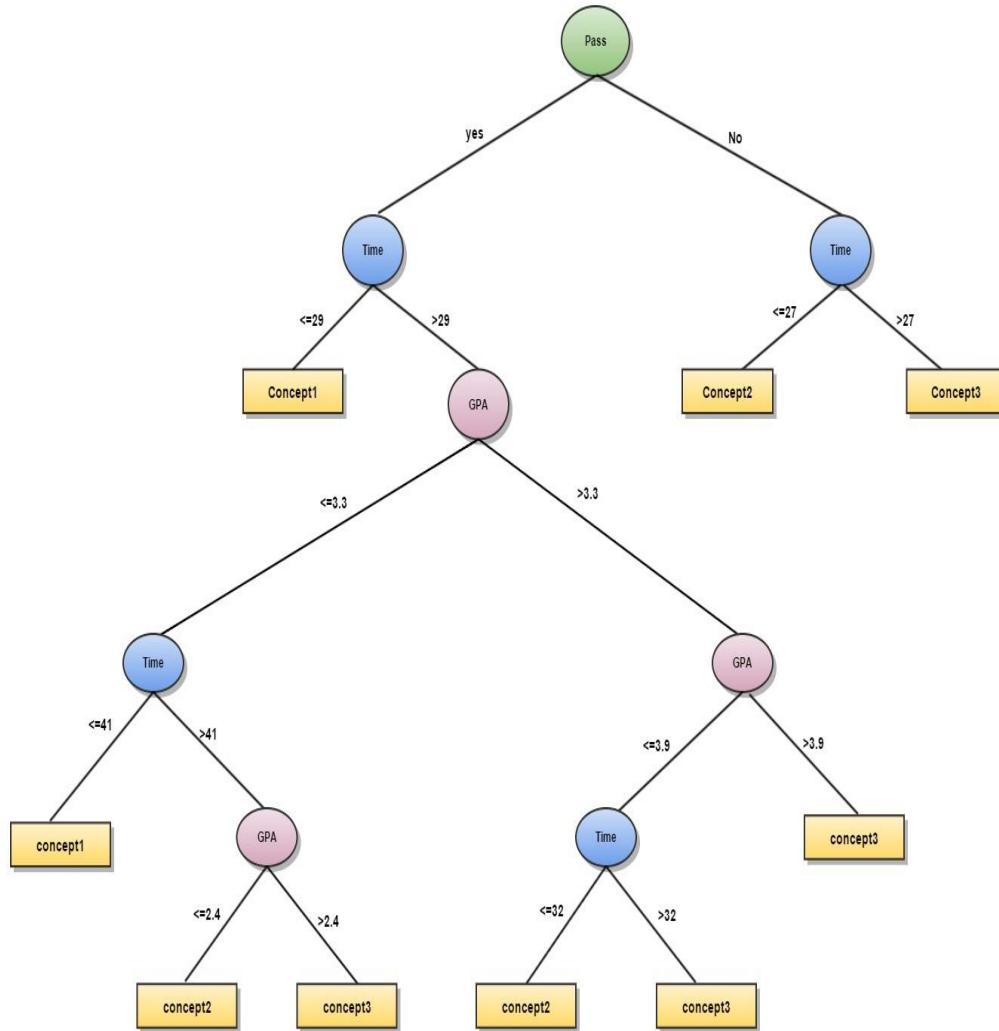


Figure 3.9 ID3 Modeled Tree for Students' Dataset

3.5 DAELS Algorithm Steps

The following steps implement the Similarity algorithm in a form intended for clarity rather than efficiency. They are described here without the benefit of machine learning and a decision tree. These aspects of the algorithm will be covered in a later chapter.

1. Set $k=1$ to specify the first concept C_k and set Failure =0
2. Student S_i studies concept C_k according to the learning styles currently stored in his or her 'learner model'
3. If the student passes the assessments go on to step 14, otherwise go to step 4
4. Define G_i , C_k , T_{ik} and LS_{ik} for student S_i and similarly define G_j , C_k , T_{jk} and LS_{jk} for each of the previous students S_j
5. Calculate the similarity between the student S_i with all students S_j who passed C_k , using the similarity equation (3.2)

6. Initialize counter to 0 for counting the number of similarities
7. For each student S_j , if $\text{Sim}(i,j,k) > 0$, there is some similarity between S_i and S_j and we increase the counter value by 1 and store the record of student S_j in a queue called the ‘Similarity-Queue[]’; i.e. Similarity-queue [count] = S_j
8. Sorting the similarity-queue[] in descending order from the most similar to the least similar
9. **If** the similarity-queue[] is not null
 - **then** Remove first element (LS_j) from similarity-queue[]
 - **else** go to step 14
10. **If** S_i learning style not equal the learning style of the student S_j
 - **then** assign it to the student S_i temporarily
 - **else** go to step 9
11. Present the concept C_k to S_i with the new learning style LS_j
12. Student S_i now studies concept C_k again. If he/she passes the assessment, then the learning style of student S_j as stored in the learner model is updated to what was just used temporarily and go to step 14
13. **If** (Student S_i does not pass) & (Failure $<= 2$)
 - **then** Failure = Failure +1 and go to step 9
 - **else** update the learning styles of S_i to the learning style of S_j that S_i used and got a highest grade from the three tries
14. If more concepts C_k remain, increment k by 1 and go back to step 2. Otherwise go to step 15
15. End of the algorithm

Note: the presentation here is for clarity rather than efficiency.

Chapter 4

Experimental Design

The aim of this PhD research is to devise, implement and evaluate ways of enhancing the capability of existing e-learning management systems by introducing ‘static’ and ‘dynamic’ adaptivity in the way information is presented to the learner. It aims to extend the concept of adaptivity to multiple delivery mechanisms, with different formats according to the Felder-Silverman representation of learning styles, and to introduce dynamic adaptivity on the basis of monitoring the learner responses to previous tasks.

Several adaptation systems that use learning styles as parameters for ‘static’ adaptation have been reported in the literature. However, the empirical studies that have been conducted to investigate their effectiveness have been unable to demonstrate significant improvements in students' performance when they are presented with course content in ways which match their preferences (Carver et al., 1999c, Ruiz et al., 2008, Siadaty and Taghiyareh, 2007, Parvez and Blank, 2008). The best that has been observed is a decrease in the time taken to complete certain learning exercises, time spent in the system and the number of visited learning requests for additional learning objects (Graf, 2007). The results of many experimental studies that have been conducted indicate that exploiting the relationship between learning style and learner preferences is still an open issue. The relationship between a student's learning style characteristics and his/her interaction behaviour in e-learning environments must be further investigated (Papanikolaou et al., 2006). These results and conclusions motivate our research in dynamic adaptivity based on learning styles.

Educational researchers have recently started to focus on how to personalize e-learning environments using aspects of personal characteristics such as the preferred learning style of the student. Adaptive educational systems address personal learning issues by providing learners with courses that fit their individual needs and characteristics such as their normally adopted learning styles. In previous research, studies have showed that integrated students' learning styles in web-based e-learning can have significant benefits and lead to better performance in students' results (Manochehr, 2006). A more recent empirical study (Kazu, 2009) drew similar conclusions. The findings showed that individual learning styles should be considered in education and instructional process to provide the best way of learning.

The methodology of our proposed research is, first of all, to investigate and propose ways for extending static adaptability to multiple delivery mechanisms and then for introducing

dynamic adaptability. These ideas are then to be demonstrated and evaluated with the aid of a case study. A “Bayes Theory” topic was chosen as a case study to illustrate the use of different delivery mechanisms with real examples. The case study was used to investigate experimentally our ideas for static and dynamic adaptability. The experiment required student volunteers to use implementations of these two approaches in preliminary form. With the help of these student volunteers as subjects, we conducted experiments using Moodle as an e-learning management system with augmented software facilities for testing our hypotheses. Each subject who participated in the study was randomly assigned to one of three groups: ‘control group’, ‘static adaptive group’ and ‘dynamic adaptive group’. The control group was provided with a non-adaptive regular on-line course on statistics. The static adaptive group was provided with the online course material adapted individually to each students’ learning style preferences as defined at the beginning of the course. These preferences were not changing during the student’s progression through the course. The dynamic adaptive group was provided with the on-line course material presented according to each individual students’ learning styles which were allowed to change as the students progressed through the course. The experiments or ‘trials’ were carried out at the King Abdulaziz University, Jeddah, Saudi Arabia.

4.1 Hypotheses

We are asking the question whether dynamic adaptation can enhance the learner’s understanding and improve learning effectiveness. The dependent variables are learning effectiveness as measured by students’ test scores, the time spent in learning each concept, and the time spent in answering the questions. According to the research question, four hypotheses are being tested. They are as follows:

H1: There will be no significant difference between the three groups in the pre-test.

H2: The dynamically adaptive group will perform significantly better in the post-test than the static group and the control group.

H3: There will be significant differences between the performances of the three groups according to the pre-test and post-test scores.

H4: Students who use the dynamically adaptive e-learning environment will spend less time in learning the concepts than do the students in the statically adaptive group and the control group.

Pretest-posttest designs are widely used in experiments for the purpose of compare groups learning knowledge before and after experiments’ treatment to measure their achievement.

A pre-test is a test given to the participants before the experiment is applied to assess participant knowledge, whereas, a post-test is the same test as the pre-test and given to participants after the experiment is completed (Dimitrov and Rumrill Jr, 2003).

Some research investigated the effect of learning styles on students' knowledge when they are considering. Research by (Coffield et al., 2004b) could find no proof that employing learning styles alone can improve students' knowledge. In our experiments, we did not consider learning styles as the only factors for personalizing the course content. We considered other factors such as the student GPA (grade point average) and the time the student spent in learning each concept. The system adapts the course content presentation according to the Similarity algorithm defined in Section 3.2. Crucially, the presentation style and content will be adapted according to the student's performance in the course. The student builds schema induction according to the dynamically adapted presentation style. The adaptation is based on the experience of previous students, taking into account their preferred learning styles, GPA, and speed of learning. The different schema indication can enhance the learning process and increase the chance of successful understanding of the concept (Felder and Silverman, 1988a).

4.2 Methodology

The purpose of the experiments is to test the hypotheses that are mentioned in the previous section 4.1 and draw appropriate conclusions.

4.2.1 Participants

The participants comprised a cohort of volunteers who were all first year students from the Statistics Department at King Abdulaziz University in Jeddah/Saudi Arabia. Students participated on a voluntary basis, and it had to be made clear that the material presented, though useful, is not part of their curriculum. This assurance was necessary to eliminate any ethical issues that could be raised from experimenting with curriculum material and knowingly disadvantaging some students. The volunteers were expected to be highly motivated to learn the chosen topic as it is interesting and relevant to the broader aspects of their subject. It will be assumed that the volunteers have no previous knowledge of the specific topic to make sure that the students have to use their natural learning styles to study the chosen topic. Students were informed that this experimental study is provided as a bonus assignment of a specific course.

In the event, in order to encourage serious participation, the instructor agreed to offer extra credits for participation in our experiments. The students were chosen from the field of

statistics because they were familiar with the statistical basis of the concepts to be taught. The students realised that it was likely that they would study ‘Bayes Theorem’ as a part of their future curriculum, and this served to increase their motivation. The GPA scores of all participants were recorded before starting the experiment. The 110 participants who participated in our experiment were divided randomly into three groups named ‘static’, ‘dynamic’, and ‘control’. Each group had students with GPAs varying between 'average' and 'good', and were of roughly the same average intellectual ability.

4.2.2 Teaching Material

The content material for our experiment was chosen from the statistics field with help from a group of academic teachers in the field. It focuses on the teaching of “Bayes Theorem”, which is one of the most important concepts of probability theory as widely employed to draw useful conclusions from experimental observations. The concept is divided into four sub-concepts and each sub-concept is further divided into four learning objects. Each of the 16 learning objects is explained as a single idea.

The teaching material has been developed as a series of Asset learning objects (ALO) with a choice of presentation styles for each ALO in Figure 4.1. This will enable us to demonstrate different presentation styles and to illustrate how we could choose between them to achieve adaptivity. According to Felder's explanation, most learners have preferences in the visual-verbal dimension for presentation, and also show preferences for building up understanding either globally or sequentially. Our research will present content matched to these recipients' understanding styles by considering the visual-verbal and sequential-global dimensions of the FSLSM. The other two dimensions will not be considered to simplify the experiments.

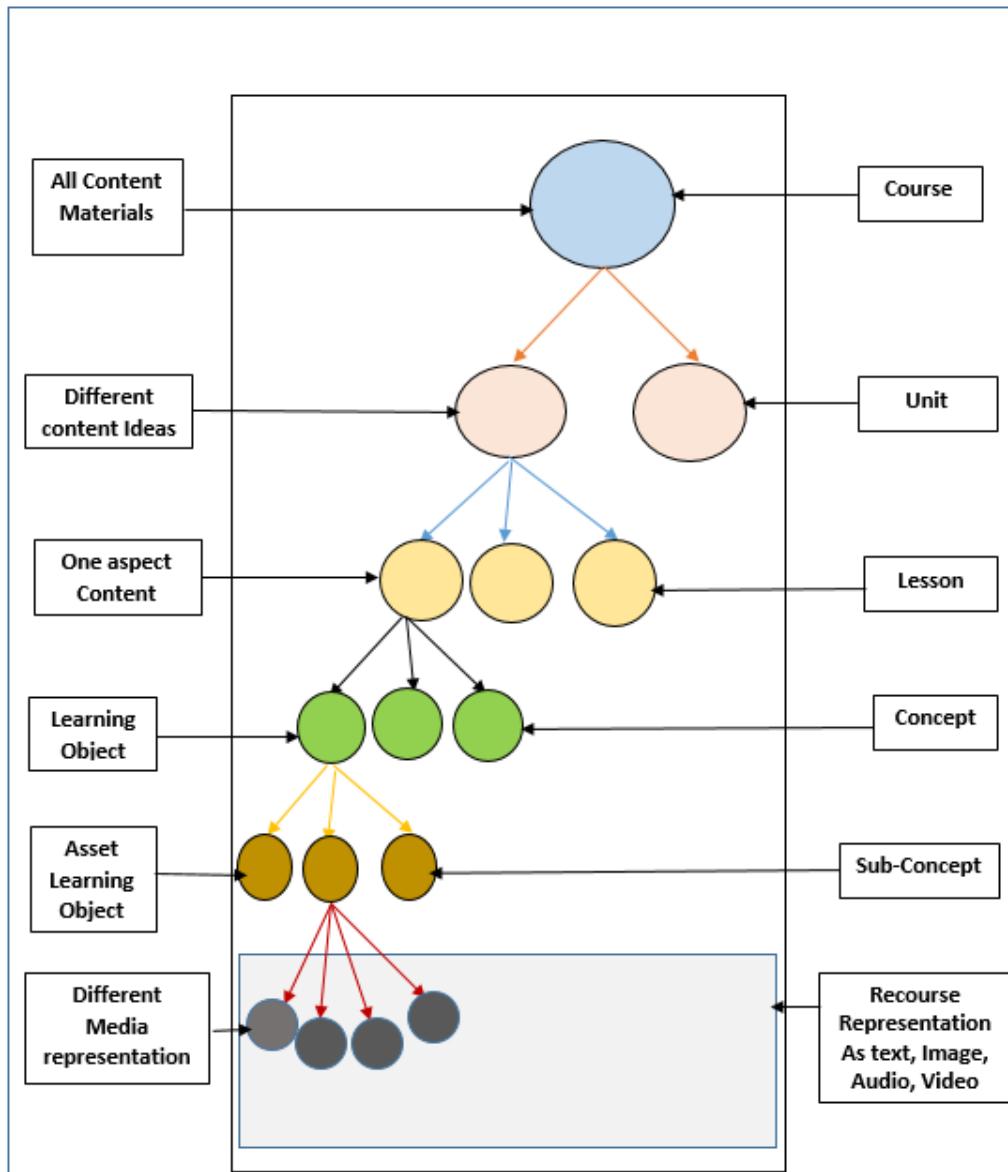


Figure 4.1 Hierarchical Organisation Of The Content Material

According to Felder and Silverman's (1988b) explanation, visual learners prefer to extract information from what they see; that is pictures, diagrams, flow-charts, cartoons, films, and demonstrations. Verbal learners gain more information from words, as provided by written and spoken explanations. Sequential learners tend to develop their understanding of concepts in clearly connected logical steps, which appear to be leading to the ultimate goal. Global learners tend to seek a general understanding of the 'big picture' first before concentrating on the detail which is often understood in apparently unconnected jumps between sub-topics.

The learning content for our concept has been structured and organized to present background, definition, problems, examples, exercises and other aspects as asset learning objects (ALO) conforming to the definition by Schreurs and Moreau (2006). According to this paper, a 'learning object' (LO) is "an independent content component of a course unit" and ALOs are "small learning content elements" within a LO such as "short text documents,

figures, images, video, audio snippets, animations, questions and answers, and tests” and other possibilities. According to our research ideas, some ALOs (not all) will be available in different presentation styles: e.g. strongly visual and strongly verbal. ALOs will be graded according to how strongly they conform to a particular style; and some ALOs will have alternative versions in the same style to allow the same point to be explained in different ways but using the same style. Initially, we will simply demonstrate the different presentation styles. Ultimately, we will discover whether such differences can be exploited as the basis of effective adaptive e-learning systems. Figure 4.2 represents the structure of the content material for one concept in our case study; i.e. “Bayes Theorem”. The concept is part of a course on “Bayesian Networks” and is composed of four learning objects (LOs): “introduction”, “the multiplication rules”, “condition probability”, and “the Bayes Theorem formula”. Each LO has four sub-concepts, called (ALOs), each representing one small idea. For example the “introduction” is divided into four ALOs: “basic concept”, classic probability”, “empirical probability”, and “probability rules”. The content of these ALOs is available in different forms as represented by different types of media such as text, audio, video, and images. These media help us to represent the content material in different ways according to the preferred learning styles different students.

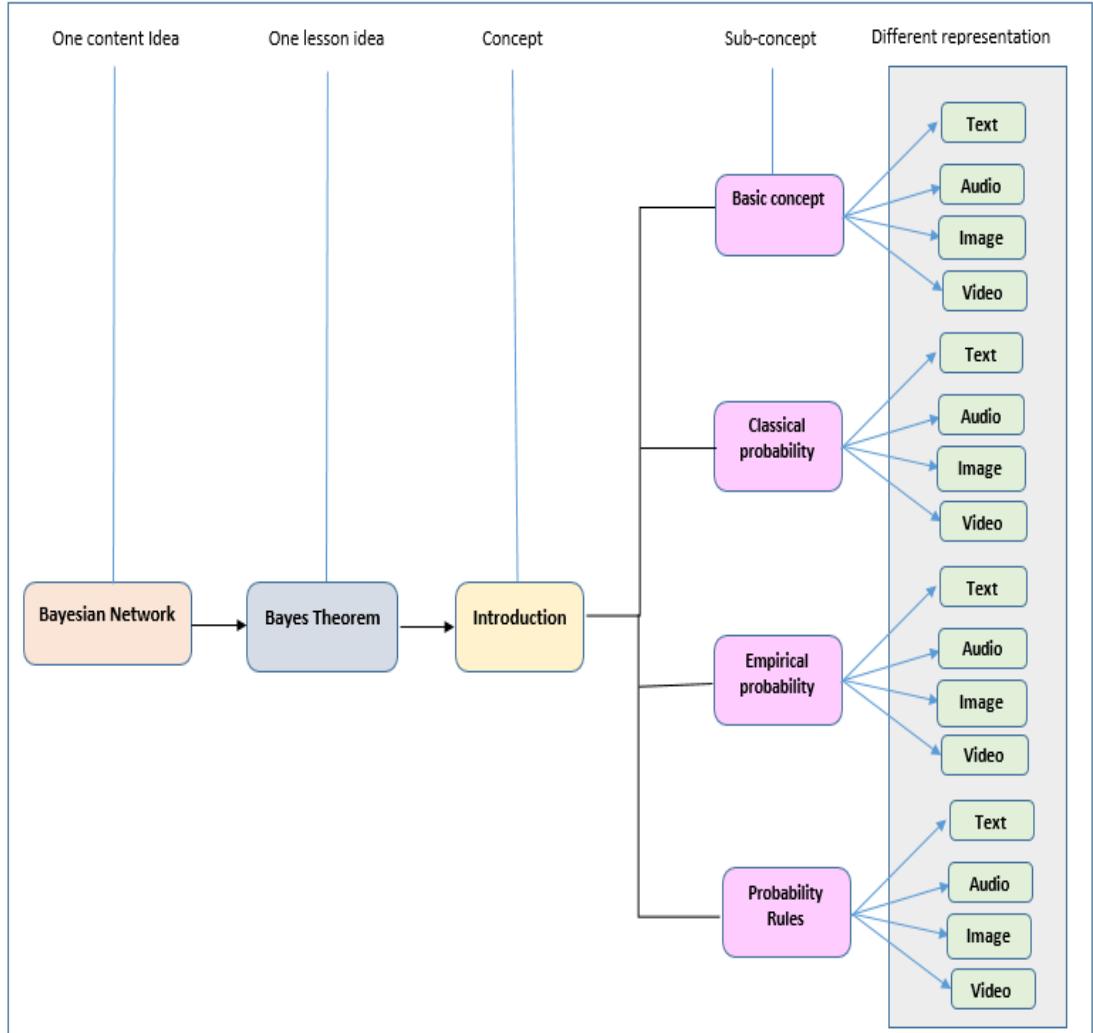


Figure 4.2 Typical Instant of "Bayes Theorem" Hierarchical Organisation

The ALOs for the concepts of "Bayes' Theorem" are capable of being presented in different delivery mechanisms. These are textual, audio, image, and video. Textual and audio are 'verbal' styles whereas Image and video are 'visual' style. Figure 4.3 and Figure 4.4 are examples of ALO presentations in verbal and visual form respectively. More details about the development and implementation of these ALOs in different presentation styles will be explained in Section 5.5.3.2.

Concept 3: {Bayes Theorem } 03

1. Bayes theorem formula

Bayes' theorem, sometimes called Bayes' Rule or 'the principle of inverse probability', follows very quickly from the ideas of probability and conditional probability. It allows us to calculate the probability of some fact 'A' being true when we know that some other fact 'B' is true. The theorem may be stated as follows:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Where $P(A|B)$ is the probability of A being true, given that B is true and $P(A)$ is the 'prior' probability of A being true. $P(B|A)$ is the probability of B given that A is true and $P(B)$ is the 'prior' probability of B being true. $P(A)$ is 'prior' in the sense that it does not take into account any information about B. It is calculated 'prior to' (before) knowing anything about B. Similarly $P(B)$ does not take into account anything known about A. $P(A|B)$ and $P(B|A)$ are conditional or 'posterior' probabilities.

Example:
Box1 contains 2 red balls and 1 blue balls. Box2 contains 3 blue balls and 1 red ball. A fair coin is tossed. If it falls heads up, box 1 is selected and a ball is drawn. If it falls tails up, box2 is selected and a ball is drawn. What is the probability that the outcome of the toss was heads given that a red ball was selected?

Show press show button to see complete diagram

Concept 3: {Bayes Theorem } 03

Solution:

Let, H is an event of a head, and T is an event of a tail
R is an event of a red ball selected
B is an event of a blue ball selected

The desired probability $P(H|R)$

$$P(H|R) = \frac{P(R|H) P(H)}{P(R)}$$

$$P(R) = \frac{2}{6} + \frac{1}{8} = \frac{11}{24}$$

$$P(H|R) = \frac{\frac{2}{6}}{\frac{11}{24}} = \frac{2}{6} * \frac{24}{11} = \frac{8}{11}$$

Show press show button to see complete diagram

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1. Bayes theorem formula

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$$P(H|R) = \frac{\frac{2}{6}}{\frac{11}{24}} = \frac{2}{6} * \frac{24}{11} = \frac{8}{11}$$

Show press show button to see complete diagram

Figure 4.3 ALO Designed in Verbal Format

1 Bayes theorem formula
Bayes' theorem, sometimes called Bayes' Rule or 'the principle of inverse probability', follows very quickly from the ideas of probability and conditional probability. It allows us to calculate the probability of some fact 'X' being true when we know that some other fact 'B' is true. The theorem may be stated as follows:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

Where $P(A|B)$ is the probability of A being true, given that B is true and $P(A)$ is the 'prior' probability of A being true. $P(B|A)$ is the probability of B given that A is true and $P(B)$ is the 'prior' probability of B being true. $P(A)$ is 'prior' in the sense that it does not take into account any information about B. It is calculated 'prior to' (before) knowing anything about B. Similarly $P(B)$ does not take into account anything known about A. $P(A|B)$ and $P(B|A)$ are conditional or posterior probabilities.

Example:
Box1 contains 2 red balls and 1 blue ball. Box2 contains 3 blue balls and 1 red ball. A fair coin is tossed. If it falls heads up, box 1 is selected and a ball is drawn. If it falls tails up, box2 is selected and a ball is drawn.

What is the probability that the outcome of the toss was heads given that a red ball was selected?

Bayes' Theorem formula: $P(H|R) = \frac{P(R|H)P(H)}{P(R|H)P(H) + P(R|T)P(T)}$

Probability tree diagram calculations:

- Path H → Box1 → Red: $P(H) * P(Box1) * P(R|Box1) = \frac{1}{2} * \frac{2}{3} * \frac{2}{3} = \frac{1}{9}$
- Path H → Box2 → Red: $P(H) * P(Box2) * P(R|Box2) = \frac{1}{2} * \frac{1}{3} * \frac{1}{4} = \frac{1}{24}$
- Total Probability of Red: $P(R) = \frac{1}{9} + \frac{1}{24} = \frac{11}{24}$
- Probability of Heads given Red: $P(H|R) = \frac{P(R|H)P(H)}{P(R)} = \frac{\frac{1}{2} * \frac{2}{3}}{\frac{11}{24}} = \frac{8}{11}$

Figure 4.4 ALO Designed in Visual Format

4.2.3 Design

Experiments have been conducted using the Moodle learning management system as the e-learning platform to test our hypotheses. The platform has been extended with additional software for implementing adaptive learning. The participants in our experiment were divided into three groups, as explained earlier in Section 4.2.1. Group 1 was the control group, Group 2 was the static group and Group 3 was the dynamic group. All three groups participated in their learning exercises in our laboratories. All participants were volunteer students from King Abdulaziz University, Jeddah, KSA (female section). These students were registered in the statistics department, were in the same Introduction to General Statistics course, and were required to have the same level of background knowledge about the case-study Bayes' theorem. None of the students had any background knowledge about our case study. All three groups completed a pre-test before they started the experiments. We used one-way ANOVA statistical analysis to check whether the three groups had significant differences in the means of their pre-test scores. No significant difference in the means of their pre-test meant that the three groups had had no difference in their background knowledge. In order to measure achievement among students, means and standard deviations were separately calculated for the performance of all students. Performance data were collected before and after the experiments using pre-tests and post-tests. The findings are presented in Table 6.5. Table 6.5 shows clear and significant differences in achievement between the pre-tests and post-tests.

Our sample size depends on the confidence level of 95% and the margin of error 5%, which is pretty much standard in most quantitative research. We used the free sample size calculator from website CheckMarket (CheckMarket, 2016) to estimate the sample size. The sample size calculator calculates the number of students needed to have statistically significant results for a specific population. In our experiment 110 students participated and 87 students complete the requirements of the experiment. According to the sample size calculator from CheckMarket website for a population of 110 participants at the level of confidence 95% and the margin of error 5% is estimated by 86 participants. Then, statistically our experiment sample size is significant to test our hypotheses.

Each of the three groups studied Bayes' theorem at different time slots on different days. The laboratory was equipped with 40 workstations with high-speed Internet connections and the required software installed. Each participant used a computer with headphones for listening to audio without disturbing others. The participants accessed our extended Moodle e-learning platform via an online website. They were also able to use the system from any other computer with a connection to the Internet. The data records of students in the static and control groups were used to provide the database of previous student records as used for the dynamic adaptation experiments involving the dynamic group.

Figure 4.5 illustrates the experiment that was carried out to test the non-adaptive, statically adaptive and dynamically adaptive schemes that were explained in Chapter 3. This will be explained in the next section.

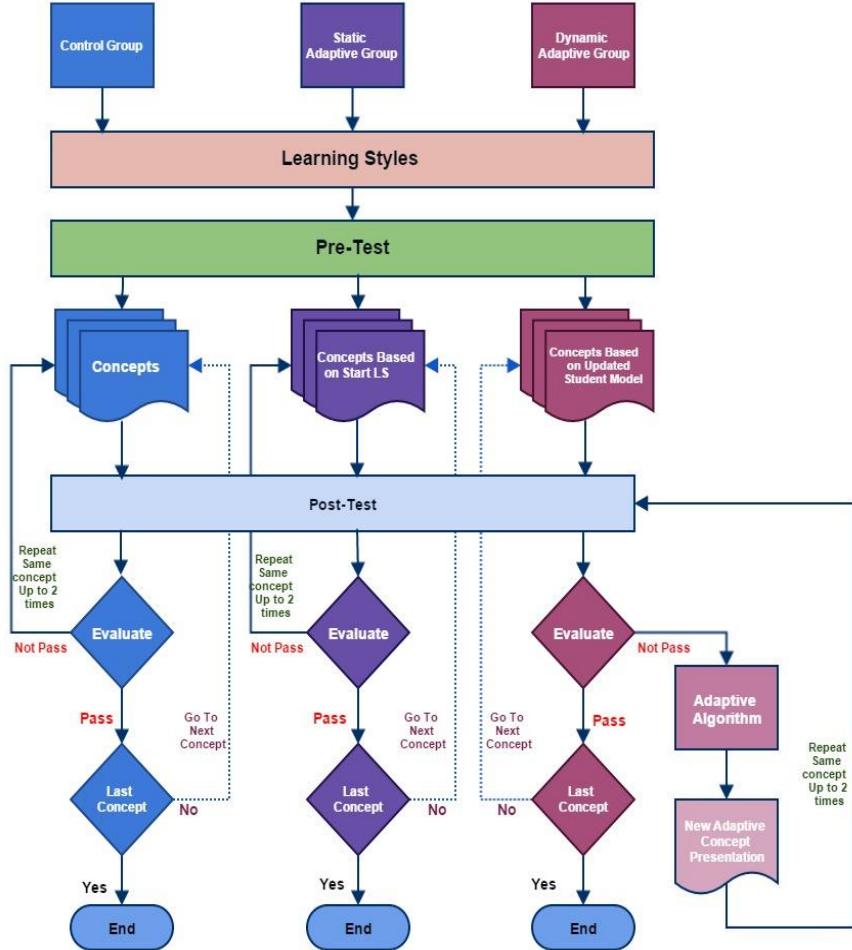


Figure 4.5 Design Experiment for the Three Groups

4.2.4 Procedures

Students participating in the experiment were assigned to three groups as explained in Section 4.2.1. When a student enters the LMS, she should register with a given username and password. Then, the system asks the student to enter her GPA and fill in the ILS questionnaire. Next, a pre-test is presented and its results are collected. After that the case study content is presented to the student according to her assigned group. The students' knowledge acquisitions were measured according to: the time spent learning each concept, the test after each concept, and the pre-test and post-test results.

4.2.4.1 Index of Learning Styles (ILS) Questionnaire

As explained in Section 3.2.1 the FSLSM instrument provides a 4-dimensional model of each learner's preferred learning style with each dimension quantified on an integer scale from 11a to 11b (or -11 to 11). The instrument is built into our adaptive system. The four dimensions are Active/Reflect (ACT/REF), Senses/Intuitive (SNS/INT), Visual/Verbal

(VIS/VER), and Sequential/Global (SEQ/GLO). It is useful to divide each of the scales into six intervals: -11 to -9, -7 to -5, -3 to -1, 1 to 3, 5 to 7, and 9 to 11.

Each learner has a score in one of the six intervals for each of the four dimensions. For example, a learner could have scores in intervals {(1-3) a for ACT/REF, (9-11) b for SNS/INT, (9-11) a for VIS/VER and (5-7) b for SEQ/GLO}. This means that the learner is in-between active and reflective, strongly intuitive, strongly visual, and moderately global. There is a total of $6^4 = 1296$ possible combinations of intervals.

According to Felder's explanation, most learners have reception preferences in the visual-verbal dimension for presentation, and also show preferences for building up understanding either globally or sequentially. This research will demonstrate content presentation matched to these reception and understanding styles by considering the visual-verbal and sequential-global dimensions of the FSLSM. The Visual/Verbal dimension was considered to have six interval scales as explained above. However, for simplification we considered the Sequential/Global dimension to have only two intervals. Consequently, we had 12 different learning styles for our experiment as shown in Figure 4.6.

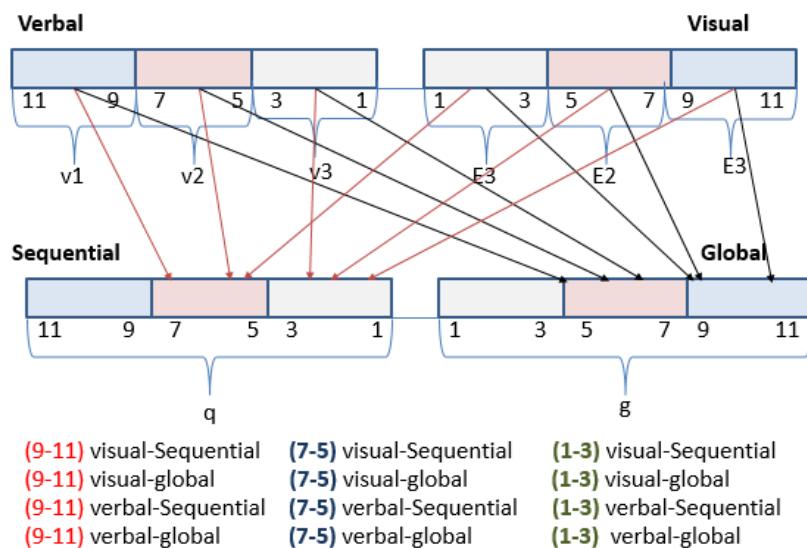


Figure 4.6 The 12 different Learning Styles

4.2.4.2 Content Representation According to the 12 Learning Styles

The sequential-global dimension affects organisation of the content as presented to the student. A sequential student would be presented with the material in order, where the order has been designed to be logical and to develop an argument step by step according to a teachers' recommendation. A global student would be presented with the list of ALO's and given the chance to go through the material in whatever order he or she prefers. The global student wants to see all the problem from the beginning to the end as a big picture. Table 4.1

shows how the content learning martial is represented according to each score interval. For example, if the student score in the verbal-visual dimension is between 9b and 11b, all the ALOs will be presented 100% visually and organised either sequentially or globally depending on the score in the other dimension. Figure 4.7 and Figure 4.8 explain how the previous example may be presented sequentially or globally according to the student ILS scores.

Table 4.1 Concept Representation According to ILS Scores

| Learning Styles | Percentage of visual-verbal Dimension | | Concept Representation style | | | | Concept Organizing |
|--------------------------|---------------------------------------|--------|------------------------------|--------|--------|--------|--------------------|
| | Visual | Verbal | ALO1 | ALO2 | ALO3 | ALO4 | |
| (9-11) visual-Sequential | 100% | - | visual | visual | visual | visual | Step by step |
| (5-7) visual-Sequential | 75% | 25% | visual | visual | visual | verbal | Step by step |
| (1-3) visual-Sequential | 50% | 50% | visual | visual | verbal | verbal | Step by step |
| (9-11) visual-global | 100% | - | visual | visual | visual | visual | List |
| (5-7) visual-global | 75% | 25% | visual | visual | visual | verbal | List |
| (1-3) visual-global | 50% | 50% | visual | visual | verbal | verbal | List |
| (9-11) verbal-Sequential | - | 100% | verbal | verbal | verbal | verbal | Step by step |
| (5-7) verbal -Sequential | 25% | 75% | verbal | verbal | verbal | visual | Step by step |
| (1-3) verbal -Sequential | 50% | 50% | verbal | verbal | visual | visual | Step by step |
| (9-11) verbal -global | - | 100% | verbal | verbal | verbal | verbal | List |
| (5-7) verbal -global | 25% | 75% | verbal | verbal | verbal | visual | List |
| (1-3) verbal -global | 50% | 50% | verbal | verbal | visual | visual | List |

Card 1: Bayes Theorem | D3

Bayes theorem formula: $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$

Where $P(B|A)$ is the probability of having true, given that B is true and $P(A)$ is the 'prior' probability of being true. $P(B|A)$ is the probability of B given that A is true and P(B) is the 'prior' probability of B being true. $P(B|A)$ is prior in the sense that it does not take into account any information about B. It is calculated 'prior to' (before) learning anything about B. Similarly $P(B|A)$ does not take into account anything known about A. $P(B|A)$ and $P(B|A')$ are conditional or 'posterior' probabilities.

Example: Box 1 contains 2 red balls and 1 blue ball. Box 2 contains 3 blue balls and 1 red ball. A box is taken at random. If 1 ball is drawn up, box 1 is selected and a ball is drawn. If it falls tails up, box 2 is selected and a ball is drawn.

Card 2: Bayes Theorem | D3

Ball

Box 1: 2 Red, 1 Blue
Box 2: 1 Red, 3 Blue

$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A'|B)P(B')}$

$P(B|A) = \frac{2/3 * 1/4}{2/3 * 1/4 + 1/3 * 3/4} = \frac{1/6}{1/2} = \frac{1}{3}$

Card 3: Bayes Theorem | D3

2. Illustration Bayes theorem by example

The number of students from different countries in one college is as follows:

| | | | | |
|---------|--------|----|--------|-------|
| Country | France | UK | Canada | Total |
| Male | 15 | 12 | 10 | 37 |
| Female | 10 | 15 | 10 | 35 |
| Total | 25 | 27 | 20 | 72 |

If we selected a boy, what is the probability that he is from France?

Card 4: Bayes Theorem | D3

Solution

$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A'|B)P(B')}$

$P(B) = \frac{25}{72} = \frac{2}{9}$

$P(B') = \frac{37}{72} = \frac{7}{9}$

$P(A|B) = \frac{15}{25} = \frac{3}{5}$

$P(A'|B) = \frac{10}{25} = \frac{2}{5}$

$P(B|A) = \frac{\frac{3}{5} * \frac{2}{9}}{\frac{3}{5} * \frac{2}{9} + \frac{2}{5} * \frac{7}{9}} = \frac{1}{3}$

The probability that the selected boy is from France is $\frac{1}{3}$.

Card 5: Bayes Theorem | D3

3 Bayes theorem in medicine

If a person does not have the disease, the probability of a negative result ($P(Neg|D')$) is 95%. If a healthy unselected individual is tested and the result is positive.

Card 6: Bayes Theorem | D3

3 Bayes theorem in medicine

Disease Test Result

$P(D) = 0.001$ and $P(D') = 1 - 0.001 = 0.999$

Probably the person having the disease and get positive result having the disease is $P(D|Pos) = 0.99$, then $P(D|Neg) = 0.01$

Card 7: Bayes Theorem | D3

4 Usefulness of Bayes theorem in life

In general Bayes theorem allows us to take additional information into account when calculating probabilities. Without the additional information, we have a 'prior' probability and with it we have a 'conditional' or 'posterior' probability.

at an outdoor ceremony in the desert. In recent years, it has rained only 5 days each year. Unfortunately, the weatherman has predicted rain for tomorrow. When it actually rains, the weatherman correctly forecasts rain 95% of the time. When it doesn't rain, he incorrectly forecasts rain 10% of the time. What is the probability that it will rain on the day of Maria's wedding?

Card 8: Bayes Theorem | D3

In term of probabilities

Tomorrow

If it rains(R) $P(R) = 5/365$ $P(R) = 0.014$

If it doesn't rain(N) $P(N) = 360/365$ $P(N) = 0.986$

Weatherman predicts(B)

If it rains 95% $P(B|R) = 0.95$

If it doesn't rain 10% $P(B|N) = 0.1$

$P(R|B) = \frac{P(R) * P(B|R)}{(P(R) * P(B|R)) + (P(N) * P(B|N))}$

$P(R|B) = \frac{(0.014) * (0.95)}{(0.014) * (0.95) + (0.986) * (0.1)}$

$P(R|B) = 0.11 = 11\%$

Figure 4.7 Content Represented by ILS score (9-11) visual and Sequential

The figure consists of four screenshots of a learning system interface, each titled "Concept 3 Bayes Theorem | 03".

- Screenshot 1:** Shows a probability calculation: $P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|\bar{B})P(\bar{B})} = \frac{\frac{1}{2} \cdot \frac{2}{3}}{\frac{1}{2} \cdot \frac{2}{3} + \frac{1}{2} \cdot \frac{1}{3}} = \frac{1}{3}$. A red circle highlights the result $\frac{1}{3}$.
- Screenshot 2:** Illustrates Bayes theorem with colored balls. It shows three boxes: one with 10 pink balls (labeled "French Students"), one with 10 blue balls (labeled "Non French Students"), and one with 10 mixed balls (labeled "Total Students").
- Screenshot 3:** Explains Bayes theorem in terms of probabilities. It states: "In general Bayes theorem allows us to take additional information into account when calculating conditional probability. For example, if we know that the event B has already occurred, we have a prior probability and all we need is additional information to calculate the conditional probability." It includes a diagram of a sun and clouds.
- Screenshot 4:** Illustrates Bayes theorem in medicine. It shows a doctor talking to a patient. The text says: "For a patient who has the disease, the probability of getting a positive test result is called sensitivity. For a patient who does not have the disease, the probability of getting a negative test result is called specificity." It includes a formula: $P(R|D) = \frac{P(D|R)P(R)}{P(D|R)P(R) + P(D|\bar{R})P(\bar{R})} = \frac{0.9 \times 0.1}{0.9 \times 0.1 + 0.1 \times 0.9} = 0.5$.

A central box labeled "Lesson Menu" contains the following numbered items:

1. Bayes theorem formula
2. Illustration Bayes theorem by example
3. Bayes theorem in medicine
4. Usefulness of Bayes theorem in life

Arrows point from the "Return to lesson Menu" link at the top to the first three items in the menu, and from the menu items to their respective screenshots.

Figure 4.8 Content Represented by ILS score (9-11) visual and Global

4.2.4.3 Control Group Experiment Procedure

This experiment was conducted using non-AELS that presents the course content materials as a regular online course, based on a teacher's idea of the best way to present the material. The students preferred learning styles preferences were recorded by the system, as derived from an ILS questionnaire, but did not affect the students' content representation. Figure 4.9 illustrates control group experiment' steps.

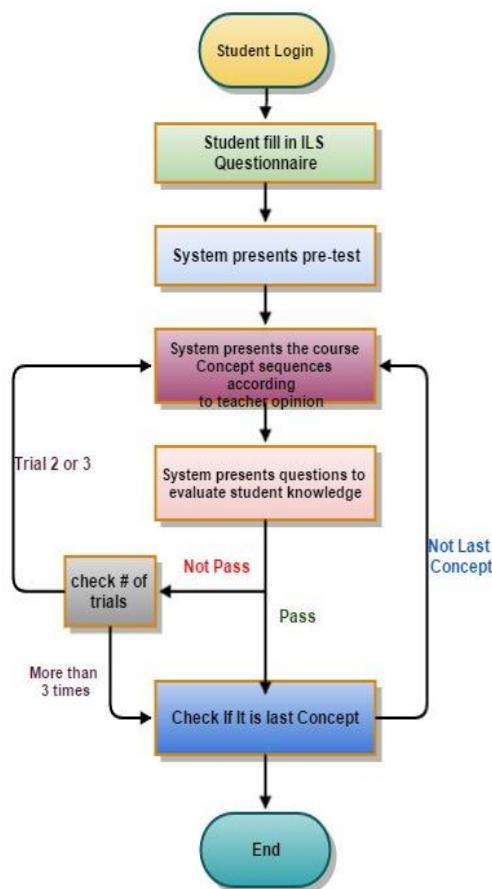


Figure 4.9 Control Group Procedure Steps

4.2.4.4 Static Group Experiment Procedure

This experiment was conducted using SAELS that presents the course content material in different ways, based on the student's learning style preferences with no change or update to a student's learning styles as obtained at the beginning of the course. A student in this experiment learns and acquires knowledge using his/her specific learning style during the whole course. Figure 4.10 illustrates experiments' steps.

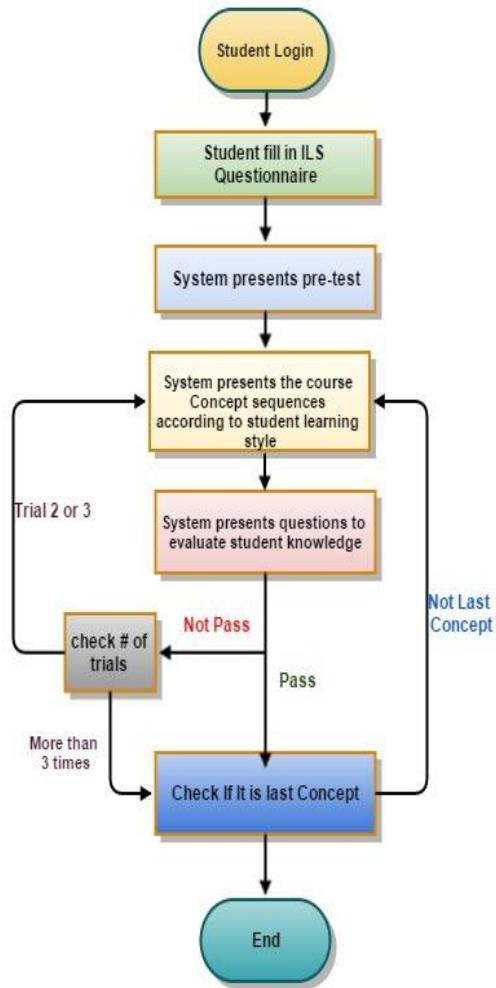


Figure 4.10 Static Adaptive Experiment Procedure Steps

4.2.4.5 Dynamic Group Experiment Procedure

This experiment was conducted using DAELS that presents the course content material in different ways, based on the student's learning style preferences. Concepts are presented according to the results of the Similarity algorithm. Adjustments and changes to the student learning styles are made based on the students' responses and the Similarity algorithm. The student in this experiment learns and acquires knowledge using his/her particular learning style that can be changed according to student achievements in the course. Figure 4.11 illustrates the dynamic adaptive experiment' steps.

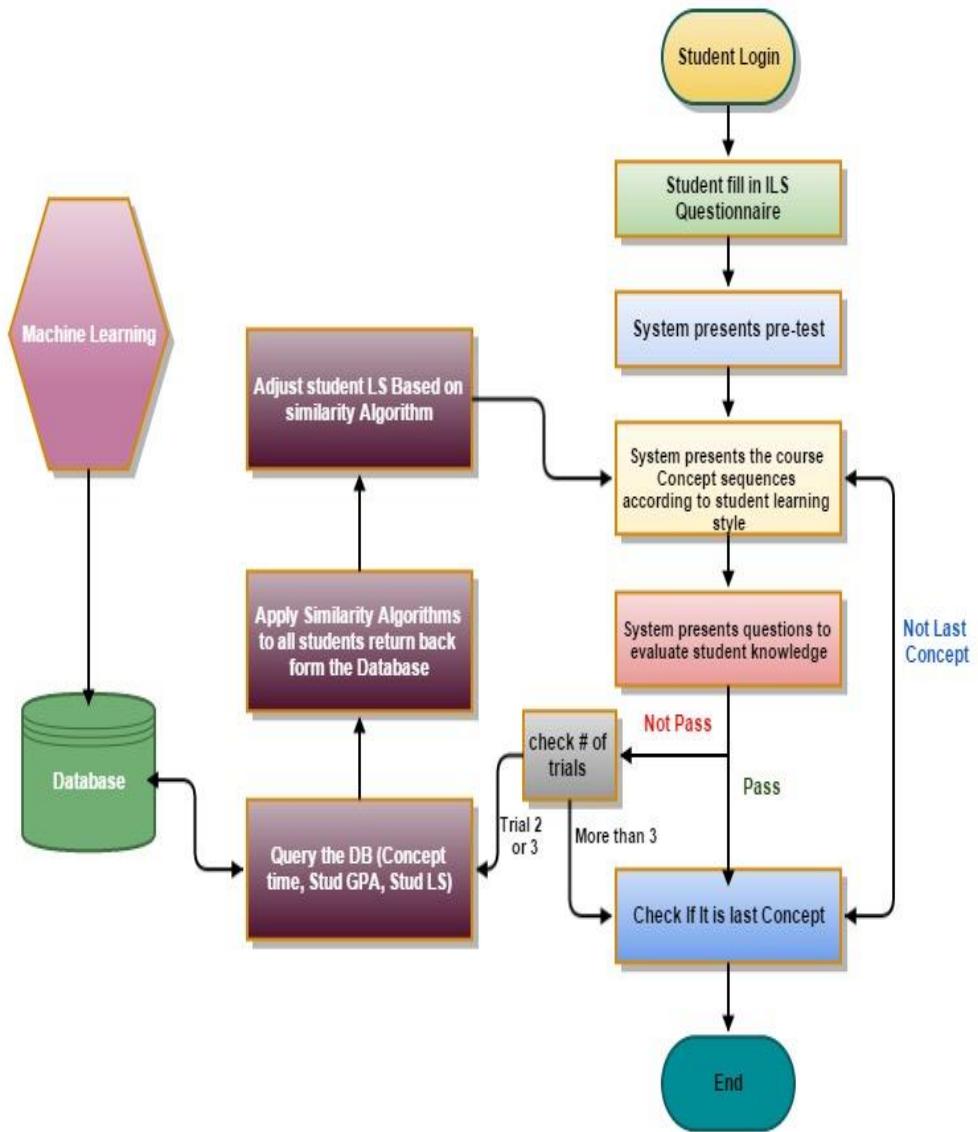


Figure 4.11 Dynamic Adaptive Experiment Procedure Steps

Chapter 5

Development of Dynamic Adaptive E-learning System

The purpose of this chapter is to present the design, analysis, and implementation of Similarity algorithms for extending the ‘Moodle’ learning management system to include our DAELS. The software development used the ‘waterfall’ approach (Royce, 1970) . The first steps were to develop the ‘capture’ and ‘analysis’ facilities, followed by the design of a suitable system architecture. The implementation uses ‘PHP’, a server-side scripting language designed for web development. PHP is highly compatible with the structure of the Moodle (Moodle, 2014) software package. The final part of this chapter is concerned with testing the extended system’s functionality and performance.

5.1 DAELS Development

According to De Koch (2001) and Parvez and Blank (2007), developing an adaptive hypermedia systems is not trivial work. It is a complex task and therefore needs an appropriate software engineering process. The ‘waterfall’ model shown in Figure 5.1 illustrates our approach which was in four phases: specification, design, implementation, and testing. The approach will be explained in the following subsections. The design and the implementation of our adaptive system faced several challenges. Among the main challenges were integrating our developed classes with Moodle classes, and implementing the machine learning algorithm introduced in Chapter 4 to facilitate the data-base searching process required for dynamic adaptivity.

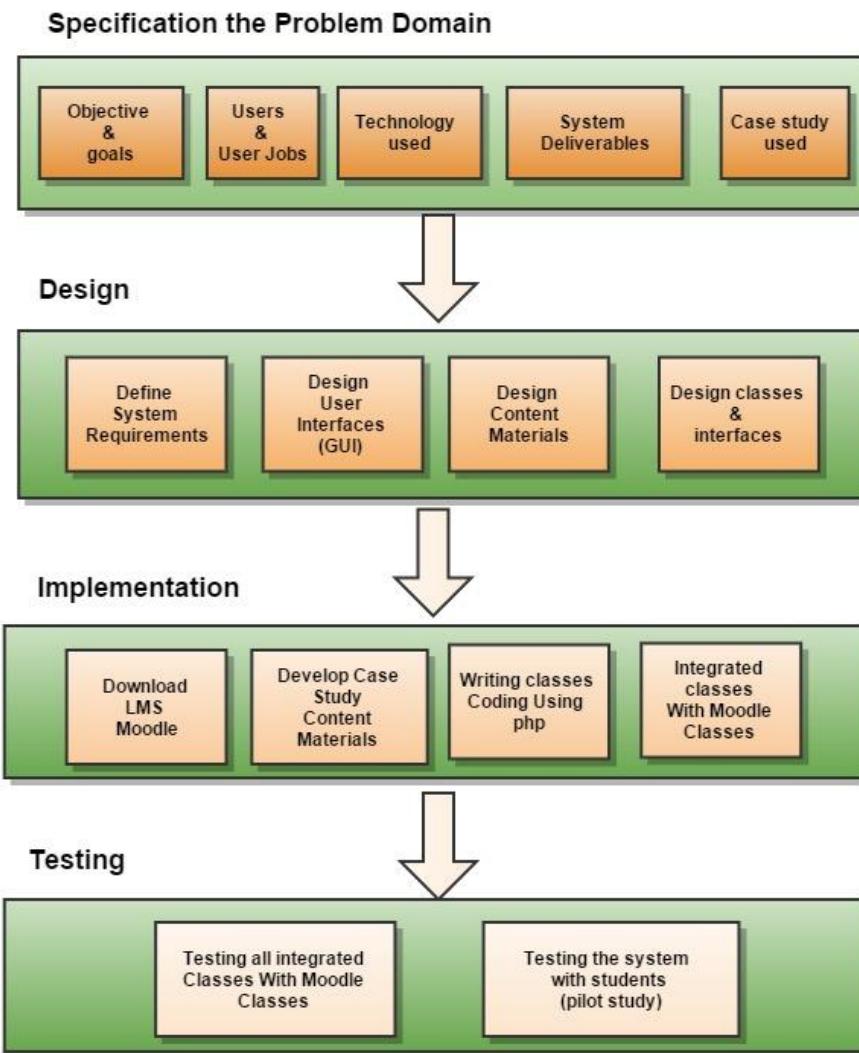


Figure 5.1 DAELS Development Phases

5.1.1 Specification Analysis Phase

An analysis of the system specification was the first step in the development of our DAELS. This required a description of the main features and functions required by the proposed mechanisms.

5.1.1.1 Objectives and Goals

The goal for our DAELS is to present learning content material according to the learning style preferences of the student and to adjust these during the learning progress. The preferences are stored in an adaptive system which should be able to detect the variety of students' preferences of their learning styles and take these data to build student profile. Consequently, based on student model data the presentation of content material will be delivered to student and which is continuously updated according to the student's interaction with the system.

The first important objective is the Similarity algorithm for dynamic adaptive that is based on the student model as described in Chapter 3. The student model provides the student GPA, the ILS scores, the time spent in learning each concept and other information.

The second objective is the inclusion of the ILS instrument in the extended Moodle software.

The third objective is the means of developing and storing the adaptive teaching material and its meta-data in Moodle in such a way that the demands of providing the material in different styles are met.

The fourth and final objective is the adaption algorithm itself and its integration with Moodle.

These objectives are associated with various performance objectives, measures, and requirements that can be used to assess the overall effectiveness of the adaptive system. The four objectives identified above provide the focus for the research and development.

5.1.1.2 Users and Users Tasks

There are three types of users in our adaptive learning system:

- *Administrator*: responsible for managing the adaptive LMS, the registration of students, backing up and troubleshooting course material, system maintenance, and supporting the teachers and students in all aspects of their interaction with the LMS.
- *Teachers*: responsible for designing the learning material according to diversity of learning styles corresponding to the FSLM model.
- *Learners*: responsible for registering, and filling in the ILS questionnaire, taking the pre-test, and learning from the course material as presented to them.

5.1.1.3 Case Study

In order to construct an adaptive e-learning environment, “Bayes Theorem” topic was chosen as a case study. This topic consists of three concepts, listed in the Appendix A. Bayes Theorem is one of the important topics of STAT 110 course that is offered to freshmen students by Statistics Department at King Abdulaziz University, Jeddah/KSA.

The Statistics topic was selected for several reasons. Firstly, the content materials of this topic has been refined and validated by expert lecturers from Statistics Department. Secondly, the topic is self-contained and not over-complicated. In addition, this topic is unlikely to have been previously encountered by the cohorts of volunteers who will help us with the experiments. Bayes Theorem was considered a suitable and desirable learning objective for potential students. Lastly, this topic is an abstract topic, which opened

opportunities for us to develop different representations for the same concept by using different media such as audio, animation, video, and text to represent the concept idea.

5.1.1.4 Technology Used

Moodle was chosen for our extended LMS because it is open source and its extensibility is well supported by detailed documentation and guidelines, and also templates for programming and incorporating new features. We used the PHP ‘hypertext pre-processing language’ to extend Moodle with our adaptive systems. PHP is a server-side scripting language designed for web development and is also used as a general-purpose programming language whose scripts can be easily embedded into HTML pages. We also used the MySQL open source relational database management system (Oracle, 2016) for creating and managing the course material and the history of all student activity. The MySQL ‘structured query language’ is used in this project for executing database queries and also editing, deleting and modifying the data., execute SQL queries, and create new tables. It is a popular choice of database for use in web applications.

Our project also uses the Apache HTTP Server and JavaScript (JS) as an interpreted computer programming language which allows client-side scripts to interact with the user, control the browser, communicate asynchronously, and alter the document content that is displayed.

Much of the audio-visual style course content was built using the Adobe Flash Builder to produce ‘small web format’ ‘SWF’ material for ‘Flash Player’. swf supports graphics and the streaming of video and audio. Adobe Flash Builder and similar packages were used to design the style and mode of delivery of the learning objects available to the adaptive LMS. Flash Builder allows the course provider to create visual layouts with highly interactive medium content such as text, graphics, animation and video.

XQuery is a query language for retrieving structured and unstructured data from XML, and text files. For our implementation, we used the latest version XQuery 3.0 developed by the XML Query at W3C (W3C, 2014). Some of the learning information in the extended LMS will be in different formats, extracted from a variety of sources. XQuery therefore proves very useful in dealing with XML and many other formats.

Weka is an open source software package that provides a collection of machine learning and data mining algorithms for data pre-processing, classification, clustering, visualization, and regression association rules (Waikato, 2013). It allows the extended LMS to provide sophisticated information searching techniques to students requiring insight into the topics they are studying and provides yet further ways of presenting the information.

5.1.1.5 System Deliverables

The deliverables of our adaptive system are the content material, the ILS instrument implementation, quizzes after each concept, and reports and logging of students activity and progress.

5.1.2 Design Phase

The next step is designing an architecture based on the specifications of the functional systems and features of adaptive e-learning systems expressed in the previous section.

5.1.2.1 System Requirement

Our adaptive system is divided into the following three sub-systems as shown in Figure 5.2.

1. A regular non-adaptive e-learning system (non-AELS) augmented with the logging of student activity and assessment results. It is used by control group students.
2. A static adaptive e-learning system (SAELS) with the logging of student activity and assessment results and presentation style adapted according to an initial ILS assessment. It is used by static group.
3. A dynamic adaptive e-learning system (DAELS) with the logging of student activity and assessment results and presentation style initially adapted to an ILS assessment and subsequently updated according to the progress and activity of the student in comparison to those of previous students according to the proposed Similarity algorithm. It is used by dynamic group students.

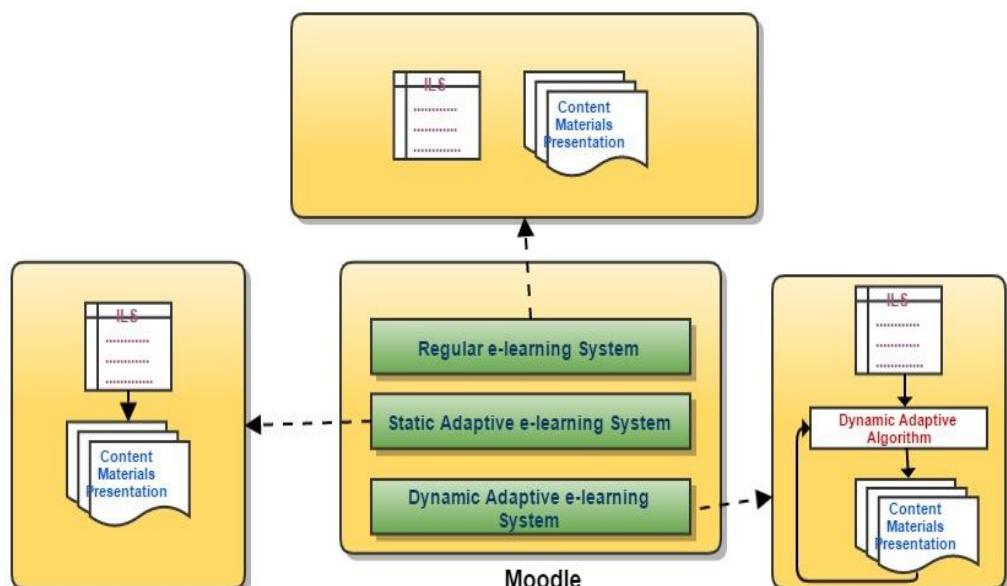


Figure 5.2 Moodle Design Phase

5.1.2.2 Design User Interfaces

This section describes the user interface and the guidelines that were taken into account for our design. The first Interface presented to the student is the registration interface, followed by the ILS questionnaire. After that, the GUI screen is presented differentially according to whether the system is required to be non-adaptive, static or dynamic. The GUI is designed in a simple way, to help students to navigate the system easily.

5.1.2.3 Design of Learning Content Material

The case study topic was designed as a hierarchical model as depicted in Figure 5.3. The learning content is structured as three concepts. Each concept is divided into learning objects. Each learning object explains a single idea as shown in Figure 5.3. Each learning object is designed and implemented to be represented by different learning styles type according to FSLSM explanations in Table 2.1. This means that each object has at least four versions. The case-study has 12 learning objects. Therefore 48 objects, including different versions of the same object, must be designed by the course provider. Refer to Section 4.2.2 for more details on the design.

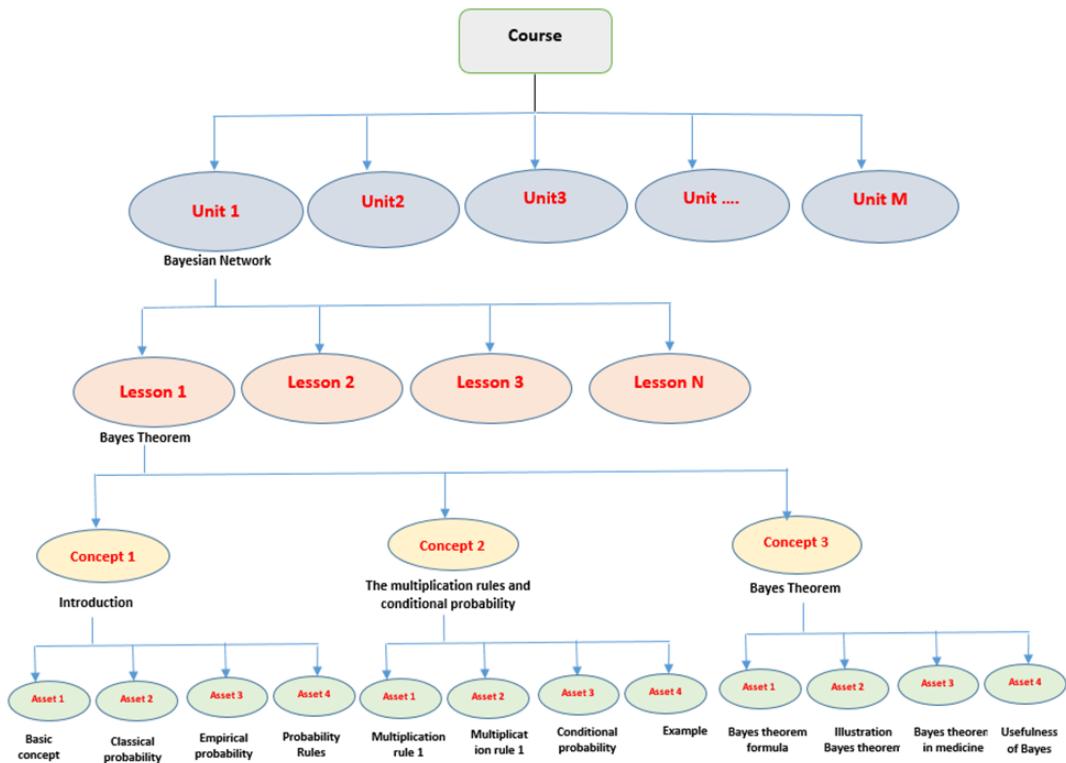


Figure 5.3 Structure Design for Learning Materials

5.1.2.4 Design Classes

We designed classes to be integrated with Moodle environment to extend it to perform the proposed adaptivity approach. Following is a summarized description of these classes.

- A class with methods for presenting a pre-test exam and transmitting the results to the student model.
- A class with methods for presenting the ILS questionnaire and then predicting preferred learning styles according to FSLSM model answer sheet. For more detail see Section 3.2.1.
- A class with methods for presenting the learning content to each student according to her preferred learning styles as currently stored in the learner model.
- A class with a method for counting the number of concept repetitions. In our adaptive systems, a student can repeat the same concept twice based on the results of the evaluation questions after each concept
- A class with methods for implementing the Similarity algorithm explained in Section 3.2.2. These methods searches for similarity with previous students by querying a database of their records and build a sorted list for all similar students.
- A class with methods for evaluating a student's knowledge on a concept.
- Classes with methods for presenting our case study topic non-adaptively as explained in Section 4.2.4.3.
- A class takes student profile from student model and presents our case study topic with static adaptation as explained in section 4.2.4.4 .A class takes student profile from student model and presents our case study topic with dynamic adaptation as explained in Section 4.2.4.5
- A class with methods for taking the output of the ID3 tree machine learning algorithm as XML code and changing it to tree structures. This is done to improve the efficiency of database searches as required by the Similarity algorithm.

5.1.3 Implementation Phase

The implementation phase extended a standard version of ‘Moodle’ to include the classes listed above. The implementation of our system’s functionality faced several problems. These problems were related to two aspects: coding using PHP programing language and the integration of this functionality with Moodle features. Details are given below:

5.1.3.1 Downloading Moodle

Moodle is a free and open-source software learning platform written in PHP. It was developed on strong pedagogical principles, providing private learning space for course providers to implement on-line courses with flexible content and collaborative activities. Moodle is used for distance learning, blended learning in universities, and as e-learning platforms in schools and business companies. It can be installed on a web server, such as the

Apache HTTP Server and a number of database management systems, such as MySQL. We have chosen Moodle because it is an open source learning management system and very popular among educators as a tool for creating online dynamic courses web sites for their students. Moodle is downloaded from the website <https://moodle.com/> into our webserver. According to our experiments, explained in Chapter 4, Moodle was extended as depicted in Figure 5.4.

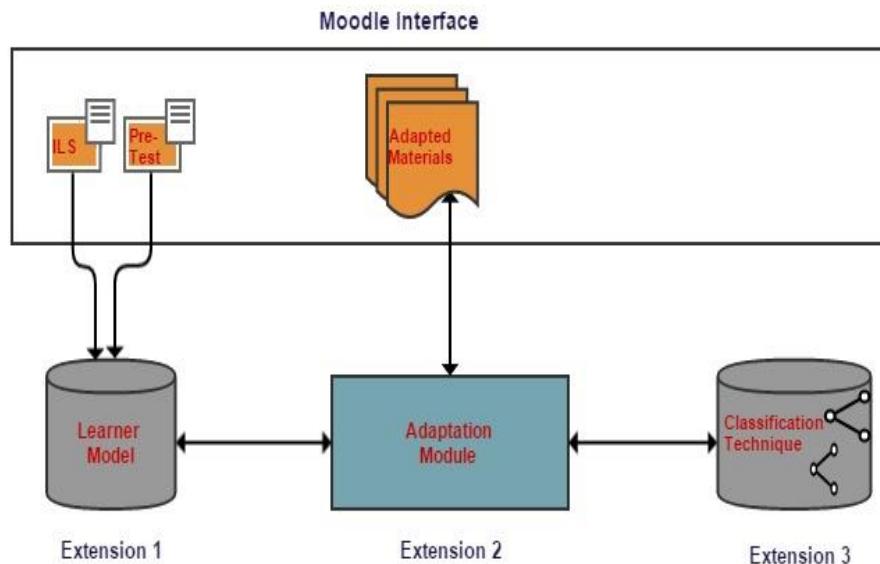


Figure 5.4 Extensions of Moodle Architecture for Providing Adaptive Content

The first extension deals with the ILS questionnaire and the pre-test for evaluating student's initial knowledge and initialising The ILS questionnaire and pre-test questions were added to the registration form in Moodle. The ILS results and the pre-test scores are calculated and stored in the student model.

The second extension deals with presenting course content in an appropriate presentation that fits the students preferred learning styles. Adaptation is done according to the adaptive algorithm explained in Chapter 3. The learning content is presented via Moodle's normal user-interface.

The third extension empowers the system to dynamically update the profiles of students in reasonable time. The importance of our adaptation design goal is to build systems that reasonable numbers of students can actually use it. The proposed adaptation method is built based on Similarity algorithm that search for similar previous students' records with success scores to adjust the current student learning styles. Thus, we need to speed up the Similarity algorithm that searches for similar student records by employing the 'decision tree' machine

learning algorithm explained in Section 3.4.2. This divides the records of previous students into classes with similar properties and thus narrows down the necessary searches.

Our extended LMS system can offer a great variety of workspace that facilitates adaptivity as well other Moodle functionality for preparing assignments and tests, managing distance classes, and enabling collaborative learning with forums, chats, file storage areas and news services. As the usage increases, the adaptive systems will accumulate a vast amount of valuable information about previous students. It becomes computationally complex for the Similarity algorithm to search this database and extract useful information to find similar students. Our solution is to use the ‘Decision tree’ method ID3 (Mitchell, 1997) to introduce classification into the decision making. ID3 is applied to the records of previous students to divide them into classes where each class contains records of students that have similar attributes.

Our data classifier consists of the following process steps as illustrated in Figure 5.5:

- MySQL is used to access the records of previous students. These records document usage, behavior, learning styles and marks which are stored in Moodle Database.. In order to extract students’ data, we used MySQL, a database administrator tool. This tool helps us to visualize, delete, edit, and modify database tables. We used this tool to select the required data using SQL queries and exported to a more convenient file format such as CSV.
- Weka is used to export the Moodle data into ‘ARFF’ files. An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes. ARFF files have two distinct sections. The first section is introduced by a @relation tag, and includes the attribute names, types, and values. The second section starts with a @data tag and contains values of attributes and their relation.
- Weka applies the decision tree algorithm to the dataset of previous student records and analyzes its output to extract information about the data. The ‘J4.8’ algorithm, is Weka’s implementation of a decision tree learner.
- The decision tree reveals information about the classification of the previous students .The results are converted to XML.
- XQuery is used to search the database to find previous students ‘similar’ to the one in process. The query returns the group of students that have the closest characteristics to the student in process. The Similarity algorithm now searches for

similar students in this extracted group instead of searching the whole database that has vast number of students.

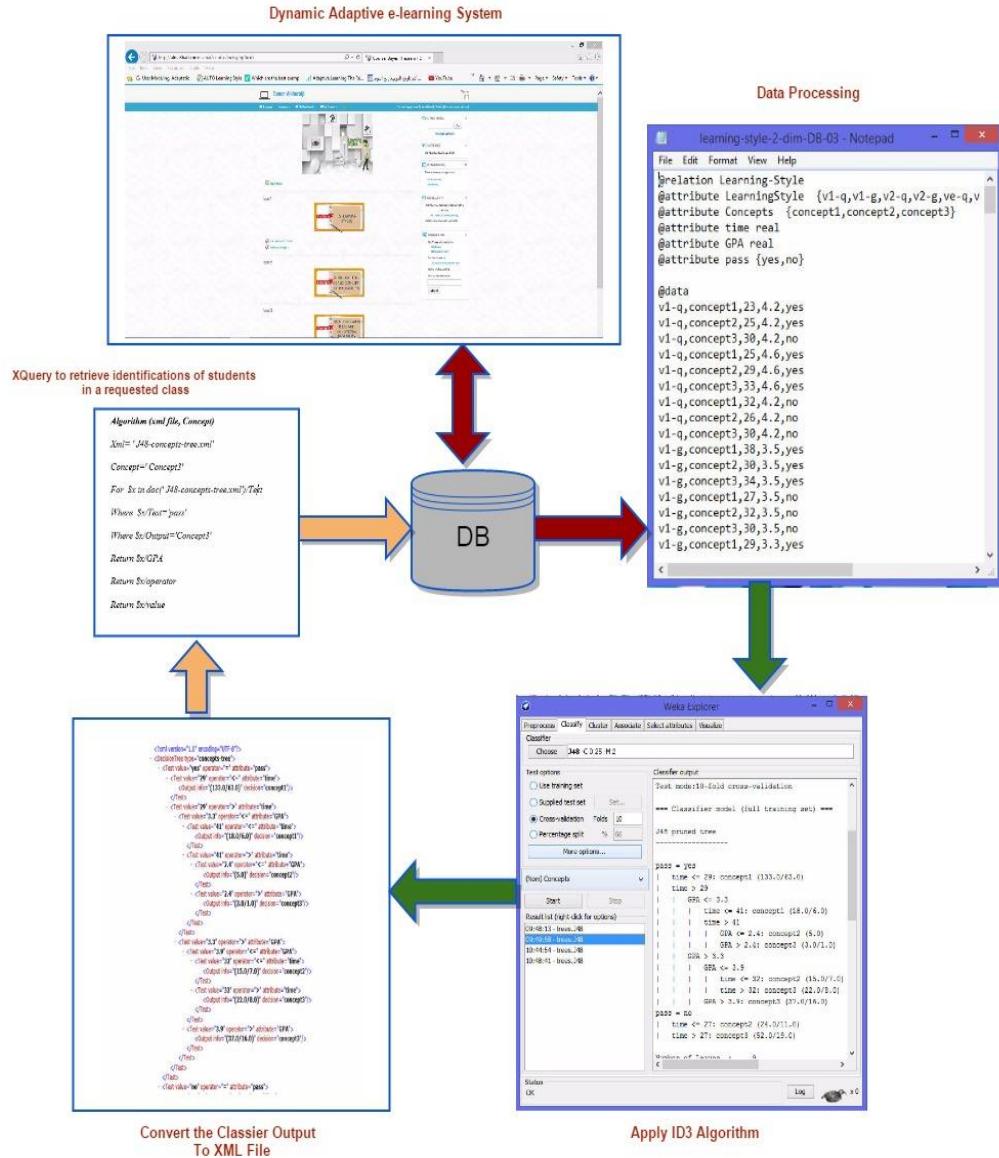


Figure 5.5 Machine Learning Classification Processing Steps

5.1.3.2 Producing Multimedia Content Material

The teaching material for Bayes' theorem was part of an introductory statistics course curriculum studied by students in the Statistical Department at King Abdulaziz University. The content was constructed by the teachers who taught the course. The content material was designed based on different stages of development. The first stage divided the material into a series of asset learning objects (ALO) with a choice of different presentation styles for each ALO, as explained in Section 4.2.2. The development of the ALOs for Bayes' theorem case study in four delivery mechanisms was carried out using Adobe Flash Builder to create

flash files for each ALO. Adobe Flash is usually used to create multimedia and software animations, vector graphics, internet applications, and mobile applications. In addition, it allowed the streaming of audio and video. We chose Flash format due to its widespread support in web browsers. The size of its output file is compact, and webpages use it as embedded swf files.

Each ALO is designed as a textual, audio, image, or video file. Based on our case study, Bayes' Theorem, we designed and developed 48 flash files. Each ALO is presented in text format as would be seen in a book. The style adopted would be that of a well-written textbook, with diagrams and equations explained by well-constructed sentences as depicted in Figure 5.6. In audio style, the emphasis is on spoken explanation, as may be given in a one-to-one tutorial. There may be, where possible, diagrams, pictures, equations referred to, isolated words or short phrase, but the emphasis is on the spoken world. The audio may refer to diagrams or equations, but they are discussed verbally.

For images, the emphasis is on using diagrams, tables, pictures, graph, charts, flow charts, tree graphs and animations. Normally, the image style is accompanied by spoken text, but with emphasis on the use of images. The main difference between audio style and image style is that in audio, the idea is conveyed by spoken words with the use of illustration tools, e.g., graphs. For images, the idea is conveyed primarily via the image while the explanation could incorporate written or spoken text. The image can be presented via a power-point presentation accompanied by a spoken commentary, as depicted in Figure 5.7.

In video style, the emphasis is on video clips, cartoons, and analogies that illustrate the idea being explained in different scenarios. Emphasis could be on action, attracting attention with sound and music, making it memorable. The video style may have speech either to explain the idea or just to act out some scenario, as shown in Figure 5.8.

The second stage of development, evaluate the teaching material by the pilot study as it explained in Section 5.14. Based on the pilot study findings, the content material for our case study was changed to make it clearer and better suited to students' levels of knowledge. Subsequently, all teaching material was redesigned with a new approach, using Adobe Flash. After that, the content material was checked again by the teachers to make sure nothing was missing during the design and development. The material was also presented to educational teachers to prove the teaching material was presented correctly, according to FSLSM explanation explained in Section 2.3.1.3. The HTML pages for our e-learning system with the adapted learning content materials were dynamically generated using MySQL.

Concept 1: Introduction { Basic Concept of probability } D1

Example:
If a family has three children, find the probability that all the children are girls.

Solution:
The sample space for gender of children for a family has three children is GGG, GBG, GGB, GGG, GGB, GBG, and GGG. There is only one way in eight possibilities for all three children girls.

$P(GGG) = \frac{1}{8}$

Equally likely events
Events that have the same probability of occurring.

Concept 2: {The multiplication rules and conditional probability } D2

Example:
Box 1 contains 2 red balls and 1 blue ball. Box 2 contains 3 blue balls and 1 red ball as shown in the following table.

| Color | Box1 | Box2 | Total |
|-------|------|------|-------|
| Red | 2 | 1 | 3 |
| Blue | 1 | 5 | 4 |
| Total | 3 | 4 | 7 |

Find the probability of selecting a red ball given that it was drawn from Box 2?

$$P(\text{Red} | \text{Box2}) = \frac{P(\text{Red and box2})}{P(\text{Box2})} = \frac{\frac{1}{7}}{\frac{4}{7}} = \frac{1}{4}$$

Concept 3: { Bayes Theorem } D3

3.Bayes theorem in medicine
This problem involves testing individuals for the presence of a disease. Suppose the probability of disease (D) is 0.001. If a person has the disease, the probability of a positive test result (Pos) is 0.90. If a person does not have the disease, the probability of a negative result (Neg) is 0.95. If a randomly selected individual is tested and the result is positive, what is the probability that the individual has the disease?

Solution:
We draw the tree diagram as shown below:

Figure 5.6 Different Verbal Style Representation

Concept 3: { Bayes Theorem } D3

2.Illustration Bayes theorem by example
The number of students from different countries in one college is as follows:
-20 from France 10 girls and 10 boys
-30 from UK 20 girls and 10 boys
-40 from Canada 30 girls and 10 boys
If we selected a boy, what is the probability that he is from France?

Concept 3: { Bayes Theorem } D3

Solution

| Gender | France | UK | Canada | Total |
|--------|--------|----|--------|-------|
| Boy | 10 | 10 | 10 | 30 |
| Girl | 10 | 20 | 30 | 60 |
| Total | 20 | 30 | 40 | 90 |

$$P(F|B) = \frac{P(B|F) P(F)}{P(B)}$$

$$P(F) = \frac{20}{90} = \frac{2}{9}$$

$$P(B) = \frac{30}{90} = \frac{3}{9}$$

$$P(B|F) = \frac{10}{20} = \frac{1}{2}$$

$$P(F|B) = \frac{\frac{1}{2} * \frac{2}{9}}{\frac{3}{9}} = \frac{1}{3}$$

The probability that the selected boy is from France is $\frac{1}{3}$

Figure 5.7 Visual Style Represented by Images and Animation

Concept 3: Bayes Theorem 03

4. Usefulness of Bayes theorem in life

In general Bayes' theorem allows us to take additional information into account probabilities. Without the additional information, we have a 'prior' probability and 'conditional' or 'posterior' probability.



Concept 3: Bayes Theorem 03

4. Usefulness of Bayes theorem in life

In general Bayes' theorem allows us to take additional information into account probabilities. Without the additional information, we have a 'prior' probability and 'conditional' or 'posterior' probability.

at an outdoor ceremony in the desert. In recent years, it has rained only 5 days out. Unfortunately, the weatherman has predicted rain for tomorrow. When it actually rains, the weatherman correctly forecast rain 90% of the time. When it doesn't rain, he incorrectly forecasts rain 10% of the time. What is the probability that it will rain on the day of Marie's wedding?



Concept 3: Bayes Theorem 03

In term of probabilities

Tomorrow

```

graph TD
    Tomorrow --> R["If it rains(R)  
P(R) = 5/365  
= 0.014"]
    Tomorrow --> N["If it doesn't rain(N)  
P(N) = 360/365  
= 0.986"]
    R --> WB["Weatherman predicts(B)"]
    N --> WB
    WB --> R90["It rains 90%  
P(B|R) = 0.9"]
    WB --> RD10["It doesn't rain 10 %  
P(B|N) = 0.1"]
    P_R_B["P(R | B) =  $\frac{P(R) \times P(B | R)}{(P(R) \times P(B | R) + P(N) \times P(B | N))}$ "]
    P_R_B["P(R | B) =  $\frac{[0.014] \times (0.9)}{((0.014) \times (0.9) + (0.986) \times (0.1))}$ "]
    P_R_B["P(R | B) = 0.11 = 11%"]

```



Concept 3: Bayes Theorem 03

Even when the weatherman predicts rain, it only rains about 11% of the time. It means there is a good chance that Marie will not get rained on at her wedding.



Figure 5.8 Visual Styles Represented as Video Explain as Scenario

5.1.3.3 Coding the Classes

All the classes mentioned in Section 5.1.2.4 were implemented in PHP. Some classes are responsible for calculations and some for displaying outputs. Some classes have methods for doing both, such as the ILS class which displays the ILS questions and also calculates the ILS scores as depicted in Figure 5.9.

| | |
|---|--|
| Question 1 Not yet answered Marked out of 1.00 Flag question Edit question | When I think about what I did yesterday, I am most likely to get? Select one: <input type="radio"/> a. a picture. <input type="radio"/> b. words. |
| Question 2 Not yet answered Marked out of 1.00 Flag question Edit question | I tend to? Select one: <input type="radio"/> a. understand details of a subject but may be fuzzy about its overall structure. <input type="radio"/> b. understand the overall structure but may be fuzzy about details. |
| Question 3 Not yet answered Marked out of 1.00 Flag question Edit question | I prefer to get new information in? Select one: <input type="radio"/> a. pictures, diagrams, graphs, or maps. <input type="radio"/> b. written directions or verbal information. |

Figure 5.9 ILS Questionnaire (Sample questions)

5.1.4 Testing

The learning content used for testing our non-adaptive and adaptive learning systems was organized in collaboration with a group of lecturers from the statistics department to create learning material similar to their existing material. The non-adaptive material and its mode of delivery was first produced based on the experience of these teachers with traditional teaching methods and their recommendations. The team then set about producing alternative versions of the same material, adapted to different learning styles. The teachers' knowledge and practical experiences of teaching students with different preferred learning styles allowed adaptive course delivery to be specified and matched to different learning styles. The matching was based on the teachers' practical experiences. For static adaptation, the decision about which styles to use is made once and not changed, whereas for dynamic adaptation, the decision may change from concept to concept.

A pilot study experiment was conducted at King Abdulaziz University, College of Computing and Information Technology, in April 2012. The participants of the pilot experiment were nine senior students of statistics and probability. From these nine students, one student achieved very low scores in the tests, and did not take much time studying Bayes' theorem. We considered the results from this student unreliable, as she appeared not to have addressed the material seriously.

The pilot study was designed to test the feasibility of performing subsequent experiments with much larger groups of students and the methodology to be adopted. The first objective of this pilot study was to functionally test the software implementation of the non-adaptive, static and dynamic systems and to check that the adaptive versions truly present appropriate course material based on preferred learning styles. The second objective was to check the suitability of our case study material in its different versions.

The reactions of these pilot study volunteers provided useful feedback. The third objective was to measure the experiment timeline and to see if the students could accomplish the topic's content in a reasonable time. In this pilot study, three performance parameters were evaluated: the score of the student on the post-test, the time taken to complete the test and the amount of time spent learning each object. All these parameters could be obtained from the student log files, either directly or after some processing.

The overall results from the pilot study were useful and encouraging. It was confirmed that the case study topic was new to all the participants and, being purely scientific, it proved to be of potential interest to them. The students' opinions on the design and the implementation of the adaptive Moodle system was that it was clear and understandable. However, the topic itself was not found to be very interesting, and the content material was not considered to be very clear. The students commented that having 10 numerical questions in one test was tedious and too long. Some participants admitted answering some questions by guessing.

Based on these findings, the learning content for our case study was changed to make it clearer and better suited to the students' levels of knowledge. Subsequently, all learning content was re-designed with a new approach, using Adobe Flash. The adaptation technique was also adjusted to be suitable for the new content. To increase motivation to study Bayes' theorem, our pilot-study volunteers were chosen from the statistics field, where the topic is known to be part of their mandatory course. Therefore, the volunteers realised that learning the topic would ultimately be of benefit to them.

5.2 Student Progress through DAELS

Figure 5.10 to 5.14 illustrate the results obtained from a student who signed up to the DAELS. She answers the ILS questionnaire as illustrated in Figure 5.9 (see Appendix B for more detail) and the pre-test questions as illustrated in Figure 5.10 (see Appendix C for more detail) and the results of these tests are stored in her learner model.

Section 1
Not yet answered
Marked out of 1.00
 Flag question

If we roll two dice, what is the outcome of the sum of the two dice is equal to 5 form an event E?
Select one:
 a. E = {1,2,3,4,5}
 b. E = {(1,4),(2,3),(3,2),(4,1)}
 c. E = {(1,4),(2,3)}
 d. E = {5}

Section 2
Not yet answered
Marked out of 1.00
 Flag question

A pair of dice is rolling. What's the probability that the sum of the numbers facing up is 7?
Select one:
 a. 1/36
 b. 2/7
 c. 1/6
 d. 7/36

Section 3
Not yet answered
Marked out of 1.00
 Flag question

A coin is tossed 60 times. 27 times head appeared. Find the experimental probability of getting heads?
Select one:
 a. 1/27
 b. 1/60
 c. 3/20
 d. 9/10

Section 4
Not yet answered
Marked out of 1.00
 Flag question

The probability that a child speaks some French is 7/20.
What is the probability that a child does not speak some French?
Select one:
 a. 13/20
 b. 3/10
 c. 3/10
 d. 1/10

Figure 5.10 Sample Questions from the Pre-Test

The student's answers to the ILS test are processed by producing the scoring sheet shown in Figure 5.11 based on FSLSM calculation, explained in full details in Section 3.2.1.

| VIS/VRB | | | SEQ/GLO | | |
|---------|---|---|---------|---|---|
| Q | a | b | Q | a | b |
| 3 | X | - | 4 | X | - |
| 7 | - | X | 8 | - | X |
| 11 | X | - | 12 | X | - |
| 15 | - | X | 16 | - | X |
| 19 | X | - | 20 | X | - |
| 23 | - | X | 24 | - | X |
| 27 | X | - | 28 | X | - |
| 31 | - | X | 32 | - | X |
| 35 | X | - | 36 | X | - |
| 39 | - | X | 40 | - | X |
| 43 | X | - | 44 | X | - |

Figure 5.11 ILS Output Scores' Sheet

Then, the scoring sheet is processed to determine student's 'initial' preference learning styles as shown in Figure 5.12. These initial learning styles are stored in the student's learner model.

| Total (sum X's in each column) | | | |
|--|---|---------|---|
| VIS/VRB | | SEQ/GLO | |
| a | b | a | b |
| 6 | 5 | 6 | 5 |
| 1a | | 1a | |
| Student learning styles Moderate visual-sequential | | | |

Figure 5.12 Calculating Student Preference Learning Styles

The method controlling dynamic adaptation now invokes the appropriate content presentation method to present the first learning object according to the initial learning styles as shown in Figure 5.13. After the student studies the course content, three to four questions are presented to the student to assess his/her understanding of the presented course content. If the student answers the questions correctly, the dynamic adaptation method invokes the content presentation method to present the student with the next concept based on his/her current learner profile. If the student does not pass the evaluation, the dynamic adaptation method calls the Similarity method to adjust the student learning styles as explained in Section 3.2.2.

The Similarity method builds a sorted queue of the records of previous students who previously studied and passed the same concept and have similar characteristics as those of the current student. Figure 5.14 illustrates the sorted queue that is produced. Then, the dynamic adaptation method calls the content presentation method to present the same concept again based on the adjusted style that is stored in learner profile. This process continues as explained in Section 4.2.4.5 and the dynamic adaptation method continues to control the actions of the system, in response to student reaction, as more concepts are studied.

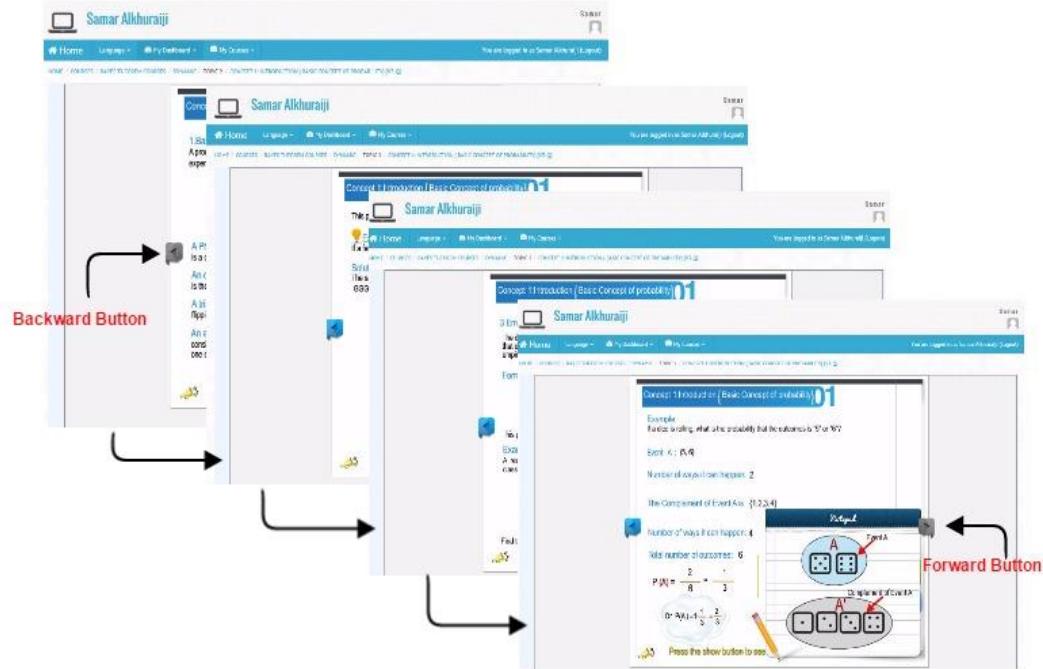


Figure 5.13 Content Presentation for Student with Moderate Visual-Sequential styles

| learning style 1 | learning style 2 | similarity |
|------------------|------------------|----------------|
| v3-q | v2-g | 0.62792890576 |
| v3-q | v1-g | 0.613486533916 |
| v3-q | E1-g | 0.575329797715 |
| v3-q | v1-q | 0.542744644628 |
| v3-q | v3-g | 0.520555791538 |
| v3-q | E2-q | 0.499205440931 |
| v3-q | v3-g | 0.481896491853 |
| v3-q | v2-g | 0.453688323249 |
| v3-q | v3-q | 0.339092956509 |

Figure 5.14 Sorted Similarity Queue

Chapter 6

Evaluation of the Experiments

The previous chapters formulated, implemented, and functionally tested a dynamically adaptive e-learning system with user modelling based on the Felder-Silverman theory of learning styles (Felder and Silverman, 1988a). We showed how to create personalized and dynamic adaptivity for online students using an extended version of the e-learning system, Moodle. We proposed a dynamically adaptive e-learning system that uses the Similarity algorithm to determine how the student profile should be updated according to the recorded experience of previous students. Students' feedback was considered at the phase of development of DAELS, as explained in Section 5.1.4. Based on students' feedback, the adaptation technique was adjusted and the learning content was re-designed with a new approach. Our primary focus in this stage was to discover whether using such a system can be shown to improve the student learning experience.

To address this question, we devised an experiment. Novice students from their first year at King Abdulaziz University were assigned randomly to three groups: a control group, static group and a dynamic group. Each group was asked to study a case-study topic concerned with Bayes' theorem. The mode of presentation to each group was different, as explained in Section 4.2.4.2. The success of each student, as assessed by means of a pre-test, post-test, and measurements of the time spent learning each concept, was recorded. The data recorded in the student profiles was analysed to assess the achievements of each of the three groups in comparison to those of the other groups. These results gathered evidence concerning the advantages of dynamic adaptation over non-adaptive and statically adaptive techniques. The following subsections provide details about the participants in the experimental evaluation, the location of the evaluation, experimental measurement tools, the data analysis approach, and the hypotheses. The last subsection is a discussion of the experimental results.

6.1 Participants

The experiments involved 110 undergraduate students registered in the Statistics Department of King Abdulaziz University, Jeddah, KSA (female section). These students were studying Introduction to General Statistics, referred to as STAT 110, a first-year undergraduate course. All of the students were volunteers and received a certificate of merit. Students who spent less than ten minutes on the ILS questionnaire were discarded because the identified learning styles were considered not to be reliable. Also, students who spent less than eight minutes learning a concept or who did not complete all three concepts were discarded

because their scores in the evaluation tests were considered unlikely to be reliable. Data obtained from the remaining 89 students were used for analyses. Among these, 20 students belonged to the control group, 32 to the static group, and 37 to the dynamic group. The participants had been assigned randomly to the groups.

6.2 Experiment Location

The participants accessed our online DAELS in our labs at female section, King Abdulaziz University Jeddah, KSA. Each lab is equipped with 40 desktop computers. All computers are running windows 8 and connected to the Internet. Each group is assigned to do the experiment in one day. All students registered in the DAELS. Students login to the system by using their registered ID and password.

6.3 Experiment Aims

The experiments aimed to test the hypotheses quoted in Section 4.1 by measuring the performance, the learning speed and efficiency of each student. When averaged over each of the three groups, these measurements will allow us to compare the effectiveness of dynamically adaptive learning with non-adaptive and statically adaptive learning. In addition, our experiments will demonstrate the flexibility of the dynamic adaptation algorithm in adjusting to the changing estimates of preferred learning style of each student as she progresses through the course material.

6.4 Experimental Measurements

The set of measures used to test the research hypotheses were represented by two types of variables: independent and dependent variables. In a scientific experiment, independent variables are variables that the researcher believes may have an effect on dependent variables. The dependent variables are the values that are observed by the researcher during the experiments and are of interest in providing useful information. In our experiment, independent and dependent variables are specified as follows.

6.4.1 Independent Variables

Three sets of independent variables are provided for quantifying:

- Usage of the dynamically adaptive e-learning system for adaptive content presentation
- Usage of the statically adaptive e-learning system
- Usage of the non-adaptive e-learning system

6.4.2 Dependent Variables

The dependent variables specified the students' test scores, the time spent in learning each concept, and the time spent in answering the questions. The test scores included pre-test and post-test scores, and evaluation test scores for each concept. The total time spent in learning all concepts was also included.

6.5 Experiment Evaluation Tools

Different kind of measurements tools were used to evaluate the adaptive system. These tools were pre-test, post-test, and evaluation assessment after each concepts. These tools were used to measure student performance.

- **Pre-test:** it is online 10 multiple choice questions presented to the students at the beginning of the course after the students register in adaptive system, worth a total of 10 points.
- **Concept learning assessment:** an on-line quiz with 3 to 4 multiple choice questions presented to each student at the end of each concept. It is given a mark out of 3 or 4
- **Post-test:** this is in the same format as the pre-test.
- **Measurements of time spent:** different timings are recorded such as the concept learning time and the time taken to answer each question.

6.6 The Experiment Tool

The extended Moodle LMS was as follows:

- Platform: Windows 8
- Programming languages: PHP, MySQL, Macromedia Flash.
- Accessed by clients using standard HTML browsers.
- Three versions: non-adaptive, static and dynamic as described in chapter 5.

6.7 Data Analysis

The hypotheses were tested statistically. We used the Analysis of Variance (ANOVA) method (Hall, 1998) with significance level $\alpha = 0.05$ to obtain 95% confidence levels. The probability of wrongly rejecting a hypothesis (Type 1 error) will then be equal to α , or 5 times out of 100. The results presented in the following sub-sections were analyzed using the 'SPSS' statistical analysis software package (V20.0). ANOVA provides a statistical test of whether or not the means of several groups are likely to be equal.

6.7.1 Hypothesis Analysis

The following statistical methods were used:

- F-test (One-Way ANOVA) was used to study the differences between the means of the three study groups (control, static, and dynamic). The F-test determines whether there is likely to be any statistically significant differences among any of the means of the three study groups. With more than two groups, the F-test does not specify which group is most responsible for the statistical differences (Hall, 1998).

The F-test value is defined as

$$F = \frac{\text{between group variability}}{\text{within group variability}}$$

$$= \frac{\sum_{i=1}^K n_i (\bar{Y}_i - \bar{Y})^2 / (K-1)}{\sum_{i=1}^{K-1} \sum_{j=2}^K (Y_{ij} - \bar{Y}_i)^2 / (N-K)}$$

where \bar{Y}_i denotes the sample mean of scores in group i , n_i is the number of observations in group i , \bar{Y} denotes the overall mean of the data, and K denotes the number of groups. Y_{ij} is the score of the j^{th} student in group i , and N is the overall sample size. This F -statistic follows the F-distribution. The statistic will be large if the between-group variability is large relative to the within-group variability, which is unlikely to happen if the population means of the K groups have the same value.

- The ‘Student’ T-Test was used to identify whether there are statistically significant differences between the scores of the pre-test and post-test for the students within the same group. The ‘paired T-Test’ is a test for dependent data, and is generally used when measurements are taken from the same sample before and after some manipulation. It is therefore applicable to analyzing the means of pre-test and post-test scores. The mean difference between the two sets of scores is computed for each group. If a difference is found, this is evident that the system has caused some change in the observed variable, i.e. the alternative hypothesis may be true. The t-test determines how large this difference must be to be statistically significant, given the number of participants in the group. The t-test decision is based on a ‘p-value’ which is the probability of achieving a difference less than or equal to the observed difference by chance, when the means are, in fact, equal. Any measured difference test resulting in a p-value less than the ‘significance level’, α , would be considered significant to a $100(1-\alpha)$ % confidence level. This would be evident for rejecting the

null-hypothesis that there is no statistically significant difference in the means, in favor of the alternative hypothesis that there is a statistically significant difference. In our evaluations, we took $\alpha=0.05$, meaning that we obtain 95% confidence-levels (Trochim, 2006).

- The Scheffe test is a statistical technique often used in conjunction with ANOVA. It is used to estimate the statistical significance of the greatest difference between any two groups when there are more than 2 groups to be compared (Stevens, 1999).
- Eta-squared (η^2) values are a measure of ‘effect size’ for group mean differences. The ‘effect size’ is the strength or importance of the relationship between two variables regardless of its statistical significance. A value of η^2 less than 0.2 represents a small effect size meaning that the impact of differences will be fairly unimportant even when the reliability of their measurement is very high, with low p-values. Values of η^2 between 0.2 and 0.8 represent a medium ‘effect size’, and for values over 0.8 or higher the impact of the differences is large (Brown, 2008).

The ‘One Way ANOVA’ test was performed on the performance scores obtained from the three groups of students, resulting in F-test values with corresponding p-values for each test to specify the significance of any differences in the means. The ANOVA F-value and P-value for each score are shown in Table 6.1. The following sub-sections test the experiment hypotheses, with $\alpha=0.05$, based on the collected data.

Table 6.1 Hypothesis Testing Results for the Effect of DAELS on Each Student Performance Score

| Student Performance | Control Group N=20 | Static Group N=32 | Dynamic Group N=37 | Significant difference |
|---------------------------|------------------------|----------------------|-----------------------|------------------------|
| Pre-Test | F = 2.613 P = .079 | | | No |
| Post-Test | F = 50.194 P = .000 | | | Yes |
| Total Learning Time Spent | F = 7.691 P = .001 | | | Yes |

N is number of students in a group

6.7.1.1 Hypothesis H1

Hypothesis H1 states that '***There will be no significant difference between the average pre-test scores for three groups.***'

Firstly, we used a one-way ANOVA to check whether the three groups had significant differences in the means of their pre-test scores. Table 6.2 shows the p-value is 0.079, which

is greater than $\alpha=0.05$. This means that it cannot be confirmed to a 95% confidence level that statistically significant differences exist between the means of the pre-test scores for the three groups. This indicates that the H1 hypothesis was satisfied and that the students in each of the three sample groups are not likely to have had very different background knowledge.

Table 6.2 Results of One Way ANOVA for Differences between the Mean Pre-test Scores of the 3 Groups

| Variable | Group | N | Mean | SD | F | P |
|----------|---------|----|------|-------|-------|------|
| Pre-Test | Control | 20 | 2.05 | .686 | 2.613 | .079 |
| | Static | 32 | 2.38 | 1.212 | | |
| | Dynamic | 37 | 1.78 | 1.109 | | |

6.7.1.2 Hypothesis H2

Hypothesis H2 states that '*The dynamically adaptive group will perform significantly better in the post-test than the static group and the control group.*'

To examine this hypothesis, a one-way ANOVA is performed to find the differences between the mean scores of the three groups in post-test scores, results are shown in Table 6.3 where it can be seen that the p-value is .000, which is less than $\alpha = 0.05$. This indicates, to a 95% confidence level, that there was a statistically significant difference between the three groups in the post-test scores.

Table 6.3 Results of One Way ANOVA for Differences between Mean Post-Test Scores of the 3 Groups

| Variable | Group | N | Mean | SD | F | P |
|-----------|---------|----|------|-------|--------|------|
| Post-Test | Control | 20 | 2.90 | 1.553 | 50.194 | .000 |
| | Static | 32 | 5.94 | 2.675 | | |
| | Dynamic | 37 | 8.51 | 1.574 | | |

In view of these differences, the Scheffe test was performed to find out which groups caused them. The results are shown in Table 6.4 where it can be seen that the differences between the mean post-test scores of the three study groups were between the 'control' group and the other experimental groups, static and dynamic, in favour of the static and dynamic groups. There is also a statistically significant difference between the static and the dynamic group in favour of the dynamic group where the dynamic group has the highest average post-test scores. This indicates that hypothesis H2 is accepted.

Table 6.4 Result of Scheffe Test to Identify Direction of the Differences between Mean Post-Test Scores of the 3 Groups

| Variable | Group | Mean | Control | Static | Dynamic |
|-----------|---------|------|---------|----------|----------|
| Post-Test | Control | 2.90 | | -3.038-* | -5.614-* |
| | Static | 5.94 | | | -2.576-* |
| | Dynamic | 8.51 | | | |

*The mean difference is significant at the level of 0.05

6.7.1.3 Hypothesis H3

Hypothesis H3 states that '*There will be significant differences between the performances of the three groups according to the pre-test and post-test scores.*'

To test this hypothesis the 'Paired Samples T-Test' was performed to find out if there is a statistically significant difference, to a 95% confidence level, between the average pre-test scores and the average post-test scores within the same group. The results of the T-Test are shown in Table 6.5 where it may be seen that:

- For the control group, the mean post-test score was 2.90 which is greater than the mean pre-test score of 2.05. The t-test gives a p-value of 0.076 which is greater than $\alpha = 0.05$. Therefore it cannot be inferred that the difference between these two means is statistically significant to a 95% confidence level.
- For the static group, the mean post-test score was 5.94 which is greater than the mean pre-test score of 2.38. The t-test gives a p-value which is less than $\alpha = 0.05$. Therefore, it can be inferred that the difference between these two means (pre-test and post-test) is statistically significant to a 95% confidence level. Using the Eta-squared (η^2) test, SPSS reported that the effect size is 0.56 which means 'medium impact'.
- For the dynamic group, the post-test score was 8.51 which is greater than the mean pre-test score of 1.78. The t-test gives a p-value of 0.001, which is less than $\alpha = 0.05$. Therefore, the difference between these two means (pre-test and post-test) is statistically significant to a 95% confidence level. SPSS gave $\eta^2 = 0.95$ which means a large impact. Based on the above tests of significance, the hypothesis H2 is accepted.

Table 6.5 Result of T-Test Analysis of Two Samples Linked (Paired-Samples T-Test) to Compare Between Two Test Means Pre and Post Scores within the Same Group

| Group | Test | Number | Mean | SD | T Value | P Value | Eta-squared (η^2) |
|----------------|------------------|--------|------|-------|---------|---------|--------------------------|
| Control | Pre-Test | 20 | 2.05 | 0.686 | -1.495 | 0.067 | - |
| | Post-Test | 20 | 2.90 | 1.553 | | | |
| Static | Pre-Test | 32 | 2.38 | 1.212 | -6.707 | 0.000* | 0.56 Medium Impact |
| | Post-Test | 32 | 5.94 | 2.657 | | | |
| Dynamic | Pre-Test | 37 | 1.78 | 1.109 | -26.594 | 0.001* | 0.95 Large Impact |
| | Post-Test | 37 | 8.51 | 1.574 | | | |

* The mean difference is significant at the 0.05 level.

6.7.1.4 Hypothesis H4

Hypothesis H4 states that '*Students who use the dynamically adaptive e-learning environment will spend less time learning the concepts than the students in the statically adaptive group and the control group.*'

To test this hypothesis, a one-way ANOVA test was performed to find differences in the mean time spent learning concepts between the three groups, at a level of significance of $\alpha = 0.05$. The results of the test are shown in Table 6.6 and indicate the following:

- The p-value obtained is 0.001, which indicates that there were significant differences between the three study groups in the learning time spent. Because of these differences, the Scheffe test was performed to find out which groups caused the differences. The Scheffe test results are shown in Table 6.7.
- Table 6.6 shows that statistically significant differences between the mean learning duration times exist between the control group and the other groups, in favour of the other groups (static and dynamic), whose means are significantly lower. However, there are no statistically significant differences in the average learning time between the static group and the dynamic group with $\alpha=0.05$.

According to the above explanations, part of the hypothesis H4 is accepted and there is a significant difference between the control group and the adaptive groups (static and control), then we can say that H4 is reject.

Table 6.6 Results of One-way ANOVA) for Differences between the Study Groups in the Learning Time Spent

| Variable | Group | N | Mean | SD | F | P |
|---------------|---------|----|--------|--------|-------|-------|
| Learning Time | Control | 20 | 129.68 | 33.369 | 7.691 | .001* |
| | Static | 32 | 94.73 | 34.739 | | |
| | Dynamic | 37 | 103.81 | 27.765 | | |

* Significant at the level of 0.05

Table 6.7 Results of Scheffe Analysis Test to Identify the Direction of the Differences between the Study Groups in the Learning Time Spent

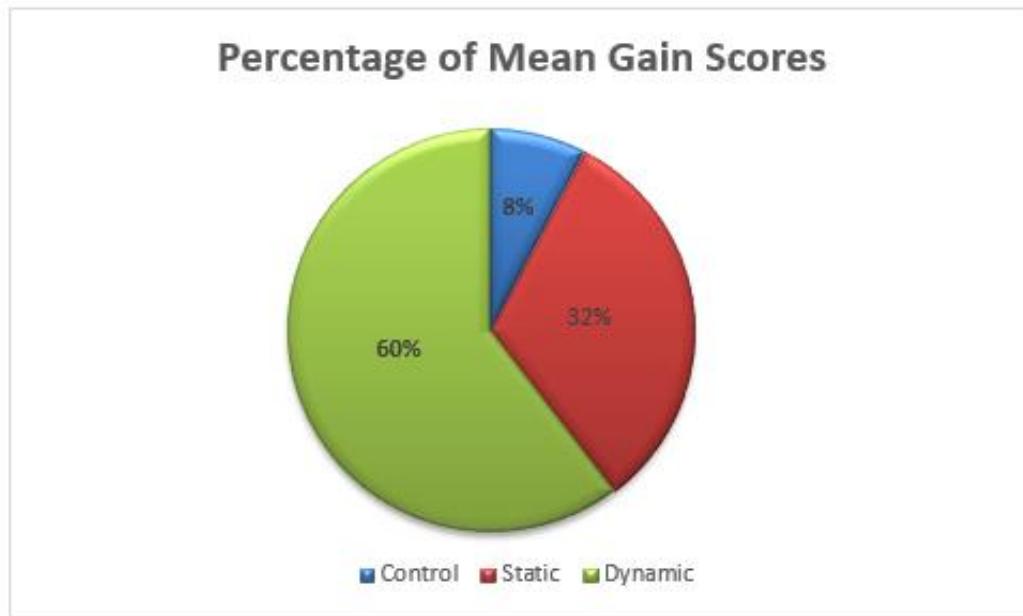
| Variable | Group | Mean | Control | Static | Dynamic |
|---------------|---------|--------|---------|---------|---------|
| Learning Time | Control | 129.68 | | 34.942* | 25.863* |
| | Static | 94.73 | | | |
| | Dynamic | 103.81 | | | |

*The mean difference is significant at the level of 0.05

6.8 Experiment Results

All the hypotheses quoted in Chapter 4 have been examined statistically. The test results indicate that all three experimental groups are likely to have benefited significantly from the learning experience with respect to the case study, as judged by the pre-test and the post-test scores.

Figure 6.1 demonstrates the percentage of mean gain scores for the adaptation of the three groups in post-test. The dynamic adaptive group had an average increase of 60% in the post-test, whereas the average score of the static group increased by 32%, and the control group had an average increase of 8%. The results reveal that the dynamic group had the highest average scores in post-test, and the control group had the lowest average increase in scores.

*Figure 6.1 Percentage Gain from Pre-test to Post-test Scores for All Groups*

The results of a t-test, as explained in Section 6.7.1.3, show the overall change for each group from pre-test to post-test, as demonstrated in Figure 6.2. The dynamic group post-test had the highest significant difference from the pre-test, whereas the control group post-test showed no significant difference from the pre-test.

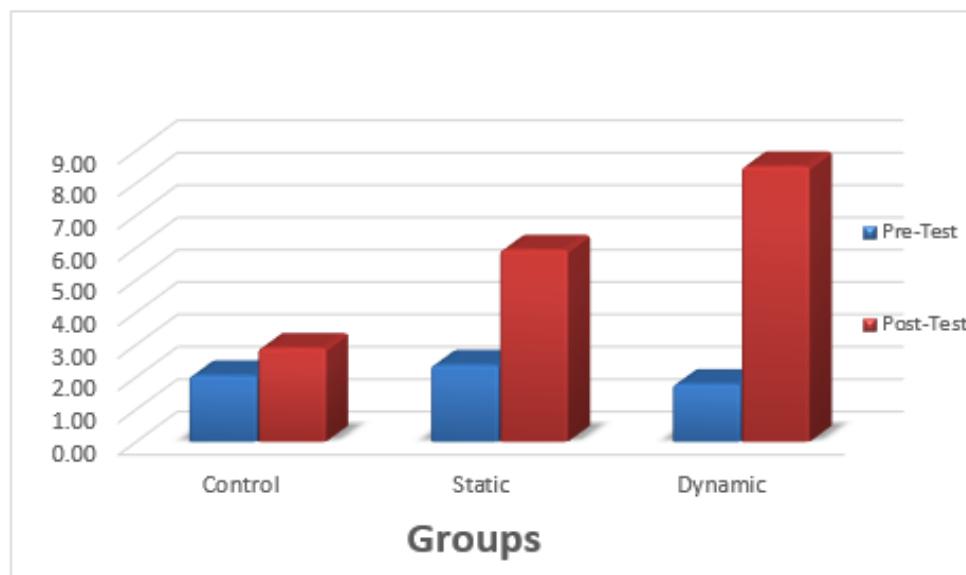


Figure 6.2 Differences between Mean Scores of the Pre-Test and Post-Test

The effect size, calculating using eta-squared (η^2), was 0.56 for the static group, which would be considered a medium effect size in Cohen's d term (Valentine and Cooper, 2003), whereas the effect size for dynamic group was 0.95, which in Cohen's d term(Valentine and Cooper, 2003) would be considered a large effect size.

The follow-up Scheffe test was conducted when the results of a one-way ANOVA were found to be statistically significant, as explained in Section 6.7.1.2. The test revealed that the dynamic group performed significantly better than the static group and the control group with respect to the post-test mean scores. The performance of the static group was significantly better than that of the control group with respect to the post-test mean scores.

Figure 6.3 demonstrates the percentage of time spent in learning the concepts for all three groups. A one-way ANOVA test was performed to find differences between the learning times between the three groups. We followed the ANOVA test with a Scheffe test to find out which groups caused the differences. The results revealed that the static group had the lowest average time spent in learning, 29%, whereas the dynamic group had an average time spent in learning that was greater by 3% of what was measured for the static group. The control group had an average time spent in learning that was 10% greater than that measured for the static group. The observed difference of 3% between the dynamic and the static groups is not statistically significant at the level of significance $\alpha = 0.05$. Even though the

hypothesis is rejected, but the spending less time to learn concepts is not necessarily an advantage. This may mean that students are internalizing the concepts more strongly, are engaging better with the material or are motivated to try harder to ensure they understand the content. Hypotheses H2 and H3 in previous sections indicate that despite students spending more time learning in dynamic groups, they perform better than static groups in post-tests.

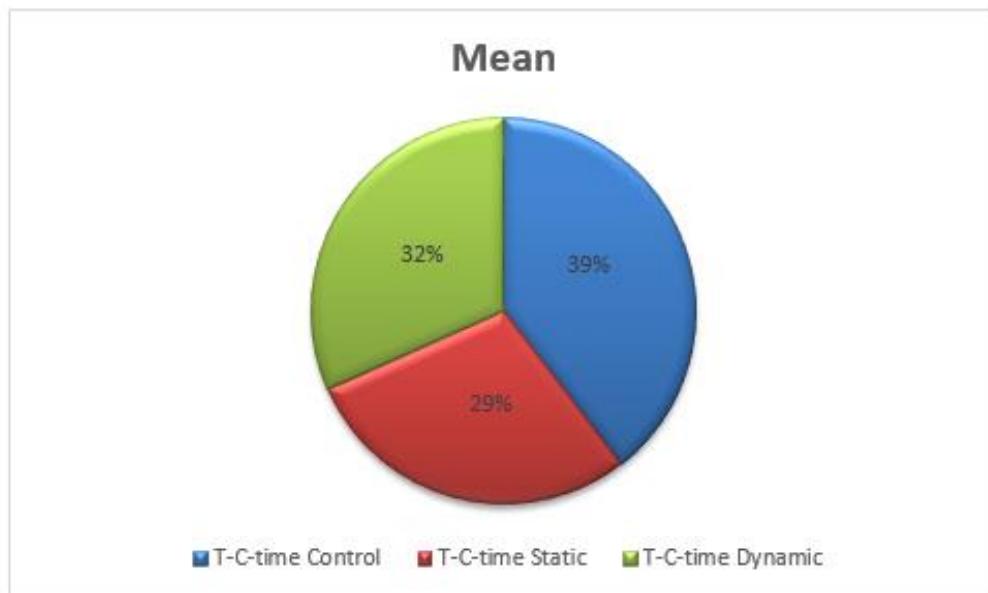


Figure 6.3 Percentage of Mean in Learning Time Spent for 3 Groups

As explained in Chapter 4, each student had the chance to repeat a concept that is not passed. Up to two repeats were allowed. In the dynamic group, each time a concept was repeated, its delivery style would change according to the Similarity algorithm. In the static group, the learning styles did not change.

Figure 6.4 presents the number of successful students in the dynamic group (red) and the static group (blue) who passed on their first, second and third tries (T1, T2, T3) for each concept (C1, C2, C3). The histogram shows that, in the dynamic group, the number of passing students increased each time the student repeated the same concept with different learning styles based on the Similarity algorithm. In contrast in the static group, the number of passing students decreased each time the same concept was repeated with the same learning styles.

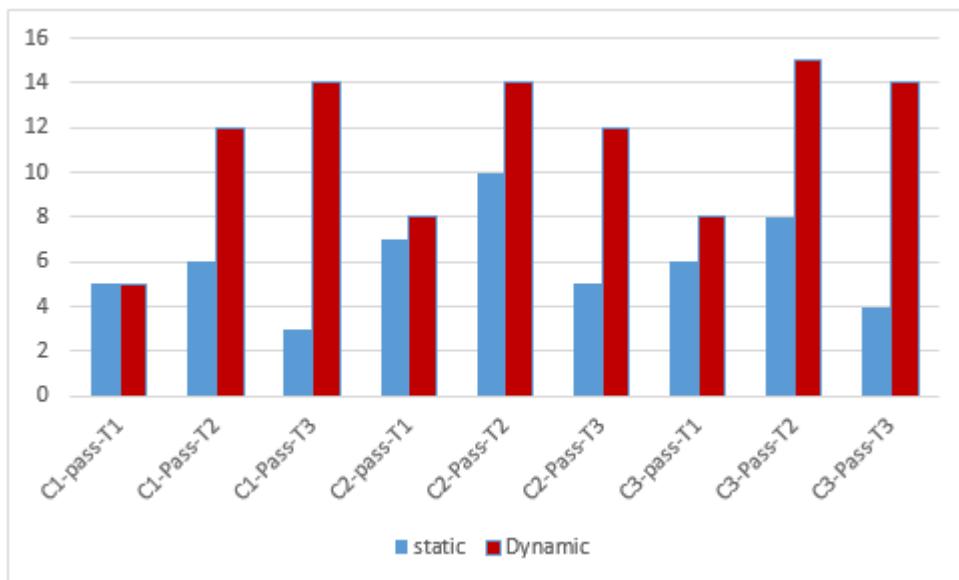


Figure 6.4. Passing Students in the Dynamic and Static Groups in each Try for the three Concepts

According to our experiment procedure, students who used a static and dynamic adaptive system had a chance to learn the same concept up to two times if they did not pass the first time. The histogram in Figure 6.4 shows that the number of successful students increased each try in the dynamic system for each concept, whereas the number of successful students decreased each try for each concept in the static system. Thus, the question was whether there was a positive correlation between the number of successful students and the change of learning style in each concept in the dynamic adaptive system. To answer this question, Pearson's correlation coefficient analysis was used to determine if there was a correlation and whether this correlation was positive or negative. The R-value for Pearson's correlation coefficient was calculated for each concept in the dynamic group with the changing of the learning styles. The results of the test are shown in Table 6.8. From Table 6.8, It is revealed that there was a positive, highly linear correlation between the number of passing students in concepts and the changing in learning styles, which was statistically significant ($r = 0.784$, $p = 0.012$). The students' performance seemed to increase with more adjustable learning styles. Our findings match many studies that have indicated that fixing the learning styles throughout the course reduces the ability for adaptability and leads incorrect results (Truong, 2015, Gilbert, 2000).

Table 6.8 Correlation between the Concepts' Tries and Changing in Learning Styles

| Variable | | Number of tries | Changing in Learning Styles |
|------------------------------------|----------------------------|------------------------|------------------------------------|
| Number of tries | Pearson Correlation | 1 | .784* |
| | Sig. (2-tailed) | | .012 |
| Changing in Learning Styles | Pearson Correlation | .784* | 1 |
| | Sig. (2-tailed) | .012 | |

*. Correlation is significant at the 0.05 level (2-tailed).

6.9 Discussion

Implementing adaptive educational systems to accommodate learner preferences has received considerable attention. Among the individual preference variables are background, cognitive styles, learning styles, prior knowledge, and goals (Ruiz et al., 2008). Many adaptive systems aim to accommodate different preferred learning styles and have different ways of presenting learning content based on individual assessments of these preferred learning styles (Akbulut and Cardak, 2012). These systems have strategies for creating adaptive learning environments. Some of these systems have been evaluated experimentally to investigate their effectiveness with respect to improving student achievement. Comparisons between adaptive and non-adaptive e-learning systems as applied to match and purposely mismatched learners have been published. Conclusions from these comparisons are quite conflicting. Some studies indicate that providing adaptive content helps students in their learning outcomes and performance. Others did not find such evidence. In what follows, we will discuss and analyse related studies in the literature and then summarise our own experimental findings.

Many studies in literature show the effectiveness of incorporating learning styles in online education and its impact on students' performance and learning styles behaviour. A study by Akbulut and Cardak (2012) presented a comprehensive overview of 70 adaptive educational systems. They identified several reasons for the inconsistent conclusions drawn about these systems. The majority of publications are concerned with providing frameworks or models for adaptivity, and few of them try to evaluate the effectiveness of using adaptive learning styles on Adaptive Education Hypermedia (AEH). The analysis of Akbulut and Cardak (2012) identified several reasons such inconsistent results are identified. Few studies have shown the effectiveness of using learning styles on AEH, whereas the majority of studies

provided a framework or model for adaptivity. Akbulut and Cardak study revealed that one third of their 70 survived studies provided a framework without empirical evaluation with students.

A study by Graf (2007) and Siadaty and Taghiyareh (2007) developed adaptive educational systems based on static student modelling that was initialized only once when students first used the system. The studies presented an overview of the behaviour and performance of students in three different groups: matched, purposely mismatched and a control group. Students were randomly assigned to these groups. Those in the matched group were provided with personalized learning content based on their assessed learning styles, while those in the mismatched group were presented with learning content purposely mismatched with their assessed learning style. The control group was given a regular class. The studies did not show any significant differences between the achievements of the three groups in terms of scores. However, Graf's study showed a significant difference between the matched, mismatched and control groups with respect to the time students needed to spend on learning activities.

Several learning style adaptive systems in the literature present dynamically adaptive environments such as the iWeaver system by (Wolf, 2007). It provides the learner with a choice of media based on student-adapted learning styles. Students can follow the system's recommendations or make their own choice of media. The majority of students accept the recommendations of the adaptive system. An analysis of experiments carried out to highlight any differences on learning performance between students given a choice of multiple media experiences and students given just one static media experience showed no significant differences overall. Assessments of students with little background knowledge having a choice of media experiences showed that there may have been some improvement due to the availability of choice. However, assessments of students with more background or greater interest indicated a negative effect of the availability of choice. The students with more experience obtained better results when they were not given a choice in statically adapted delivery style.

Arthur is a learning system presented in (Gilbert, 2000), which is designed to dynamically adapt instructional style according to student's performance in tests. In the 'Arthur' system, a course is divided into different concepts and each concept is implemented by different instructors using multiple versions of the same learning object with different styles, such as: visual-interactive, auditory-text, auditory-lecture, and text style. The instructors are initially selected at random when the student registers in the system. When a student passes the test

at the end of a concept, Arthur assumes that the instruction style used to present that concept matches the student's preferred learning style. The next learning object is presented in the same style. If a student fails the test, Arthur uses a 'case-based reasoning' method to compare the failing student's characteristics and performance in tests to the characteristics and performances of other students who previously passed the concept test. The system then tries to choose an instructor who has worked successfully in the past with similar types of students. Investigations of Arthur have been carried out. Significant differences were observed in the learning styles behaviour of students who completed all the course concepts successfully and those who did not. It was found that 64% of successful students used more than one learning style to complete their study of all the course concepts.

A recent study by (Kanimozhi and Cyril, 2015) concerns an adaptive system for on-line students based on 'cognitive architectures'. The main aim of this work was to develop an intelligent system using ACT-R for interactive learning. ACT-R is a theory of cognition developed by John Anderson at Carnegie-Mellon University. It is about how humans collect information about a problem and divide it into subtasks. The intelligent system ACT-R acts as an interface between the agent and the environment. The ACT-R system works with regular classroom students. Two types of content are available: difficult and easy. Students can switch between two modes: listening mode and default mode, the latter being the difficult one. Evaluation results showed that students' performance in tests was enhanced in this cognitive environment.

A study by Parvez and Blank (2008) used 'Design First-ITS', which is an intelligent tutoring system that provides one-to-one tutoring to novice students. The study provides a feedback infrastructure based on the FSLM learning styles model. To evaluate their feedback system, they had three student groups: a textual-feedback group and a learning-style-feedback group, who both received feedback from the system, and a no-feedback group, which did not receive any feedback at all. Each student in all groups took a pre-test to measure their prior knowledge before using the system. Then, students logged into the system, filled in an ILS questionnaire, and then performed their learning tasks. After the students had completed their learning tasks, they were given a post-test to assess what they had learned. The results showed significant differences between the pre-test and the post-test for the learning-style-feedback group. However, the analysis results showed less significant differences between the pre-test and post-test for the no-feedback groups and the textual-feedback groups.

Findings from previous studies offer insights into different developments, achievements, evaluations and open problems in the field of adaptivity in web-based systems incorporating

learning styles. Analysed studies show that the majority of methods for measuring learning styles used direct questionnaires to predict student-preferred learning style or were included a collaborative way. The effect of adaptivity based on learning styles in online web-based with respect to students' performance revealed conflictive results. The findings of such research can contribute to improving the performance and efficiency of the adaptive educational system. Our study is different from these studies in several ways. Our proposed work presents dynamic adaptation, which changes the content presentation based on students' previous performance. Our proposed Similarity algorithm approach dynamically updates the student's model to perform content adaptations according to students' learning styles. We used various approaches that allowed us to capture information about the learning styles. Rather than a discrete representation of each learning-style dimension, we used continuous representation to represent learning styles as a set of points in two-dimensional space, which is more suitable for our situation, where we need to find the similarity relationship between two learning styles via the Similarity algorithm.

The experimental results obtained using our extended LMS evaluation have allowed an analysis of the outcomes for the control group, static group, and dynamic group. Table 6.1 shows the result of applying ANOVA to examine whether there was a significant difference between the pre-test and post-test, scores of the three groups. The averaged pre-test scores for the three groups show no statistically significant differences, which means that the experiment should not be seriously biased by different levels of background knowledge.

The mean post-test scores of the three groups showed significant differences. The Scheffe test revealed that the dynamic group had the highest increase in average post-test scores, and the control group had the lowest. We conclude that the dynamic group students enhanced their learning more than the students in the other groups.

Conclusions can also be drawn about the study time needed by students in different groups. Students from the static and dynamic groups spent almost the same amount of time studying the case-study material, whereas the control group took 10% longer.

The dynamic group students achieved a mean score that was 60% more than that of the static group. Also, the static group achieved a mean score that was 32% more than that of the control group. This is in line with our expectations and confirms that learning courses with presentations that fits the individual's learning style can be beneficial. Furthermore, learning styles that are dynamically changed according to students' performance and progress while studying a course can enhance students' learning capability even more.

In summary, we have shown how a LM system such as Moodle can be extended to provide static and dynamic adaptivity based on student learning profiles. We have experimentally tested the proposed algorithms for providing adaptivity and shown that they can be effective in supporting students' performance. Moreover, this study provides evidence for generally enhancing LM systems with adaptivity, not just to help students learn more efficiently but also to help instructors develop better course material for online e-learning.

Chapter 7

Conclusions and Future Work

The aim of this research was to formulate ways of making a better, more dynamic e-learning environment and to investigate it experimentally. This research provides three main contributions. First, it developed a dynamically adaptive e-learning system based on student learning styles. The adaptation method is based on the novel Similarity algorithm. The algorithm aims to take advantage of the experience of previous students that used the system and studied the same course. The DAELS mechanism was implemented as an extension to the learning management system (LMS), Moodle. Second, the study diagnosed learning styles using in a new procedure: a continuous representation that represents learning styles as a set of points in two-dimensional space rather than as a discrete representation of each learning style dimension. In the context of our research, this new representation allowed us to identify the similarity between two learning styles in a more accurate way. Third, this study provides an experimental evaluation of the extended LMS in its three versions: non-adaptive, static and dynamic. Experimental results were encouraging for the dynamically adaptive version in comparison to the other two.

The development of the dynamically adaptive version was based on integrating new technology with traditional pedagogy. This chapter reviews the research presented in this thesis. It provides a summary of the results and describes the main achievements of this work. It also discusses limitations of the approach and highlights relevant areas for future work.

7.1 Conclusions

The aim of our work was to provide a means of personalizing e-learning to individual students' needs. Each student has a different viewpoint and personal preferences for styles of learning. These preferences concern their navigation through the material and also its presentation style. This thesis is concerned with methods for detecting students' preferred learning styles and adapting the presentation of learning material, either statically or dynamically, according to these preferred styles. We developed a conceptual framework for the process of creating dynamic adaptation. This framework employs machine-learning algorithms with 'artificial intelligence'.

The first research question asked how learning styles could be accommodated in an adaptive e-learning system. The second question asked whether a DAELS could be more beneficial

than a non-AELS or a SAELS. A survey of the literature on adaptive educational systems and learning styles theories produced many useful ideas and quite a few system designs but inconclusive answers to the second question. Based on many of the ideas in the literature, including the widely accepted Felder-Silverman model of learning styles, a system was formulated, implemented and analysed to determine whether the underlying ideas could be proven capable of positively influencing students' performances in learning. The steps undertaken in this research were as follows:

1. A system capable of being made adaptive was implemented by extending the Moodle LMS.
2. The Felder-Silverman learning style model (FSLSM) was implemented as the initial means of assessing and indexing the preferred learning styles of users. The model was simplified to have just two dimensions with style indices quantized to six levels in the verbal-visual dimension and just two levels in the sequential-global dimension
3. Adaptivity can be provided once the learning styles are known. Learning materials for providing adaptive courses in LMSs were designed and developed to be presented in different multimedia forms, according to the Felder-Silverman model. These concepts were implemented in Moodle, which enables Moodle to automatically generate and present courses that fit students' learning styles.
4. Static adaptivity to the quantised learning styles was implemented based on the availability of different versions of the learning material. A case study concerned with Bayes' Theorem provided an exemplar for this development and subsequently for experiments with real users.
5. Dynamic adaptivity was introduced based on the Similarity algorithm proposed in Chapter 3. This required all system interactions of previous students to be recorded in a database, such as reading, writing, tests scores, and performing various tasks. Links to the records of previous students who are most similar to the current student who fails an assessment are extracted from the database and placed in an ordered list. A new presentation of the failed concept is then given according to the preferred learning style of the most similar previous student. If the current student fails again, the second most similar previous student is selected. The concept presentation is repeated to him but this time with a delivery type matching his or her new learning style.
6. The proposed non-AELS, SAELS and DAELS versions of the extended LMS were tested functionally, tested on students' performance by means of a limited pilot study

and then evaluated by means of a full-scale experiment involving 110 students. There were 89 students participating in the experiment after 21 were excluded from the experiment for not meeting the experiment's requirements. Most of those students were from the non-adaptive group. The proposed non-adaptive content may not match their level of learning styles. If they were presented with adaptive e-learning system that matched their style, they might benefit from an e-learning system that adapted to their needs.

The results of evaluating our proposed DAELS are signify the research directed by the following hypotheses:

- All groups are predicted to have no significant difference between them in the pre-test.
- All groups are predicted to have a significant positive performance outcome from pre-tests to post-tests.
- The dynamic group is predicted to have a more significant positive performance outcome of the post-tests than those in the control group and static group.
- All groups are predicted to have positive significant difference between them in the time spent in learning the concepts

7. After conducting the full-scale experiment that compared the effects of non-adaptive, static and dynamic presentation, the research hypotheses quoted in Chapter 4 were examined statistically. The results showed that for all three groups, there was a performance improvement in terms of mean pre-test and mean post-test scores. The dynamic group had the highest improvement, and the control group had the lowest. The statistical analysis showed that the improvement in the performance of the dynamic group was statistically significant to a 95% confidence level. Further analysis was undertaken to show that there was a reasonably strong correlation between the effects of repeating the concept in the dynamic adaptation method and changing the learning styles. The correlation results indicate that the students' performance was improved by the dynamic adaptation.

The outcome of this research provides grounds for further investigations into the value of dynamic adaptive systems. Such work would contribute further to an already well-established research area concerned with incorporating traditional learning style theories into the learning process. Through the findings and discussion of experimental results, learning styles may be influenced by learners' past experiences. They are not constant traits that can be measured once and for all using explicit questionnaires. Further study needs to focus on

dynamic modelling to develop practical dynamically adaptive e-learning systems that are more strongly adaptive to the changing nature of attributes such as student knowledge, background and preferred learning styles.

7.2 Limitations

The statistical significance of the results presented in this thesis is limited by the number of participants in the experiments. All participants were volunteer students from King Abdulaziz University, taking the same major and the same courses, and they were required to have the same level of background knowledge about the case study. This requirement restricted the number of students who could participate in our experiments. After disregarding 21 students whose commitment was not considered strong enough judging by their approach to the initial assessments, there remained a total of 89 students: 20 students in the control group, 32 in the static group and 37 in the dynamic group. We would have preferred at least 50 students in each group. This restricted number limited some inference that may be concluded from the experiments; for example, the timing differences between the static and dynamic groups could not be resolved to a 95% confidence level.

Machine learning requires a large amount of data to discover patterns and relationships for making decisions and data classification. The limited size of our database limited the number of examples that could be used to train our ‘decision tree classifier’. Also, our database is new, previously untested and not available in large repositories to import and increase our training dataset. It was necessary to use the records of previous control and static groups to populate the database used for the Similarity algorithm in dynamic adaptation. Although this demonstrated that the algorithm was working, better or more indicative results may have been obtained from a much larger database.

7.3 Future Work

The conclusions and the results of this thesis suggest the need to apply the experiments to a larger number of students. This will increase the reliability of the statistical tests and also provide a larger database for the Similarity algorithm. The experiments on the adaptive systems could be carried out over a longer period of time, with different course content; allowing larger groups of students to use our system will help us refine the DAELS by adding more features to be taken into account by the Similarity algorithm. New features could include more sophisticated assessments of student learning styles and interaction, feedback, and navigation paths. Extending student models in this way may allow more precise adaptations for better student performance and efficiency.

The existing extended LMS would benefit from the integration of more Moodle functionalities, such as ‘chat with colleagues’, searching facilities, reviewing previous questions, and bookmarking. Such added services could be used, for example, to monitor sessions to investigate which aspects of the adaptation process are most appreciated by students and which are having the most beneficial effects.

Further support must be provided to teachers, with authoring tools to aid them in creating learning material that matches the required learning styles. Such tools will enable teachers to create learning material from pre-existing material in other styles and also discover new ways of presenting the learning material. Course content would be associated with metadata for facilitating its use in adaptive systems and allowing convenient export to or import from different e-learning environments.

In future work, we suggest using machine learning techniques in different ways with different classification algorithms. This will enhance the way a current student can be given course content based on the records of previous students with similar records.

From this thesis, it is evident that dynamically adaptive e-learning systems can motivate students and improve their learning outcomes. However, more research is needed to explore and study students’ learning styles behaviour in e-learning environments to discover which factors are affecting their achievement. A better understanding of students’ learning styles may eventually lead to the widespread acceptance and use of adaptive algorithms in e-learning systems that can provide efficient and practical adaptive systems.

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Appendix A

Bayes Theorem

Concept 1: Introduction (Basic Concept of probability)

1. Basic concept

A process such as flipping a coin, rolling a die, or drawing a card from a deck are called probability experiments.

A Probability experiment is a chance process that leads to well-defined results called outcomes.

An outcome is the result of a single trial of a probability experiment.

A trial means flipping a coin or rolling one die once.

An event consists of a set of outcomes of probability experiments. An event can be one outcome or more than one outcome.

A sample space is the set of possible outcomes of a probability experiment.

Example of sample space

| Experiment | Sample Space |
|----------------|--|
| Toss one coin | Head, tail |
| Roll a die | 1,2,3,4,5,6 |
| Toss two coins | Head-head, tail-tail, head-tail, tail-head |

Tree diagram

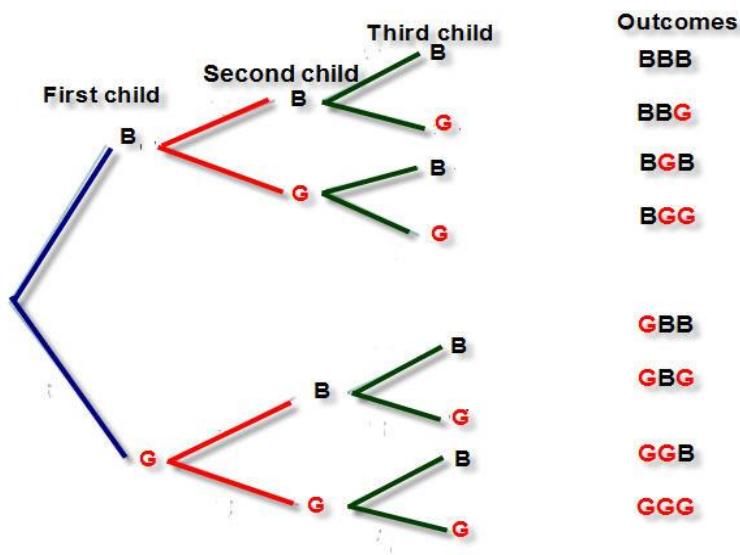
Is a device consisting of line segments emanating from a starting point and also from the outcome point? It is used to determine all possible outcomes of a probability.

Example:

Use a tree diagram to find the space for the gender of three children in a family.

Solution

Since there are two possibilities (boy or girl) for the first child, draw two branches from a starting point and label one B and the other G. Then if the first child is a boy, there are two possibilities for the second child (boy or girl), so drew two branches from B and label one B and the other G. Do the same if the first child is a girl. Follow the same procedures for the third child. See the complete diagram below.



2. Classic probability

Classic probability uses sample space to determine the numerical probability that an event will happen. Classic probability assumes that all outcomes in the sample space are equally likely to occur.

Equally likely events are events that have the same probability of occurring.

Formula of classic probability

The probability of any event E is

$$\frac{\text{Number of outcomes in } E}{\text{Total number of outcomes in the sample space}}$$

This probability is denoted by

$$P(E) = \frac{n(E)}{n(S)}$$

This probability is called classical probability and it uses the sample space S.

Example

If a family has three children, find the probability that all the children are girls.

Solution

The sample space for gender of children for a family has three children is

BBB, BBG, BGB, GBB, GGG, GGB, GBG, and BGG. There is only one way in eight possibilities for all three children girls.

$$P(GGG) = \frac{1}{8}$$

3. Empirical probability

The difference between classical an empirical probability is that classical probability assumes that certain outcomes are equally likely (such as the outcomes when a die is rolled),, while empirical probability relies on actual experiences to determine the likelihood of outcomes.

Formula for Empirical probability

$$P(E) = \frac{\text{frequency for the class}}{\text{total frequencies in the distribution}} = \frac{f}{n}$$

This probability is called empirical probability and is based on observation

Example

A researcher asked 25 people if they like the taste of a new soft drink. The responses were classified as “yes” or “no”. The results were categorized in a frequency distribution as shown.

| Response | Frequency |
|-----------|-----------|
| yes | 15 |
| no | 8 |
| undecided | 2 |
| Total | 25 |

Find the probability that a person responded “no”.

$$P(E) = \frac{f}{n} = \frac{8}{25}$$

4. Probability Rules

There are four basic probability rules.

- **Probability Rule 1**

The probability of any event E is a number (either fraction or decimal) between and including 0 and 1. This is denoted by $0 \leq P(E) \leq 1$.

- **Probability Rule 2**

If an event E cannot occur (i.e., the event contains no members in the sample space), its probability is 0.

- **Probability Rule 3**

If an event E is certain, then the probability of E is 1.

- **Probability Rule 4**

The sum of the probability of all the outcomes in the sample space is 1.

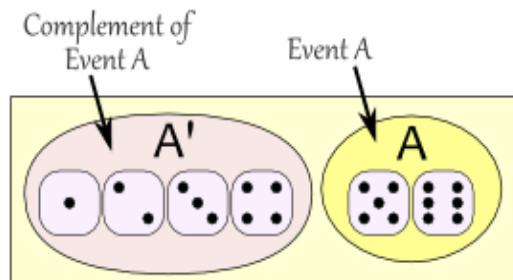
- **Complementary Event**

The complementary of an event E is the set of outcomes in the sample space that are not included in the outcomes of event E. The complement of E is denoted by \bar{E} .

$$P(\bar{E}) = 1 - P(E) \quad \text{or} \quad P(E) = 1 - P(\bar{E}) \quad \text{or} \quad P(E) + P(\bar{E}) = 1$$

Example

If a dice is rolling, what is the probability that the outcomes is "5" or "6"?



Event A: {5, 6}

Number of ways it can happen: 2

Total number of outcomes: 6

$$P(A) = \frac{2}{6} = \frac{1}{3}$$

The Complement of Event A is {1, 2, 3, 4}

The number of ways it can happen: 4

Total number of outcomes: 6

$$P(A') = \frac{4}{6} = \frac{2}{3}$$

$$\text{Or } P(A') = 1 - \frac{1}{3} = \frac{2}{3}$$

Let us add them:

$$P(A) + P(A') = \frac{1}{3} + \frac{2}{3} = 1$$

Yes, that makes 1

It makes sense, right? Event A plus all outcomes that are not Event A make up all possible outcomes.

Concept 2: The multiplication rules and conditional probability

1. Multiplication rule 1 independent events

The multiplication rules can be used to find the probability of two or more events that occur in sequence such as, rolling a die and getting a 6, and then rolling a second die and getting a 3?

Multiplication Rule 1

When two events are independent, the probability of both occurring is

$$P(A \text{ and } B) = P(A) \cdot P(B)$$

Example

A coin is flipped and a die is rolled. Find the probability of getting a head on the coin and a 4 on the die.

Solution

$$P(\text{head and 4}) = P(\text{head}) \cdot P(4) = \frac{1}{2} \cdot \frac{1}{6} = \frac{1}{12}$$

2. Multiplication rule 2 dependent events

When the outcome or occurrence of the first event affects the outcome or occurrence of the second event in such a way that the probability is changed, the events are said to be dependent events.

Multiplication Rule 2

When two events are dependent, the probability of both occurring is

$$P(A \text{ and } B) = P(A) \cdot P(B|A)$$

P (B|A) the condition probability of an event **B** in relation to an event **A** is the probability that event **B** occurs after event **A** has already occurred. We can say that the probability that event **B** occurs given that event **A** has already occurred.

Example:

A person owns a collection of 10 balls, of which 5 are red. If 2 balls are selected at random, find the probability that both are red balls.

Since the events are dependent,

Let assume that the 1st selected red ball is R1 and the 2nd selected red ball is R2

$$P(R1 \text{ and } R2) = P(R1) \cdot P(R2|R1) = \frac{5}{10} \cdot \frac{4}{9} = \frac{20}{90} = \frac{2}{9}$$

3. Formula for conditional probability

The conditional probability of an event B in relationship to an event A was defined as the probability that event B occurs after event A has already occurred.

Formula for conditional probability

The probability that the second event B occurs given that the first event A has occurred can be found by dividing the probability that both events occurred by the probability that the first event has occurred. The formula is

$$P(B|A) = \frac{P(A \text{ and } B)}{P(A)}$$

Example:

A box contains black chips and white chips. A person selects two chips without replacement. If the probability of selecting a black chip and white chip is $\frac{15}{56}$, and the probability of

Selecting a black chip on the first draw is $\frac{3}{8}$, find the probability of selecting the white chip on the second draw, given that the first chip selected was a black chip.

Solution

Let **B = selecting a black chip**, **w = selecting a white chip**

Then

$$P(w|B) = \frac{P(B \text{ and } w)}{P(B)} = \frac{\frac{15}{56}}{\frac{3}{8}} = \frac{5}{7}$$

Hence, the probability of selecting a white chip on the second draw given that the first chip selected was black is $\frac{5}{7}$

4. Example of conditional probability

Box 1 contains 2 red balls and 1 blue ball. Box 2 contains 3 blue balls and 1 red ball as shown in the following table:

| Color | Box1 | Box2 | Total |
|-------|------|------|-------|
| Red | 2 | 1 | 3 |
| Blue | 1 | 3 | 4 |
| Total | 3 | 4 | 7 |

Find the probability of selecting a red ball given that it was drawn from Box 2?

$$P(\text{Red} | \text{Box2}) = \frac{P(\text{Red and Box2})}{P(\text{Box2})} = \frac{\frac{1}{7}}{\frac{4}{7}} = \frac{1}{4}$$

Concept 3: Bayes Theorem

1. Bayes theorem formula

Bayes' theorem, sometimes called Bayes' Rule or 'the principle of inverse probability', follows very quickly from the ideas of probability and conditional probability. It allows us to calculate the probability of some fact 'A' being true when we know that some other fact 'B' is true. The theorem may be stated as follows:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

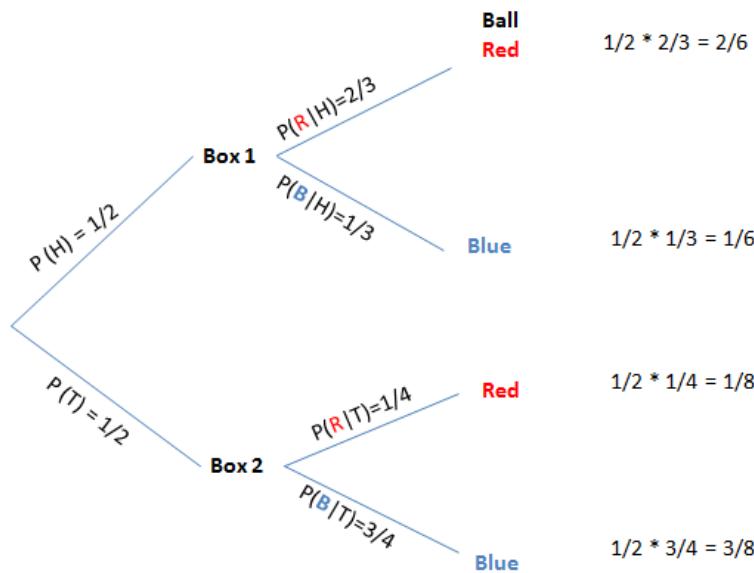
Where $P(A|B)$ is the probability of A being true, given that B is true and $P(A)$ is the ‘prior’ probability of A being true. $P(B|A)$ is the probability of B given that A is true and $P(B)$ is the ‘prior’ probability of B being true. $P(A)$ is ‘prior’ in the sense that it does not take into account any information about B. It is calculated ‘prior to’ (before) knowing anything about B. Similarly $P(B)$ does not take into account anything known about A. $P(A|B)$ and $P(B|A)$ are conditional or ‘posterior’ probabilities.

Example:

Box1 contains 2 red balls and 1 blue balls. Box2 contains 3 blue balls and 1 red ball. A fair coin is tossed. If it falls heads up, box 1 is selected and a ball is drawn. If it falls tails up, box2 is selected and a ball is drawn. What is the probability that the outcome of the toss was heads given that a red ball was selected?

Solution:

We will use the diagram tree to explain the example as shown down



Let, H is an event of a head, and T is an event of a tail

R is an event of a red ball selected

B is an event of a blue ball selected

The desired probability $P(H|R)$

$$P(H|R) = \frac{P(R|H)P(H)}{P(R)}$$

$$P(R) = \frac{2}{6} + \frac{1}{8} = \frac{11}{24}$$

$$P(H|R) = \frac{\frac{2}{6}}{\frac{11}{24}} = \frac{2}{6} * \frac{24}{11} = \frac{8}{11}$$

2. Illustration Bayes theorem by example

The number of students from different countries in one college is as follows:

- 20 from France 10 girls and 10 boys
- 30 from UK 20 girls and 10 boys
- 40 from Canada 30 girls and 10 boys

If we selected a boy, what is the probability that he is from France?

Solution:

| Gender | France | UK | Canada | Total |
|--------|--------|----|--------|-------|
| Boy | 10 | 10 | 10 | 30 |
| Girl | 10 | 20 | 30 | 60 |
| Total | 20 | 30 | 40 | 90 |

Let , **B** is the event of selected Boy

F is the event of France

The desired probability is $P(F|B)$,

$$P(F|B) = \frac{P(B|F)P(F)}{P(B)}$$

$$P(F) = \frac{20}{90} = \frac{2}{9}$$

$$P(B) = \frac{30}{90} = \frac{3}{9}$$

$$P(B|F) = \frac{10}{20} = \frac{1}{2}$$

$$P(F|B) = \frac{\frac{1}{2} * \frac{2}{9}}{\frac{3}{9}} = \frac{1}{3}$$

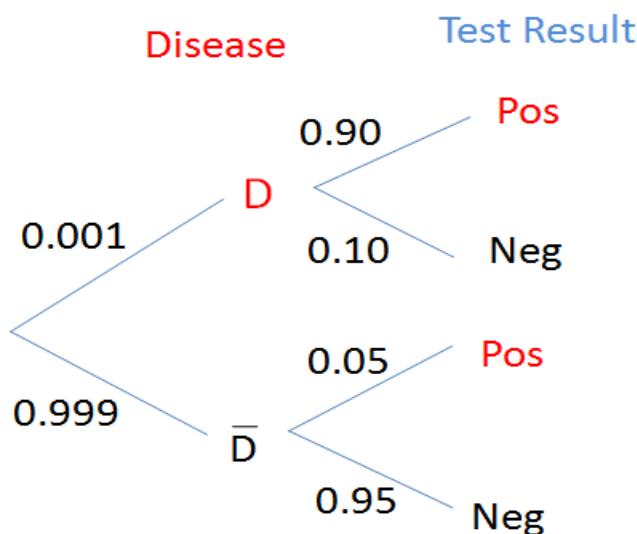
The probability that the selected boy is from France is $\frac{1}{3}$

3. Bayes theorem in medicine

This problem involves testing individuals for the presence of a disease. Suppose the probability of disease (D) is 0.001. If a person has the disease, the probability of a positive test result (Pos) is 0.90. If a person does not have the disease, the probability of a negative result (Neg) is 0.95. If a randomly selected individual is tested and the result is positive, what is the probability that the individual has the disease?

Solution

We draw the tree diagram as shown below:



$$P(D) = 0.001 \quad \text{and} \quad P(\bar{D}) = 1 - 0.001 = 0.999$$

Probability the person having the disease and got positive result having the disease is $P(\text{Pos}|D) = 0.90$, then $P(\text{Neg}|D) = 1 - 0.90 = 0.10$

Probability the person does not have the disease and got negative result is $P(\text{Neg}|\bar{D}) = 0.95$ then $P(\text{Pos}|\bar{D}) = 1 - 0.95 = 0.05$

The desired Probability $P(D|\text{Pos})$ probability diseases given that has a positive result

$$P(D | Pos) = P(D) \cdot P(Pos|D) = \frac{P(D) \cdot P(Pos|D)}{P(Pos)}$$

$$\begin{aligned} P(Pos) &= P(D) \cdot P(Pos|D) + P(\bar{D}) \cdot P(\bar{Pos}|D) \\ &= 0.001 * 0.90 + 0.05 * 0.999 = 0.0009 + 0.04995 = 0.05085 \end{aligned}$$

$$P(D | Pos) = \frac{0.0009}{0.05085} = 0.018$$

3. Usefulness of Bayes theorem in life

In general Bayes' theorem allows us to take additional information into account when calculating probabilities. Without the additional information, we have a 'prior' probability and with it we have a 'conditional' or 'posterior' probability.

Example

Marie is getting married tomorrow, at an outdoor ceremony in the desert. In recent years, it has rained only 5 days each year. Unfortunately, the weatherman has predicted rain for tomorrow. When it actually rains, the weatherman correctly forecast rain 90% of the time. When it doesn't rain, he incorrectly forecasts rain 10% of the time. What is the probability that it will rain on the day of Marie's wedding?

Solution

- Event R. It rains on Marie's wedding.
- Event N. It does not rain on Marie's wedding
- Event B. The weatherman predicts rain.

In terms of probabilities, we know the following:

- $P(R) = 5/365 = 0.0136985$ (It rains 5 days out of the year)
- $P(N) = 360/365 = 0.9863014$ (It does not rain 360 days out of the year)
- $P(B|R) = 0.9$ (When it rains, the weatherman predicts rain 90% of the time)
- $P(B|N) = 0.1$ (When it does not rain, the weatherman predicts rain 10% of the time)

We want to know $P(R | B)$, the probability it will rain on the day of Marie's wedding, given a forecast for rain by the weatherman. The answer can be determined from Bayes' theorem, as shown below.

$$P(R|B) = \frac{P(R) \cdot P(B|R)}{P(R) \cdot P(B|R) + P(N) \cdot P(B|N)}$$

$$\begin{aligned} P(R|B) &= \frac{0.014 * 0.9}{(0.014 * 0.9) + (0.986 * 0.1)} \\ P(R | B) &= 0.11 = 11\% \end{aligned}$$

Even when the weatherman predicts rain, it only rains about 11% of the time. It means there is a good chance that Marie will not get rained on at her wedding

Appendix B

INDEX OF LEARNING STYLES*

DIRECTIONS

Enter your answers to every question on the ILS scoring sheet. Please choose only one answer for each question. If both “a” and “b” seem to apply to you, choose the one that applies more frequently.

1. I understand something better after I
 - a) try it out.
 - b) think it through.

2. I would rather be considered
 - a) realistic.
 - b) innovative.

3. When I think about what I did yesterday, I am most likely to get
 - a) a picture.
 - b) words.

4. I tend to
 - a) understand details of a subject but may be fuzzy about its overall structure.
 - b) understand the overall structure but may be fuzzy about details.

5. When I am learning something new, it helps me to
 - a) talk about it.
 - b) think about it.

6. If I were a teacher, I would rather teach a course
 - a) that deals with facts and real life situations.
 - b) that deals with ideas and theories.

7. I prefer to get new information in
 - a) pictures, diagrams, graphs, or maps.
 - b) written directions or verbal information.

8. Once I understand
 - a) all the parts, I understand the whole thing.
 - b) the whole thing, I see how the parts fit.

9. In a study group working on difficult material, I am more likely to
 - a) jump in and contribute ideas.
 - b) sit back and listen.

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- 10.** I find it easier
 - a) to learn facts.
 - b) to learn concepts.
- 11.** In a book with lots of pictures and charts, I am likely to
 - a) look over the pictures and charts carefully.
 - b) focus on the written text.
- 12.** When I solve math problems
 - a) I usually work my way to the solutions one step at a time.
 - b) I often just see the solutions but then have to struggle to figure out the steps to get to them.
- 13.** In classes I have taken
 - a) I have usually gotten to know many of the students.
 - b) I have rarely gotten to know many of the students.
- 14.** In reading nonfiction, I prefer
 - a) something that teaches me new facts or tells me how to do something.
 - b) something that gives me new ideas to think about.
- 15.** I like teachers
 - a) who put a lot of diagrams on the board.
 - b) who spend a lot of time explaining.
- 16.** When I'm analyzing a story or a novel
 - a) I think of the incidents and try to put them together to figure out the themes.
 - b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.
- 17.** When I start a homework problem, I am more likely to
 - a) start working on the solution immediately.
 - b) try to fully understand the problem first.
- 18.** I prefer the idea of
 - a) certainty.
 - b) theory.
- 19.** I remember best
 - a) what I see.
 - b) what I hear.
- 20.** It is more important to me that an instructor
 - a) lay out the material in clear sequential steps.
 - b) give me an overall picture and relate the material to other subjects.
- 21.** I prefer to study
 - a) in a study group.
 - b) alone.
- 22.** I am more likely to be considered
 - a) careful about the details of my work.
 - b) creative about how to do my work.

- 23.** When I get directions to a new place, I prefer
a) a map.
b) written instructions.
- 24.** I learn
a) at a fairly regular pace. If I study hard, I'll "get it."
b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."
- 25.** I would rather first
a) try things out.
b) think about how I'm going to do it.
- 26.** When I am reading for enjoyment, I like writers to
a) clearly say what they mean.
b) say things in creative, interesting ways.
- 27.** When I see a diagram or sketch in class, I am most likely to remember
a) the picture.
b) what the instructor said about it.
- 28.** When considering a body of information, I am more likely to
a) focus on details and miss the big picture.
b) try to understand the big picture before getting into the details.
- 29.** I more easily remember
a) something I have done.
b) something I have thought a lot about.
- 30.** When I have to perform a task, I prefer to
a) master one way of doing it.
b) come up with new ways of doing it.
- 31.** When someone is showing me data, I prefer
a) charts or graphs.
b) text summarizing the results.
- 32.** When writing a paper, I am more likely to
a) work on (think about or write) the beginning of the paper and progress forward.
b) work on (think about or write) different parts of the paper and then order them.
- 33.** When I have to work on a group project, I first want to
a) have "group brainstorming" where everyone contributes ideas.
b) brainstorm individually and then come together as a group to compare ideas.
- 34.** I consider it higher praise to call someone
a) sensible.
b) imaginative.
- 35.** When I meet people at a party, I am more likely to remember
a) what they looked like.
b) what they said about themselves.
- 36.** When I am learning a new subject, I prefer to
a) stay focused on that subject, learning as much about it as I can.
b) try to make connections between that subject and related subjects.

- 37.** I am more likely to be considered
- a)** outgoing.
 - b)** reserved.
- 38.** I prefer courses that emphasize
- a)** concrete material (facts, data).
 - b)** abstract material (concepts, theories).
- 39.** For entertainment, I would rather
- a)** watch television.
 - b)** read a book.
- 40.** Some teachers start their lectures with an outline of what they will cover. Such outlines are
- a)** somewhat helpful to me.
 - b)** very helpful to me.
- 41.** The idea of doing homework in groups, with one grade for the entire group,
- a)** appeals to me.
 - b)** does not appeal to me.
- 42.** When I am doing long calculations,
- a)** I tend to repeat all my steps and check my work carefully.
 - b)** I find checking my work tiresome and have to force myself to do it.
- 43.** I tend to picture places I have been
- a)** easily and fairly accurately.
 - b)** with difficulty and without much detail.
- 44.** When solving problems in a group, I would be more likely to
- a)** think of the steps in the solution process.
 - b)** think of possible consequences or applications of the solution in a wide range of areas.

Appendix C

Pre and Post Test Questions

Q1: if we roll two dice, what is the outcome of the sum of the two dice is equal to 5 form an event E?

- (a) $E = \{1, 2, 3, 4, 5\}$
- (b) $E = \{(1, 4), (2, 3), (3, 2), (4, 1)\}$
- (c) $E = \{(1, 4), (2, 3)\}$
- (d) $E = \{5\}$

Q2: A pair of dice is rolling. What's the probability that the sum of the numbers facing up is 7?

- (a) $1/6$
- (b) $2/7$
- (c) $7/36$
- (d) $1/36$

Q3: A coin is tossed 60 times. 27 times head appeared. Find the experimental probability of getting heads?

- (a) $1/27$
- (b) $9/20$
- (c) $1/60$
- (d) $3/20$

Q4: The probability that a child speaks some French is $7/20$. What is the probability that a child does not speak some French?

- (a) $13/20$
- (b) $3/10$
- (c) $3/20$
- (d) $1/10$

Q5: A box contains 3 red balls, 2 blue balls, and 5 yellow balls. A ball is selected and its color noted. Then it is replaced. A second ball is selected and its color noted. Find the probability of selecting 1 blue ball and then 1 yellow ball?

- (a) $P(\text{blue and yellow}) = 1/25$
- (b) $P(\text{blue and yellow}) = 3/50$

- (c) $P(\text{blue and yellow}) = 1/10$
 (d) $P(\text{blue and yellow}) = 2/10$

Q6: Two cards are chosen at random from a deck of 52 cards without replacement. What is the probability of choosing two kings? Note: the total number of card is 52 and 4 kings.

- (a) $4/663$
 (b) $1/221$ correct
 (c) $1/69$
 (d) None of the above

Q7: A recent survey asked 100 people if they thought women in the armed forces should be permitted to participate in combat. The results of the survey are shown:

| Gender | yes | No | Total |
|--------|-----|----|-------|
| Male | 32 | 18 | 50 |
| Female | 8 | 42 | 50 |
| Total | 40 | 60 | 100 |

Find the probability that the respondent answered yes, given that the respondent was a female?

- (a) $P(\text{yes} | \text{Female}) = 8/40$
 (b) $P(\text{yes} | \text{Female}) = 8/60$
 (c) $P(\text{yes} | \text{Female}) = 8/100$
 (d) $P(\text{yes} | \text{Female}) = 8/50$

Q8: consider two box boxes. The first contains two white and seven black balls, and the second contains five white and six black balls. We flip a fair coin and then draw a ball from the first box or the second box depending on whether the outcome was head or tails. What is the probability that the outcome of the toss was heads (H) given that a white ball (W) was selected $P(H|W)$?

- (a) $P(H|W) = 1/9$
 (b) $P(H|W) = 22/67$
 (c) $P(H|W) = 5/22$
 (d) $P(H|W) = 67/198$

Q9: Incidence of a rare disease (D). Only 0.001 adults are afflicted with a rare disease ($P(D) = 0.001$) for which a diagnostic test has been developed. The test is such that when an individual actually had the disease, positive result will occur 0.99 of the time ($P(Pos|D) = 0.99$), whereas an individual without the disease will show a positive test result only 0.02 of the time ($P(Pos|\text{not } D) = 0.02$). If a randomly selected individual is tested and the result is positive, what is the probability that the individual has the disease $P(D|Pos)$?

- (a) $P(D|Pos) = 0.001$
- (b) $P(D|Pos) = 0.952$
- (c) $P(D|Pos) = 0.047$
- (d) $P(D|Pos) = 0.05$

Q10: There are two boxes containing colored balls. The First Box contains 50 red balls and 50 blue balls. The Second Box contains 30 red balls and 70 blue balls. One of the two Box is randomly chosen (both boxes have probability $\frac{1}{2}$ of being chosen) and then a ball is drawn at random from one of the two Boxes. If a red ball is drawn, what is the probability that it comes from the first Box?

- (a) $P(\text{Box1}|\text{Red}) = 5/8$
- (b) $P(\text{Box1}|\text{Red}) = 2/5$
- (c) $P(\text{Box1}|\text{Red}) = 1/2$
- (d) $P(\text{Box1}|\text{Red}) = 8/10$