Concept-based and Fuzzy Adaptive E-learning (CaFAE)

Mesfer Al Duhayyim

Thesis Submitted for the Degree of Doctor of Philosophy

Informatics Department

University of Sussex

May 2019

Declaration

I hereby declare that this thesis has not been and will not be, submitted in whole or in part to another University for the award of any other degree.

Signature: Mesfer Abdullah M Al Duhayyim

University of Sussex

Thesis submitted by Mesfer Al Duhayyim for the Doctor of Philosophy

Abstract

E-learning systems have been available for several decades and are now ubiquitous in higher education, however, the vast majority of these e-learning systems do not adapt to the student. Adaptive e-learning gives students the appropriate learning materials based on their abilities in the subject area being studied. This thesis presents a novel adaptive e-learning system (CaFAE) that has been designed to show learners their knowledge level for each concept in the subject area using a coloured concept map, and then recommend a bespoke learning path based on a ranked concept list.

This work has made several key contributions, including a differential assessment strategy, coloured concept map visualisation, ranked concept list ordering and bespoke learning path. This thesis evaluates the effectiveness of the proposed system by conducting a pilot study at the University of Sussex, followed by a full study with a teaching group as part of the Algorithms and Data Structure course in Prince Sattam bin Abdulaziz University in Saud Arabia. From the experimental outcomes, it can be seen that the proposed system has made an identifiable contribution to the subject understanding for the students who used the interventional (adaptive) system over those who used the non-interventional (non-adaptive) system. These students also show increased engagement and attainment and expressed satisfaction with the system.

Acknowledgements

ALLAH says: "And when your Lord proclaimed: If you give thanks, I will give you more" [The Holy Quran: Ch.14, Ver: 7]. Firstly, I thank ALLAH for giving me the patience and strength to complete my PhD thesis. Secondly, I would like to thank many people who supported me during my study. I would like to express my great gratitude to my first supervisor Dr.Paul Newbury for his guidance, encouragement, support, useful suggestions and comments from the beginning of my study to the end. I also would like to thank my second supervisor Dr.Phil Watten for his support and valuable advice.

My sincere thanks to Prince Sattam bin Abdulaziz University (PSAU) and Saudi Arabian Cultural Bureau (SACB) for giving me the opportunity to complete my PhD study and support me financially and morally.

I would also like to thank my parents for their continuous prayers; Without them, it would not have been possible to complete my study successfully. A special thanks to my wife for her motivation and support, and a big thank to my kids (Almaha and Abdullah) for patience and for the time I spent away from them. Also, I would like to thank my brothers, my sister, my relatives, my colleagues and friends for their moral support and prayers during my PhD journey.

Publications

- Al Duhayyim, Mesfer and Newbury, Paul (2019) **Concept-based and fuzzy adaptive e-learning: Case Study.** ICCIS 2019 : International Conference on Computer and Information Sciences, Aljouf, Kingdom of Saudi Arabia, 10-11 April 2019. Published in: 2019 International Conference on Computer and Information Sciences (2019 ICCIS). Institute of Electrical and Electronics Engineers (Accepted)

- Al Duhayyim, Mesfer and Newbury, Paul (2018) **Concept-based and fuzzy adaptive e-learning.** ICIEI 2018 The 3rd International Conference on Information and Education Innovations, London, United Kingdom, June 30 - July 02, 2018. Published in: Proceedings of the 2018 The 3rd International Conference on Information and Education Innovations. 49-56. Association for Computing Machinery ISBN 9781450364409

Table of Contents

List of Figures

List of Tables

Abbreviations

A	Adaptation
AH	Adaptive Hypermedia
AI	Artificial Intelligent
AISLE	Artificial Intelligence-based Learning Evaluation
AITS	Adaptive Intelligent Tutoring System
ATI	Aptitude Treatment Interaction
BNs	Bayesian Networks
C.Name	Concept Name
C.No	Concept Number
C.W	Concept Weight
CaFAE	Concept-based and Fuzzy Adaptive E-learning
CCM	Coloured Concept Map
CCME	Coloured Concept Map Effectiveness
CER	Concept Error Value
CI	Concept Impact
CM	Course Map
DEPTHS	Design Pattern Teaching Help System
DPs	Design Patterns
EL	Ease of Learning
E-Learning	Electronic Learning
FuzKSD	Fuzzy Knowledge State Definer
IR	Information Retrieval
ITS	Intelligent Tutoring System
LM	Learning Materials
LMS	Learning Management Systems
LOs	Learning Objects
LS	Learning Style
MPRLS	Moodle-based Personalized Remedial Learning System
OPCOMITS	Object Oriented Programming Tutor using Concept Map Model
PeRSIVA	Performance, Results, Satisfaction, Individual state, Validity of conclusions, Adaptation’s validity
PSAU	Prince Sattam bin Abdulaziz University
RCL	Ranked Concepts List
RCLE	Ranked Concepts List Effectiveness
SITS	Solution-based Intelligent Tutoring System
SU	System Usability
TAS	Test Assessment System
TRS	Test Remedial System
US	User Satisfaction
VLE	Virtual Learning Environment

Chapter 1: Introduction

1.1 E-learning

E-learning is a “delivery of a learning, training or education program by electronic means” (Stockley, 2003). In practice, this delivery may be through computers, smartphones or similar electronic devices which are linked by a communication network, or by radio or television. Technology not only is widening the availability of opportunities for education but also successfully combating a number of traditional obstacles to learning, such as lack of provision of different learning styles as the students have different preferable ways to learn, and also lack of learning support to enable students to learn the subjects, whenever and wherever, based on their own pace.

Twenty years ago, CDs were seen as the leading-edge e-learning technology (Bezovski and Poorani, 2016) and training CDs were sometimes used as the basis of workshops. IT lessons constituted the content in more than 95% of these training CDs at the time. The late 1980s introduction of multimedia saw CD-based systems represented as a potentially transformative way of accessing large works of reference and strengthening their learning potential (Alevizou, 2002). Encyclopaedias and similar resources could now make home users’ personal computers significant educational tools. Microsoft, for example, used Funk and Wagnall’s printed encyclopaedia as the basis for its 1993 multi-media CD offering, Encarta (Alevizou, 2002).

Five years later, the World Wide Web had surpassed training using CDs by not only making educational materials and instructions available online but also by personalising the experience – an effect supported by chat rooms, interactive content, newsletters and study groups (Cross, 2004). Since then, a large number of educational institutions, companies and organisations around the world have taken on the integration of asynchronous e-learning educational systems by means of VLEs (virtual learning environments) (Georgouli, 2011). A VLE is a software system designed to improve e-learning both for groups and for individuals. Available on the internet, they take care of a range of functions including downloading and uploading; educational material management; monitoring; and evaluating progress. Social software, such as blogs, wikis, and RSS, can be integrated into a VLE, and integrating external modules, web services and plug-ins underlies the majority of VLEs.

The majority of e-learning at present uses the Internet accessed through a series of different devices, such as desktops, laptops and mobile phones etc. Mostly, the educational material available is predesigned, covers fixed courses, and entails interaction between students and educators. E-learning systems currently available make efficient use of the facilities provided by existing communication technologies to deliver the content but are not equipped to respond to learners' reactions and perceived needs (Ab Hamid et al., 2006). For example, students taking the same course may have widely different learning styles, backgrounds and cultures, as well as different expectations and different ideas about what learning is (Blanchard et al., 2005, R-Moreno et al., 2008).

E-learning management systems, such as Blackboard (Blackboard, 2019) and Moodle (Moodle, 2019b) are common in e-learning and have been very successful, providing teachers and administrators with the necessary software features and supporting them in creating manageable courses for online instruction (Godwin-Jones, 2006). However, they do not make it possible to deal effectively with the differences between individual learners (Cristea and Stash, 2006, Graf, 2005, Graf and List, 2005, Popescu et al., 2007). To personalise an e-learning program means that the material must be modified to fit the needs of individual students, and presentation must also be modified in line with their ability to learn and understand. Questionnaires are one way to understand what modifications are needed; the extent to which students succeed or fail with existing material is another (Chen et al., 2005, Esposito et al., 2004).

Traditional e-learning systems have typically not been adapted to take account of the knowledge level, existing skills and/or learning style of individual students. However, adaptive e-learning systems are capable of improving the learning experience through personalisation to meet those individual characteristics (Alshammari et al., 2014). This has made adaptive e-learning systems a current e-learning trend with the ultimate goal of personalising the material and the way it is presented to provide the closest possible match with an individual's needs (Alshammari, 2016). Some of the learner's characteristics that can be successfully integrated into an adaptive system are: the individual's existing knowledge level; the individual's learning style; and the consequence of whether the learner approaches the system in a positive or negative manner (Brusilovsky, 2001, Leka et al., 2016). Jameson defines an adaptive system as the one that is interactive and can infer from the way individual users react and behave, how they learn and how they apply themselves – it first "sees" the way the individual learns and then adapts the way it teaches to fit that learning style (Jameson, 2009, Leka et al., 2016).

The aim of this research is to design an adaptive e-learning system that combines two adaptive mechanisms, fuzzy logic (Zadeh, 1996) and concept maps (Cañas et al., 2003, Plotnick, 1997). The concept map would be driven by the fuzzy logic and would show the knowledge level that the student has for each of the topic's concepts, while a concept list of learning materials would allow weaknesses in the learner's understanding of the subject to be addressed. Before the teaching materials are provided to the user, the system would carry out an initial pre-test to obtain information about the level of understanding a learner has for the concepts to be taught. After the learning system has been used, a post-test would assess the learner's success. This research aims to demonstrate that an adaptive e-learning system of this type will improve not only the learner's understanding and knowledge but also their engagement and motivation.

1.2 Problem Statement

The inspiration for this research is the idea that combining two different adaptive e-learning techniques can produce an AITS (adaptive intelligent tutoring system) capable of improving learning outcomes (Phobun and Vicheanpanya, 2010). The two techniques in question were: AH (Adaptive Hypermedia) and ITS (intelligent tutoring systems). A review of the current state of these techniques shows that, though popular at the end of the twentieth century and the beginning of the twenty first, the terms have been superseded by adaptive e-learning and there has been little research into AH and ITS. The two terms however represent concepts relevant to this research.

The majority of e-learning systems were developed to create an environment acceptable to both learners and tutors. The benefits these systems bring to the process of learning are many, but they are not able to take into account the level of knowledge users have, individual feedback, students' learning style, and whether more suitable learning material exists. A number of adaptive mechanisms have been used in e-learning; however, many are appropriate to some courses but not to others. What works when teaching computer programming, for example, may not be right when teaching History. Determining which system best fits which subject requires an understanding of the subject and a review of research; things necessary to know include: the systems' effectiveness, their relevance, and what distinguishes one from another.

This research reviews adaptive e-learning systems developed over the past ten years and explores how they have been used as ways of identifying individual learners' understanding, presenting the material, establishing remedial content, and determining relationships between concepts. This background is then used to propose a novel adaptive e-learning system.

1.3 Research Aim

The aim of this research is to find ways to increase learners' level of knowledge and understanding, and to improve motivation and engagement by designing an adaptive e-learning system that will be effective through the use of a combination of fuzzy logic and a concept map for evaluation of learners' level of knowledge and consequent content adaptation.

1.4 Research Approach and Objectives

This thesis presents and implements a new adaptive e-learning system, CaFAE (Concept-based and Fuzzy Adaptive E-learning), and then evaluates it. The system is designed to adapt to student needs as a result of a Coloured Concept Map (CCM) and Ranked Concepts List (RCL).

Implementation is carried out using a developed platform operating under the Moodle learning management system. To identify understanding levels, students are tested on the subject area before they begin learning the materials (called pre-test). On the basis of their pre-test results. students are given the CCM and RCL which constitute the adaptive system's two components.

The main objective of this research is the identification and investigation of the adaptive mechanisms affecting e-learning systems' effectiveness. The aim is to improve students' performance and engagement with the online learning systems. The objectives may be summarised as follows:

- Critically review and investigate the adaptive mechanisms most frequently used by e-learning systems to evaluate their suitability for adaptation in e-learning.
- Develop an adaptive e-learning system combining a fuzzy logic system and a concept map.
- Apply the developed system to analyse how adaptive techniques influence the use of e-learning using two components:
  - *Coloured Concept Map (CCM):* helps to establish students' knowledge levels and increases their motivation and engagement.
  - *Ranked Concepts List (RCL):* suggests the concepts appropriate to be learned in an orderly way.
- Functionally test the proposed system to show how well it works and the effect it has on learners.
- Evaluate the proposed system experimentally with students to show its effectiveness.

1.5 Research Questions and Hypotheses

The central question in this research is: Can an adaptive e-learning system enhance learners' understanding, knowledge, motivation and engagement, and make learning more effective as compared to a standard e-learning system?

The experimental results will be compared using three sub-questions:

1- Is student understanding, knowledge, engagement and motivation improved by the proposed adaptive e-learning system?

2- Do students express satisfaction with the engagement provided by an adaptive learning system as being a more active learning process?

3- Does the system meet students' learning requirements without a need for additional tools?

To answer the primary and secondary questions of this research, an adaptive e-learning system is developed and evaluated in this thesis using these evaluation techniques:

- *Questionnaires:*

  - A pre-experiment questionnaire to ascertain the students' experience of e-learning and, more specifically, their experience of adaptive e-learning systems before exposure to the proposed system.

  - A post-experiment questionnaire to measure students' satisfaction with the proposed system and its features, and to know their thoughts about adaptive mechanisms after they had used the proposed system.

- *Tests:* pre- and post-test questions are used to assess the students' abilities before and after they have used the proposed system.
- *Hypotheses:* There are general hypotheses which are formulated on the basis of students' results in the pre and post-tests; the adaptive system will show an improvement in understanding; the adaptive system will outperform the non-adaptive system and the adaptive system will be usable.

These five key hypotheses, formulated and tested based on the results of the students' test scores and time spent learning the materials and answering the questions, are as follows:

H1: The pre-test will show no significant difference in knowledge level between the adaptive group and non-adaptive group.

H2: Post-test, the adaptive group will significantly outperform the non-adaptive group in knowledge level.

H3: Comparison of pre-test and post-test scores will reflect significant differences in the performance of the two groups separately and combined, i.e. post-tests in both groups will show improvements.

H4: Less time will be needed to learn the concepts and answer post-test questions by those using the adaptive e-learning system as compared to those using the non-adaptive e-learning.

H5: Students will find the adaptive system engaging with good usability.

1.6 Research Contribution

This research contributes to the knowledge and practice concerning e-learning systems by providing adaptive techniques that have a positive influence on learners' performance. The main research contributions of this thesis are:

- Critical review of the adaptive mechanisms most frequently used in e-learning systems and their contribution to learners' improved performance and motivation. While literature exists on such theories and models, this review justifies the need for a new adaptive e-learning system (that is proposed in this thesis).
- Utilization of a combination of two adaptive techniques (fuzzy logic and concept map) to influence learners' performance and engagement. This combination of these two adaptive techniques produce two main objects (Coloured Concept Map and Ranked Concepts List) that increase the students' understanding and engagement levels (Al Duhayyim and Newbury, 2018). These two adaptive techniques have not previously been considered in e-learning systems studies.
- Implementation of a bespoke test system based on multiple-choice answers were answers have a variable value of correctness.
- Contribution to understanding comparisons between an adaptive e-learning system and a standard e-learning system utilizing two different groups (Al Duhayyim and Newbury, 2019):
    - The experimental group: students using the adaptive e-learning system.
    - The control group: students who use a standard e-learning system.
- Application of the proposed adaptive e-learning system in a pilot experiment and a full experiment in two different universities to evaluate statistically the proposed system's performance.
- Unique mixed method: This design and research method also contributes to adaptive e-learning, through using different data obtained via the students' outcomes in the system from various sources such as questionnaires, test scores, etc., which assisted in achieving the objectives. Thus, using combined methods to collect the data (qualitative and quantitative) backs up the significance of results from the research, which was unique. The methods used here are for analysing and explaining the efficacy of the CaFAE system, which provides adaptation benefits to students.

1.7 Thesis Outline

This section shows the order of the thesis chapters and provides a brief description of each.

Chapter 1:

It introduces the research area and definition of the research problem. It presents the main objectives of this research together with the research questions and hypotheses. It describes the approach to the research and briefly lists the research contributions.

Chapter 2:

It provides literature review covering aspects of e-learning adaptivity, and critically reviews common adaptive mechanisms. The focus is on the importance of e-learning systems in education and the theories, methods and techniques used to provide adaptivity to learners. The review identifies the knowledge gaps and answers the main research question by analysing current systems and their limitations.

Chapter 3:

It presents the design of a new adaptive e-learning system and explains in detail the role played by adaptive mechanisms in evaluating system outcomes. It discusses the working of the coloured concept map and ranked concepts list, how students' knowledge level is evaluated, and the appropriate learning materials recommended.

Chapter 4:

Chapter 4 discusses the research methodology which was employed in the full studies as well as in the pilot. It can explain the research design, philosophy, approach, strategy, method and data collection techniques in addition to the analytical procedures used in the research.

Chapter 5:

Chapter 5 provides a data analysis of the pilot study data. Additionally, it discusses the findings and presents an assessment of the research hypotheses from both the non-adaptive and the adaptive group results alongside their feedback.

Chapter 6:

Chapter 6 provides a collection of the data from the full study (as in Chapter 5). It also presents a discussion of the findings and an assessment of the research hypotheses from the non-adaptive and adaptive group results alongside their feedback.

Chapter 7:

It discusses the general findings of the pilot study and the full study.

Chapter 8:

It presents the general conclusions of the thesis, reflecting the relationship between the findings and the research questions and hypotheses. Detailed research contributions and limitations are explained together with recommendations for future work for both practitioners and researchers.

Chapter 2: Literature Review

2.1 Introduction

E-learning is generally used for web-based instruction to allow learners to access online courses through the internet (Phobun and Vicheanpanya, 2010). In e-learning, it is assumed that the learners are capable of learning independently and are self-motivated. The benefits of e-learning systems have been examined extensively in previous investigations (Liaw, 2008). However, there are also several limitations to existing e-learning systems. Two of the key issues with traditional e-learning are: each learner views the same learning content and is provided with the same learning style; there can be a lack of feedback and tutor interaction in the learning process (Vasilyeva et al., 2008). The absence of feedback and tutor interaction is one of the critical e-learning issues that limits the learning of users. In the worst cases, this limitation can make the learners stop using the e-learning system or even to drop the course (Pechenizkiy et al., 2008). Based on these two key factors (reviewing same contents and learning style, and lack of feedback and tutor interaction) this chapter will critically review different adaptive e-learning systems and techniques that have sought to find solutions to these limitations.

Typically, e-learning systems are designed without taking into account an individual's learning style, or existing skills and knowledge level. Adaptive e-learning systems, however, can personalise learning material to focus on a learner's individual characteristics and can thereby improve the learning experience (Alshammari et al., 2014).

Adaptive e-learning systems is an emerging trend in this domain. The ultimate goal is to personalize learning material and its sequencing to match the needs of an individual learner as much as possible. Characteristics of learners which may be integrated into adaptive e-learning systems include: affective state of learner's positive or negative attitude about the system; learning style; and existing level of knowledge (Brusilovsky, 2001, Leka et al., 2016). According to (Jameson, 2009), an adaptive system is interactive and learns, infers, and/or makes decisions, from behaviour of individual users concerning their mode of learning acquisition and application. In other words, it "sees" how an individual learns, and from that information, adapts its teaching methods for that individual (Jameson, 2009, Leka et al., 2016).

2.2 Adaptation in E-Learning

In computer-based education, researchers have become increasingly interested in the subject of adaptation in e-learning, and two important terms have emerged: adaptivity and adaptability. Adaptivity describes the modification of e-learning lessons in response to user behaviour, with such modification being based on what amounts to an artificial intelligent (AI) or procedural application using rules that are predefined and connect with a series of different parameters. Adaptability, on the other hand, is what happens when it is the user who modifies and changes the learning process by personalising e-learning lessons to suit themselves (Khemaja and Taamallah, 2016, Klašnja-Milićević et al., 2017). Adaptability is also defined as the people or student's capacity to adapt with a new changing, behaviour, emotion and challenging circumstances in the e-learning area (Martin, 2010). Hence, this research is focused on the adaptivity of e-learning system.

Currently, adaptation in general in e-learning makes use of new technologies and modes of expression that are developed originally in computer-based training and adaptive hypermedia systems (Klašnja-Milićević et al., 2017). The purpose of adaptive e-learning is to increase the effectiveness of e-learning by presenting content in a way that is adapted to an individual user in order to match the way that user behaves and the knowledge that user has. The underlying assumption of adaptive e-learning is that the learning characteristics of each learner are different, and that various kinds of learners benefit from different educational settings, as proposed by ATI (aptitude treatment interaction) (Cronbach and Snow, 1977, Esichaikul et al., 2011). Presenting the contents of the course flexibly so that it is adapted to the characteristics of the individual learner allows an e-learning system to achieve the best possible learning outcome (Brusilovsky, 1999, Brusilovsky and Peylo, 2003, Shute and Towle, 2003, Esichaikul et al., 2011).

The purpose of adaptive e-learning is provision of the right information at the right time to the right student. Adaptive e-learning systems monitor usage and can adjust content for each user automatically in order to obtain the best learning results. Adaptive systems are supported by a model for each student built on that student's existing knowledge, preferences, and goals; this model allows interaction of the e-learning system with the user to be adapted in a way that meets the user's needs (Brusilovsky, 1999, Brusilovsky and Peylo, 2003). An adaptive e-learning system can make material more usable, thereby increasing the effectiveness of e-learning systems, leading in turn to better knowledge acquisition by the student (Esichaikul et al., 2011). An adaptive e-learning system constructs a model for each student based on their existing knowledge, preferences, and goals. This model is used all through the system/student interaction so that the system is adapted to the maximum possible extent to that student's needs (Beldagli and Adiguzel, 2010, Brusilovsky and Nijhavan, 2002). Stoyanov and Kirchner, define an adaptive e-learning system in these words: "…an interactive system that personalizes and adapts e-learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise." (Stoyanov and Kirchner, 2004). The definition given by Burgos, is that adaptive e-learning is "a method to create a learning experience to the student, but also to the tutor, based on the configuration of a set of elements in a specific period aiming to increase of the performance of a pre-defined criteria" (Burgos et al., 2006). These criteria may be one of the following: economic, user satisfaction, time-based, educational (Beldagli and Adiguzel, 2010).

2.3 Adaptive E-learning Techniques

Various adaptive techniques have been used in adaptive e-learning systems in different forms to provide adaptation services to the e-learning environment. In fact, adaptive e-learning techniques answer three fundamental questions which are considered as main components of the adaptive frameworks: what can they adapt, to what they can adapt, how can they adapt (Alshammari, 2016, Brusilovsky, 1996). These adaptive techniques have been used in different aspects of e-learning environment to provide adaptivity and personalization. For example, some researchers have used adaptive techniques to determine the knowledge level of an individual student (Chrysafiadi and Virvou, 2013a, Dogan and Dikbıyık, 2016, Hsieh et al., 2012). Others have used an adaptive mechanism to identify the learning styles and preferences of each learner (Alkhuraiji, 2016, Alshammari, 2016, Özyurt et al., 2013b). Adaptive algorithms have been used to evaluate and adapt the learning content for each student based on their performance (Aris and Badawi, 2017, Dolenc and Aberšek, 2015, Gutiérrez et al., 2016). Therefore, many adaptive techniques have been employed in the last decade, such as concept maps (Dogan and Dikbıyık, 2016), fuzzy logic (Almohammadi et al., 2017), expert system (Hafidi and Bensebaa, 2013), Bayesian network (Hooshyar et al., 2016), overlay model (dos Santos Guimarães et al., 2016), stereotypes (Chrysafiadi and Virvou, 2015) etc. to provide an effective adaptation system in the learning process. The following sections review the key adaptive techniques applied to e-learning systems.

2.3.1 Concept Maps

A concept map is a method of denoting relationships between ideas, images, or words. There are various uses of concept maps, such as stimulating the generation of ideas, brainstorming, communicating complex ideas etc (Cañas et al., 2003, Plotnick, 1997). For example, using concept maps in the science classroom, where learners are provided only the concepts and asked to connect concepts with a directional arrow, then name the arrow with a word or short phrase that represents the relationship between the two connected terms (Figure 2.1). Therefore, it can be read as a statement, such as “Water has density”. The statement of these two words linked by an arrow and phrase are called propositions (Vanides et al., 2005). Concept maps are also used in assessing learner’s knowledge of learning goals, concepts, and the relationship between those concepts. There are two key uses of concept maps in the adaptive e-learning: they are used to show the structure of learning materials, and they are also used to capture the understanding of the student of those materials. In the context of this thesis, a concept map model is a way of generating a domain model by classifying the relationship between concepts in a specific course. This being particularly appropriate to the learning of programming languages and computer science theory which has a series of related concepts many of which need to be understood in a certain order, e.g. classes, methods, inheritance etc.

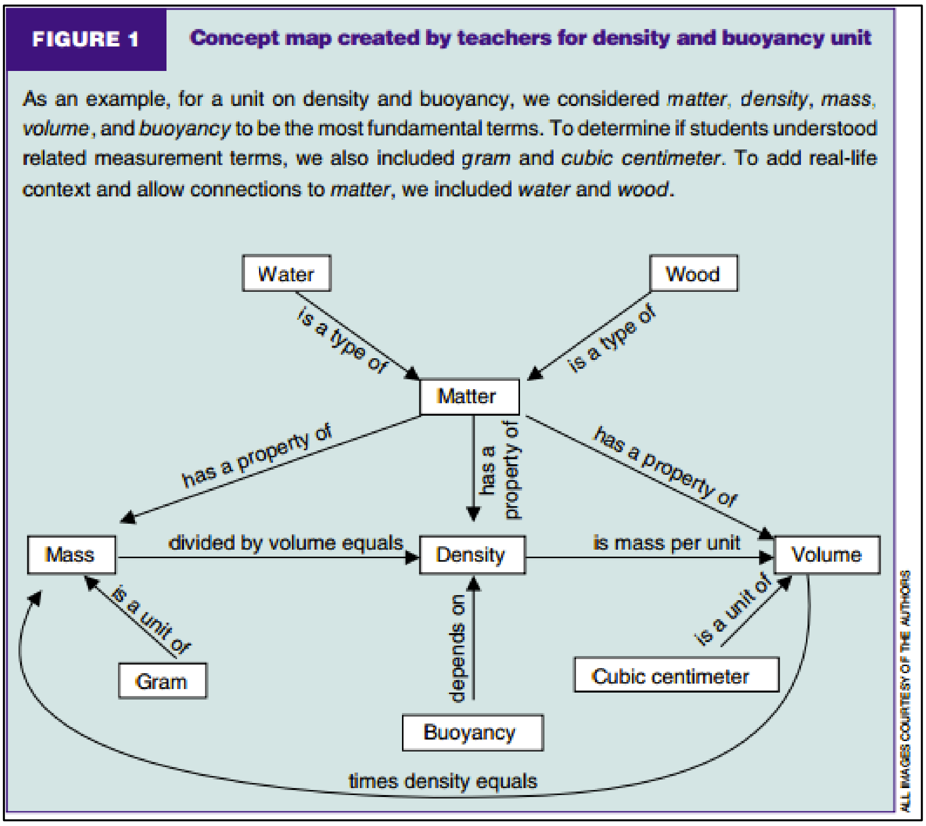


Figure 2.1 Concept map created by teachers for density and buoyancy unit (Vanides et al., 2005)

- <u>Virtual 3D Objects:</u>

A web-based 3D interactive concept map is developed to help the students learn and motivate the challenging topics in Engineering drawing course in (Violante and Vezzetti, 2015). They have used concept maps to provide teaching, learning and evaluations of the student learning to the learners. In this concept map, a virtual 3D object describes a real-world object, and this supports students to imagine the actual global situation and helps them in collecting information and its processing to have better understanding about the problem and how to solve it. Violante and Vezzetti, as shown in Figure 2.2, have used the "threaded fasteners" topic as an experiment for their concept maps approach; more specifically, how to connect the hole to the kind of fastener correctly and how to properly represent the hole on an engineering 2D drawing with a simplified representation.

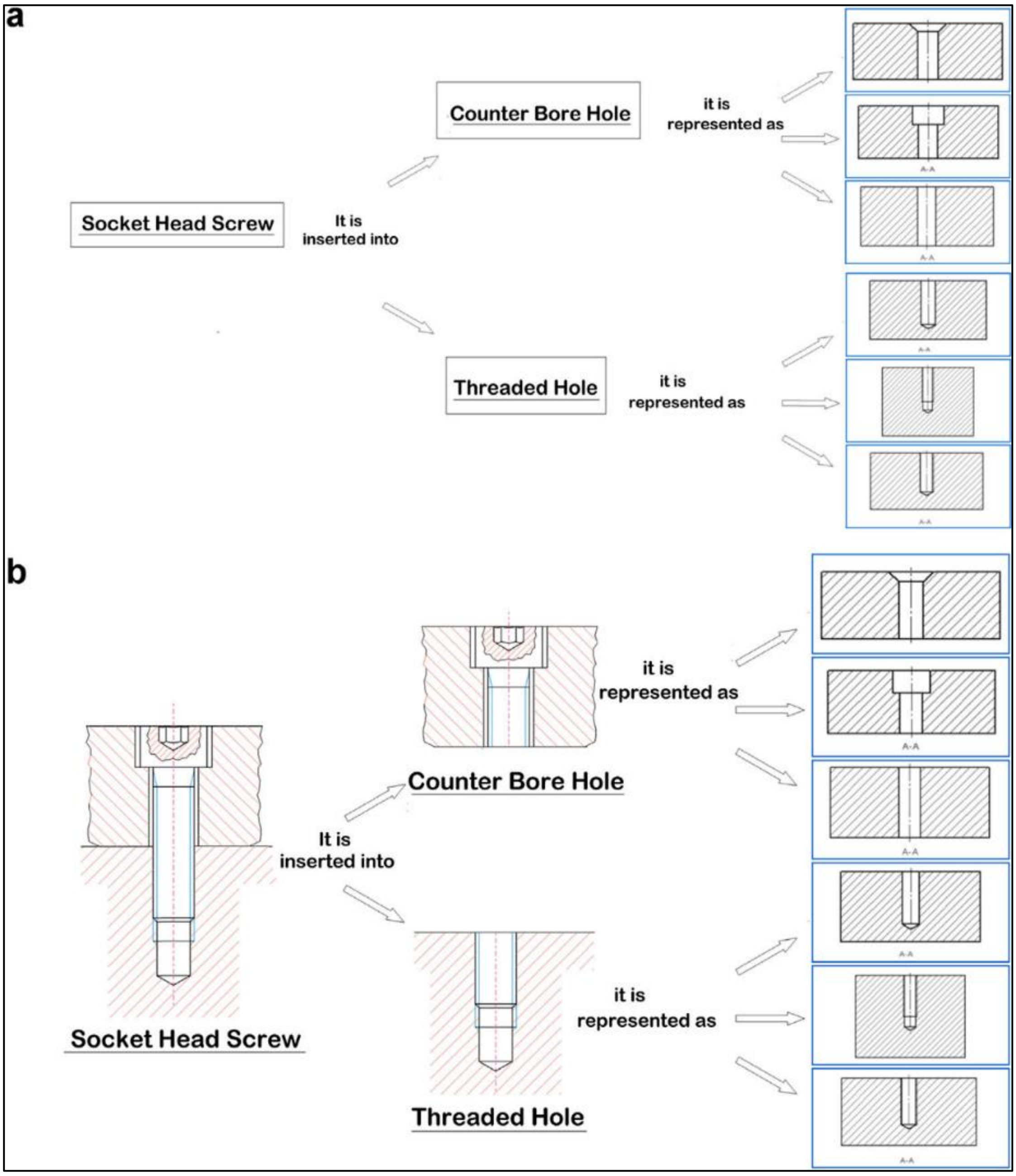


Figure 2.2 Two examples of concept maps about the topic "socket head screw." (a) classical concept map (b) 2D concept map (Violante and Vezzetti, 2015)

As shown in Figure 2.3, three interactive 3D objects are included in the concept map: a socket head screw that consists of two moulded parts, the clearance hole which is at the top, and the threaded hole which is at the secondary part. With these 3D interactive visualizations, the students can measure the hole pattern present in the high and lower part, and then determine the correct 2D design of each hole. Violante and Vezzetti have used this example to show the structure of the learning and to evaluate the understanding of students using concept maps.

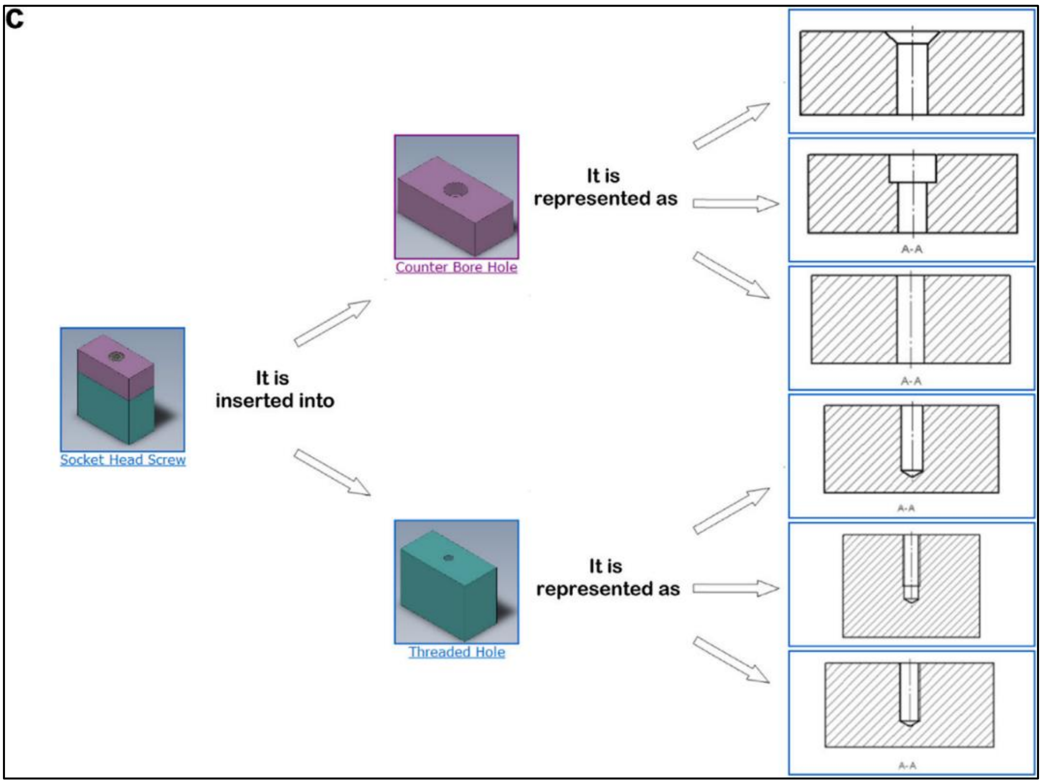


Figure 2.3 An example of concept maps about the topic "socket head screw." (c) Web-based 3D interactive concept map (Violante and Vezzetti, 2015)

Violante and Vezzetti have conducted an empirical study on 32 students to test their spatial abilities. They have manipulated with a flat shape with numbered sides, and a three-dimensional shape with lettered sides, and have participated to indicate which numbered side corresponds to which lettered side. The results of their research showed that the concept maps helped the students to know how to correspond the shapes to the appropriate sides. Even though this shows good evidence of the advantages of using concept maps in e-learning this research is not in itself adaptive. They could improve their work by using 3D animations with immediate step-by-step instructions and apply it to students with both low spatial ability and high spatial ability.

- <u>AISLE:</u>

A more adaptive use of concept maps is that explored by Awati and Dixit. The concept map in this instance has been used to calculate student knowledge about a specific topic "History of America" automatically (Awati and Dixit, 2017). Markov chains technique is applied to determine the score of student understanding, along with XML parsing technique to analyse and assess the concept maps that the students have created (Markov, 1971). The framework for student learning assessments provides the score of student understanding about the topic and generates feedback for the teacher and the student as shown in Figure 2.4. Awati and Dixit have used artificial intelligence-based learning evaluation tool (AISLE) to perform learning evaluation of concept maps using three main units: XML analyser module, Markov chain analysis module, and user interaction module.

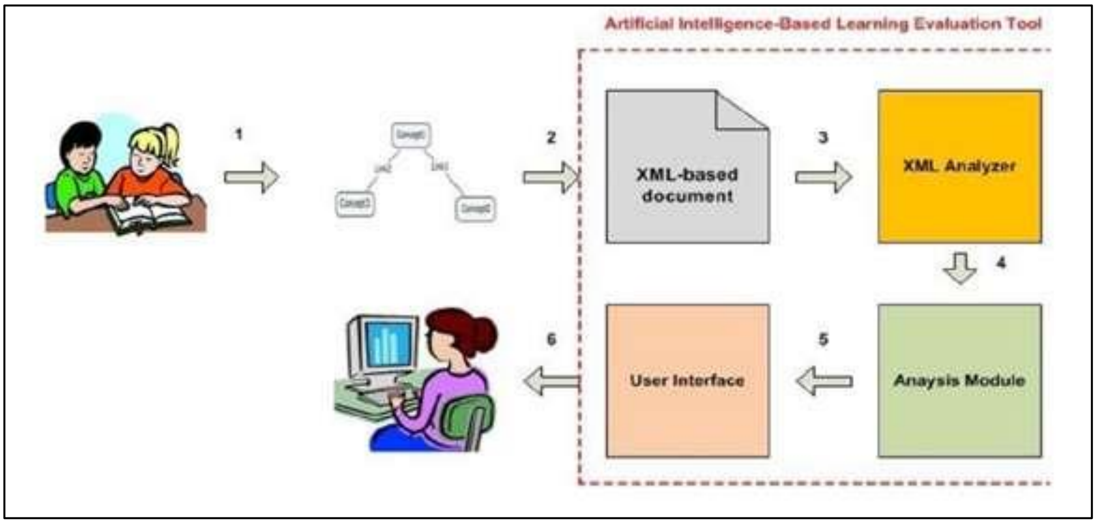


Figure 2.4 system Architecture (Awati and Dixit, 2017)

In the XML analyser module, the concept maps are converted into XML documents by using Java and XML parser. After generating XML files, the required data is gathered, and hierarchy is created by Markov chain analysis module. The analysis is performed by this unit and conveyed to the user interaction module for providing analysis to the instructor in the form of charts and/or graphs. The Cmap tool (Cañas et al., 2004) is used by students to construct the concept maps and are given to the XML analyser module. In the concept map, there are three levels: Gist level, which is assumed to have only one gist level element and that is root node or subject of the topic; Support level, which is the concept after the root node; Detail level, which includes the concepts that are connected to the support level and considered as details nodes. XML Dom parser (Wang et al., 2007) is used to collect the information from a generated XML file for any concept maps. The values from this XML can be obtained based on the number of concepts in the hierarchy, the number of relations that connect to the different level in the concept map hierarchy, and the score that is calculated to each concept map in the hierarchy (Score). After calculation of these values, XML Dom parser can produce the summation of all scores in each level. Awati and Dixit have mentioned that this tool couldn't maintain a large number of students because graph is a complicated method, and it is hard to identify student's gaps in comprehending the topic. A powerful user interface is needed to show the outcomes of students. They have proposed a new module in their system, Result Analysis Module, to display the results of the students. It provides concept logical result of each student, rank of the students among their classmates, strengths and weaknesses of the concepts for students in understanding the topic. However, a key output of this research is that concept maps can be used to show a student’s understanding of a topic.

- <u>OPCOMITS:</u>

Dogan and Dikbıyık developed an adaptive intelligent system called OPCOMITS (Object Oriented Programming Tutor using Concept Map Model) based on a concept map model to organise topics in a hierarchal approach and measure the student's knowledge about a topic to adapt learning (Dogan and Dikbıyık, 2016). This system structures the course based on the expert's desire, measures the student's knowledge levels about a topic, suggests enhancement feedback, diagnoses students' weaknesses and guides them to related chapter topic in the domain for improvements. It uses concept maps to structure the learning material, and similarly concept maps to understand how much the students know the subject area and recommend them with the appropriate contents using the concept error rate. An Object-Oriented Programming course is used to evaluate the proposed system.

In the OPCOMITS system, which is shown in Figure 2.5, two primary users, which are experts and students, login into the system. Experts can set up the courses, concepts, chapters and topics followed by questions in the concept map using the "Content Management System for Experts" module in the system. Experts can create a domain model by identifying concept-subject, concept-question, concept-prerequisite and concept relationships. Experts can also control the concept learning level, and students' success displayed in chapters. The system keeps the course content and topic saved that the student achieved continuously in the student model, and all the student information on student model is employed in the decision-making process of the teaching model. At the end of each chapter, significant guidance is produced based on knowledge level and the evaluation conducted.

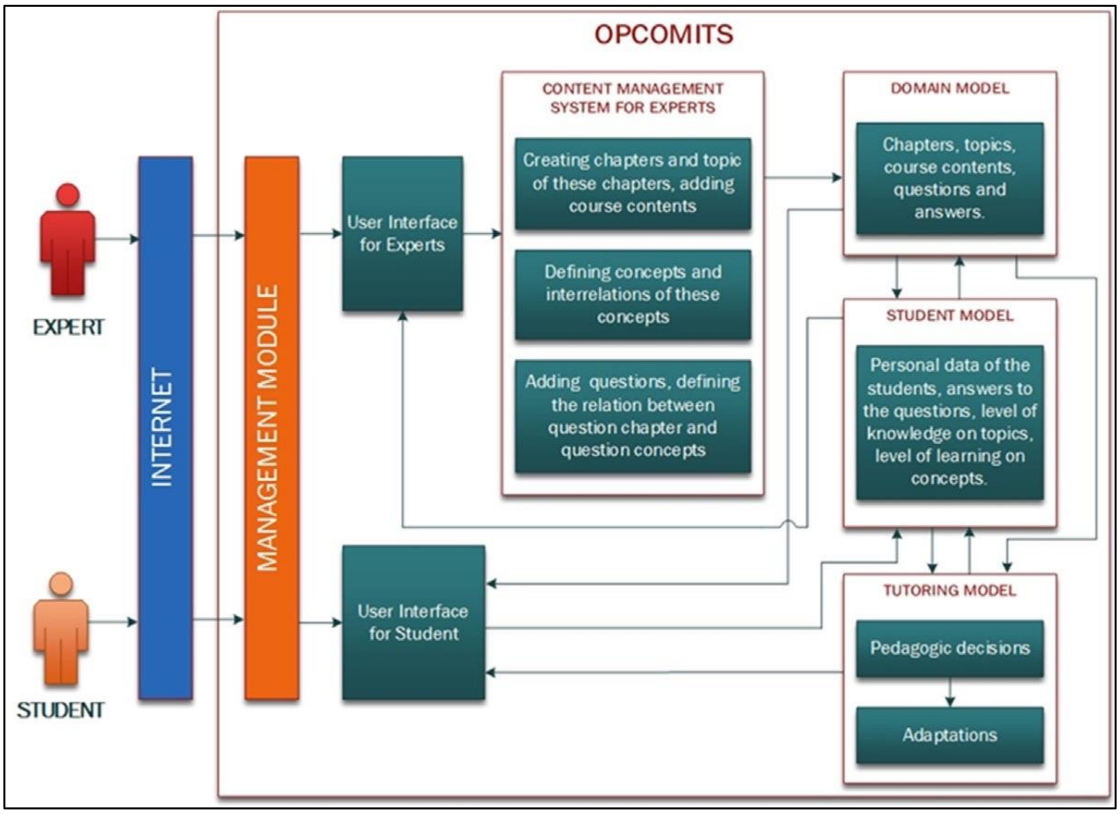


Figure 2.5 The architecture of OPCOMITS (Dogan and Dikbıyık, 2016)

In Student model, an individual student or learner can follow their adaptive path or navigate support through the system for each concept. The student interacts with each concept and then answers questions based on that concept's contents. The system evaluates the student's knowledge level adaptively for each concept when the student completes all topics in the chapter by calculating the concept error rate (CER). CER represents how much the students have done wrongly answering the question that is related to a particular concept. Therefore, the learners are determined based on their knowledge levels and coloured concept maps are generated to show them their understanding levels of the subject area as shown in Figure 2.6.

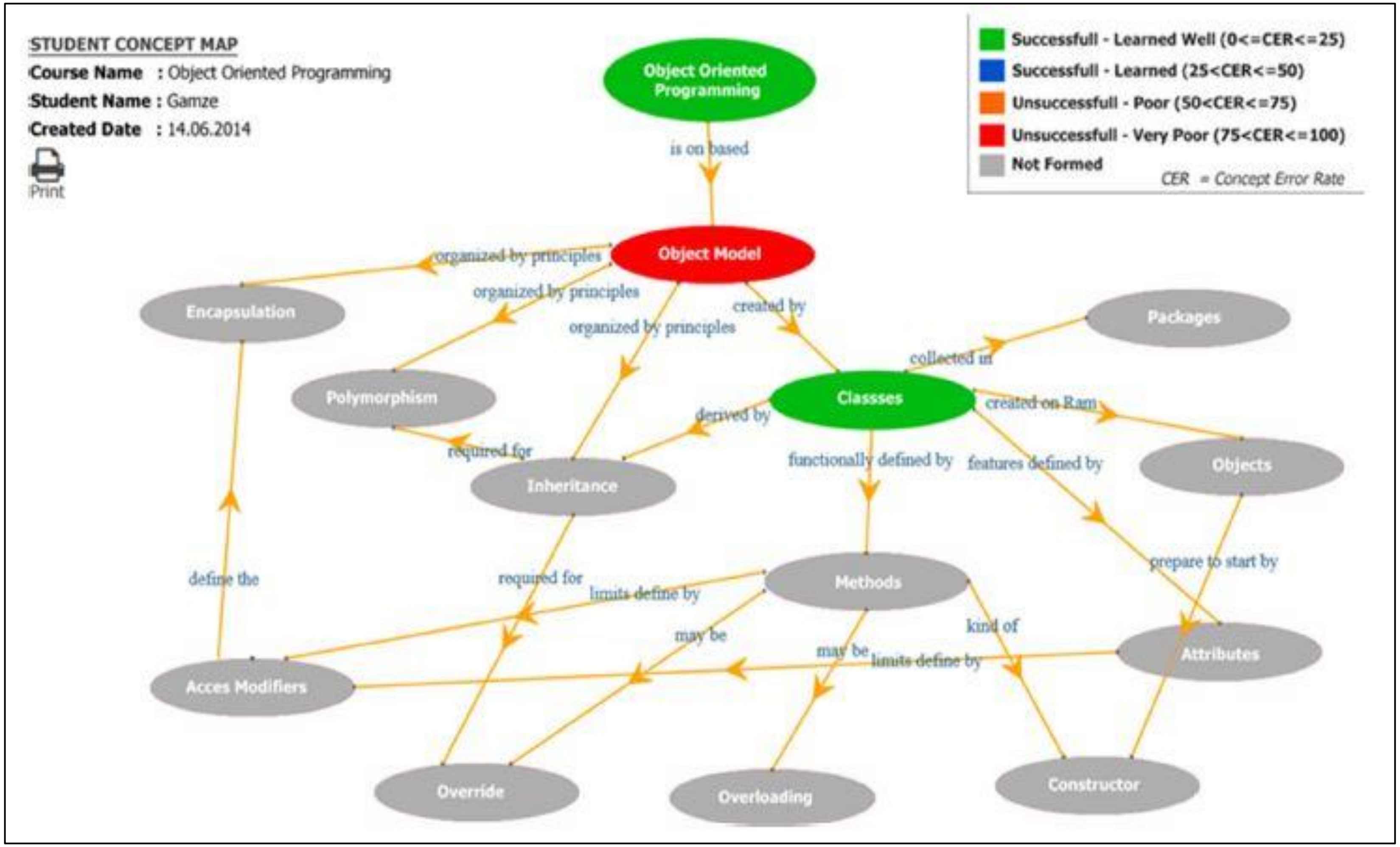


Figure 2.6 Student concept map screen (Dogan and Dikbıyık, 2016)

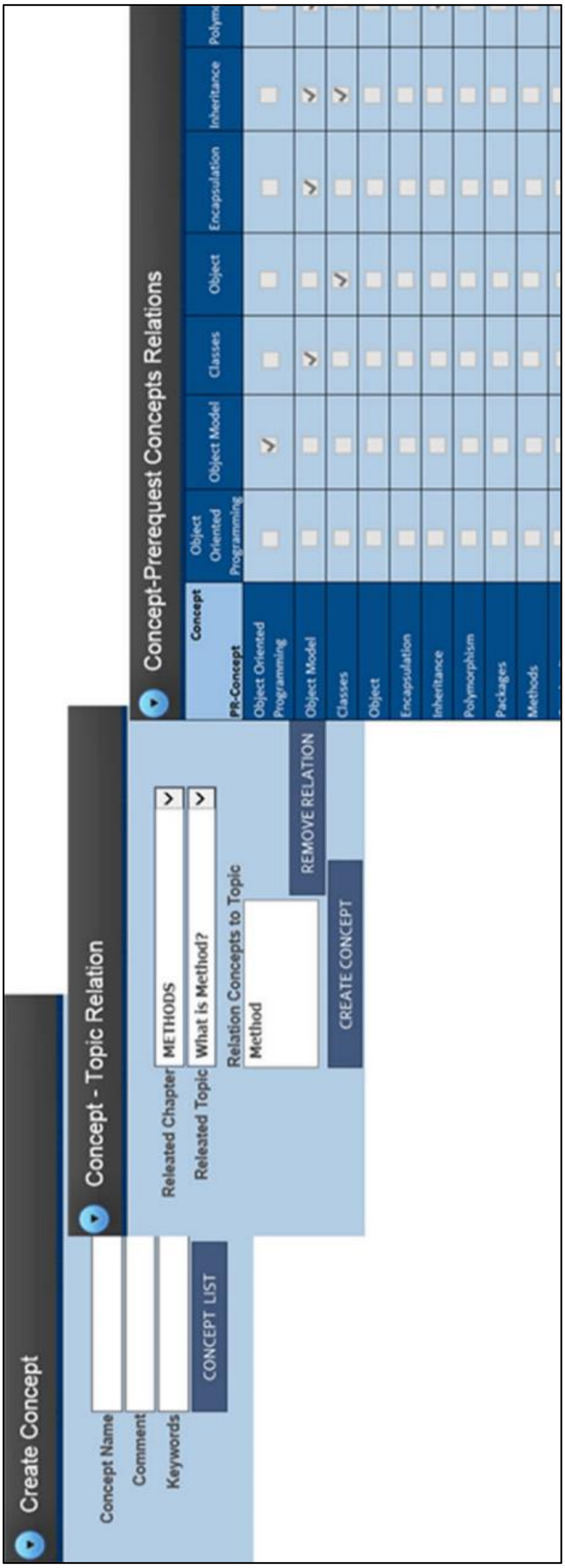


Figure 2.7 Creating concept and concept relations defining screens for experts (Dogan and Dikbıyık, 2016)

Domain model can be created by experts through the "Content Management System for Experts" to use the system operations which are: content operations, concept operation, and question operations. In content operations, the expert can create different types of content for each concept, such as visual, textual, auditory, and kinaesthetic content. In concept operations, when the expert creates the content, concepts are set to be added using the "Content Management System for Experts" and relates each concept with one or more topics (Figure 2.7). "Concept–topic relation means what concepts in the system are connected to which topic in the course content. This information is used to guide students to the topic content based on the result of the student evaluation. The expert determines the concept map by identifying concept-prerequisite and concept relationships. In question operations, the expert can create questions. Concept–question relation describes the level of relationship between the concepts and the questions provided by the expert to define the scope of learning the concepts."

The system was tested with a dataset of 40 students enrolled in an object-oriented programming course at Istanbul Arel University in Istanbul, Turkey. Those students were divided into two groups, experimental and control, to investigate the impact of adaptation using concept map model and to define the influence on learning accomplishment. They have used a t-test for these two groups to compare them by utilizing the pre-test and post-test results of the empirical study. The analytical investigation pointed out that the change from the pre-test to the post-test results was greater for the experimental group than the control group. These results showed that the students who learned using OPCOMITS achieved much better than the students who learned with conventional e-learning.

Although this experiment gained positive results for a programming course and it works for well-structured subjects, it suggests that it would work well for most subjects in the area of computer science. They also provide a method to form learning content and determine students' learning problems. Students can learn each concept in different learning styles depending on the content that the expert creates, such as textual content, visual content, auditory content, or kinaesthetic content, but combining different learning styles may be more effective and increase the student's learning achievement. Dogan and Dikbıyık have mentioned to improve this investigation using data mining techniques, such as Bayesian Networks, Fuzzy logic theory, decision tree etc. to perform enhancements according to the results collected from analysing data gathered from the students and to identify the prerequisite relationship between the concepts. Adding these adaptive techniques to OPCOMITS system could help to add the appropriate contents based on the student's performance and it could be capable to identify the concepts and determine the relationships between them.

2.3.2 Overlay Model

The overlay model was designed by (Stansfield, 1976) for students who possess incomplete but correct domain knowledge. In overlay modelling, the student model is a subset of the domain model revealing expert-level knowledge. The overlay model technique enables the domain model of the individualized and/or adaptive tutoring system as a representation of specific concepts and topics. Consequently, its complexity is because of the domain model's structure, design, and student knowledge appraisal (Martins et al., 2008). Therefore, the overlay model defines user knowledge for each individual concept and is the reason for extended use. Overlay models are incomplete as an advanced model since they do not account for how the user makes an inference, and how new knowledge is combined with previous knowledge. This is why an adaptive and/or personalised tutoring system is representative of student modelling by combining the overlay model with other student modelling methods, e.g. stereotypes, perturbation and fuzzy techniques.

The overlay technique has been used by (Kumar, 2006a, Kumar, 2006b) when programming a tutor as a way of modelling students, and when (Glushkova, 2008) developed the DeLC system it modelled the level of knowledge that learners had by using a qualitative overlay. Because Glushkova wanted also to model a number of other things, the system combined stereotype modelling (discussed below) with the overlay. The other things that were modelled included how learners accessed training resources and learners' behaviours, habits and preferences. When (Limongelli et al., 2009) constructed the LS-Plan, a framework that allows e-learning to be adapted and personalised, they also used a qualitative overlay model. Competence in mathematics in e-learning environments is modelled by IWT (Albano, 2011) using an overlay model that applies a representation of the knowledge domain derived ontologically. Thinking style is integrated into their adaptive hypermedia system (AHS-TS) by (Mahnane et al., 2012) by the application of an overlay model. PDinamet is a web-based adaptive system for secondary education physics teaching developed by (Gaudioso et al., 2012) that enables the appropriate learning resources to be selected effectively and in personalised form by use of an overlay model.

However, Rivers has identified the inadequacy of overlay models for complex student modelling in that they take no account of how users infer things, how they integrate new knowledge into their existing store of knowledge or how learning changes their representational structures (Rivers, 1989). The overlay model does not make it possible either to identify incorrect knowledge acquired or possibly acquired by the student and nor does it distinguish individual learners' personality, behaviours, preferences and cognitive needs. It is because of those shortcomings that a number of personalised and/or adaptive learning systems when modelling students combine the overlay model with such other techniques as stereotyping, fuzzy techniques and perturbation (Chrysafiadi and Virvou, 2013c).

2.3.3 Stereotypes

An additional approach frequently used for student modelling is stereotyping. Stereotypes were presented by (Rich, 1979) for student modelling in the GRUNDY system. The stereotype technique is used for classifying ever adaptive system user into a group based shared attributes. These groups are called stereotypes. More specifically, a stereotype regularly includes the basic knowledge about a group of users. New users are enrolled into a suitable stereotype if individual characteristics match those of the stereotype. The stereotype is an important way to rationalize about users and a solution to the problem of initializing the student model by allocating a student into a particular group (Tsiriga and Virvou, 2002). The stereotype technique is beneficial in that the knowledge of a certain user is decided upon from the related stereotype(s). Additionally, information about user stereotypes can be maintained with low repetition without using the knowledge deriving process for all users (Zhang and Han, 2005).

However, stereotypes can also cause issues. Stereotypes are inflexible since they are constructed in a handcrafted manner before a real user has dealt with the system. They are also not updated until someone specifically does so (Tsiriga and Virvou, 2002). Additionally, (Kass, 1991) states that stereotypes face two problems. Firstly, to use the stereotypes the system user groups must be divided into classes; although, these classes may not exist. Secondly, even if it could identify classes of system users, the system creator needs to create the stereotypes, which is time consuming and can cause errors. Additionally, stereotypes are not flexible and any system involving allocating students into set groups risks not addressing the particular needs of students.

2.3.4 Fuzzy Logic Theory

Another adaptive technique often used in e-learning is Fuzzy logic which was introduced by (Zadeh, 1965) as a method for computing with words (Zadeh, 1996). It can manage uncertainty in problems having ambiguous and incomplete data as well as individual subjectivity (Drigas et al., 2009). "Fuzzy logic is design of multi-valued logic that enables intermediate values between regular evaluations, such as true/false, yes/no, high/low, and big/small. Ideas such as rather tall or very fast can be declared mathematically and treated by computers to apply a more human-like approach of thinking in computer programming" (Hájek, 2006, Zadeh, 1984). Therefore, fuzzy logic theory is very applicable to the job of modelling student understanding. Fuzzy logic theory enables reasoning in real-life uncertainty scenarios without an actual border in standard set theory (Yen et al., 1998, Zimmermann, 2011), or the phrase "only slightly understood" may be represented as a score, e.g. between 65 and 75. Similarly, the phrase "understood fairly well" may represent a score between 80 and 90 in the field of learning environment.

A fuzzy set is a set of objects with fuzzy boundaries, with low, medium or high to understand specific concept levels of the subject matter (Negnevitsky, 2005). For the assignment of a fuzzy set, it is represented as a function with elements mapped to the set based on their membership degree. A weakly understood concept is a good example of a fuzzy set. The fuzzy set elements of "weak concepts" are all weak concepts, however their membership degrees are based on their levels. Triangles and trapezoids are standard membership functions applied in fuzzy expert systems. The fuzzy set theory addresses linguistic variables. A linguistic variable is a fuzzy variable. For instance, in a programming language course, the statement "If-Statement concept is weak" is an indication that the linguistics variable 'If-Statement' takes the linguistic value 'weak'. A linguistic variable represents a concept with uncertain or fuzzy values expressed in fuzzy sets. Hedges is another term in fuzzy sets, these are fuzzy set qualifiers for changing the form of fuzzy sets. This includes adverbs such as 'very', 'somewhat', 'quite', 'more', 'less' and 'slightly'. Hedges implements an analytical concentration process by decreasing the membership degree of fuzzy elements (e.g. very low concept), expansion by increasing the membership degree (e.g. more or less low concept), and reinforcement by increasing the membership degree above 0.5 and decreasing those below 0.5 (e.g. indeed low concept). A way of describing the hedges is illustrated in Figure 2.8. An individual with a height of 185cm is considered as a member of the tall men set with a degree of membership of 0.5. Additionally, he is a member of the set of very tall men with a degree of 0.15 (Negnevitsky, 2005).

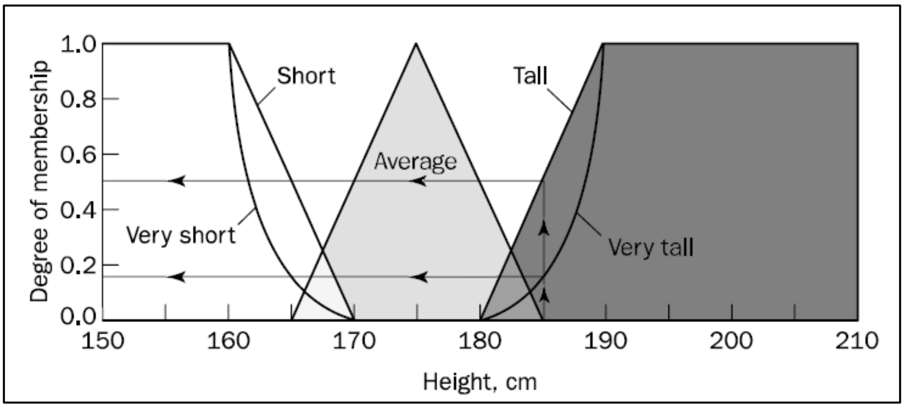


Figure 2.8 Fuzzy sets with very hedge (Negnevitsky, 2005)

Fuzzy sets interact with its operations, the main operations of which are: complement, containment, intersection and union. A fuzzy rule is a conditional statement in the form (IF x is A, THEN y is B), where x and y are linguistic variables, and A and B are linguistic values defined by fuzzy sets. For instance, if the understanding of a concept is weak, then the remedial learning material is large.

Fuzzy inference is where there is an expression of the mapping from a particular input to an output by using the fuzzy sets theory. The fuzzy inference process has four stages: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and defuzzification. There are two primary fuzzy inference system types, which are the Mamdani and Sugeno methods

(Mamdani and Assilian, 1975) (Takagi and Sugeno, 1985). These two inference techniques vary in how outputs are defined. The Mamdani approach is popular in fuzzy expert systems as it can use expert knowledge in fuzzy rules. Yet, Mamdani-type fuzzy inference needs a greater degree of computational load. The Sugeno method uses a single spike, a singleton, as the rule membership function sequential for enhancing the fuzzy inference computational performance. Thus, the Sugeno system is effective in control applications, particularly for dynamic nonlinear systems, since it operates with optimization and adaptive systems. Researchers use both techniques in adaptive e-learning systems based on the description of outputs (Negnevitsky, 2005).

Fuzzy expert systems use uncertainty to simulate human rationalizing and thinking processes. Usually, a fuzzy expert system is structurally based on knowledge, determined by a fuzzy rule set of the IF-THEN form (antecedent and consequent), including a fuzzy logic quantification of linguistic information from experts, for example values and variables. Creating a fuzzy expert system includes defining fuzzy rules and fuzzy sets, evaluating and then harmonizing the system to match the specific conditions.

- <u>ELGuide:</u>

The fuzzy logic theory has been used to personalize tracking for each student, provide students with materials, and give advice to them, and for modelling student’s understanding using (eLGuide) system (Zafar and Albidewi, 2015). Fuzzy clustering, fuzzy relation, and information retrieval (IR) have been used to discover knowledge-based structure and identify relationships between the knowledge material contents and their relevant documents. To personalize tracking or navigation of each student, the difficulty level of each concept and student's knowledge level are considered to produce a learning path for each learner. Each registered student can select and interact with different concepts or learning units. After each concept, there are self- assessment quizzes for that concept, so the students can know their ability or performance after taking the assessments, before they take the final test. The system computes and updates student's knowledge level based on their performance by taking the assessments, recommends different options of taking following concepts regarding their knowledge of the previous concept, and generates advice for the student about which next concept they should take.

To measure the students' abilities, Zafar and Albidewi use time-consuming measurement which means how many times the student reviews and interacts with a learning object. In fact, they have used two types of measurements in the knowledge assessment; a measure of belief (MB, used as a measure for understanding the concept) and a measure of disbelief (MD, used as a measure for not understanding the concept). Therefore, the fuzzy logic system has been used to recommend the suggested concepts by using three input linguistic variables (concept knowledge, level of difficulty, and knowledge of prerequisite concepts) to produce an output linguistic variable (Level of recommendation). Each of these variables has its own linguistic values. Concept knowledge variable has three linguistic values (very low, low, and high), and the level of difficulty of the concept has also three linguistic terms (easy, medium, and difficult). Four linguistic values (not known, little known, sufficiently known, and well known) to describe the knowledge of prerequisite concepts. The fuzzy rules have been used here to produce 18 rules as computation of these three input variables. The output variable (level of recommendation) categories the concepts in five levels (learned, more recommended, recommended, less recommended, and forbidden "not allowed to learn") using linguistic variables. They have used adaptive navigation support which includes different types of coloured concepts. As shown in Figure 2.9, a grey colour represents the learned concepts which mean that the students do not need to learn these concepts again and the red colour represents forbidding concepts as well as the green colour for recommended concepts. So, when the students start interacting with these concepts, the values of both MB and MD are updated in the student model. These values are used to calculate the concept knowledge and then the difficulty level of the concept and the average of the prerequisite concept knowledge (if any) are fuzzified. A crisp value is produced as a result of this calculation and the fuzzy inference decides which fuzzy membership function is suitable for this value. Therefore, fuzzy logic has been used by Zafar and Albidewi to identify the student's understanding that leads to the creation of the learning path of concepts.

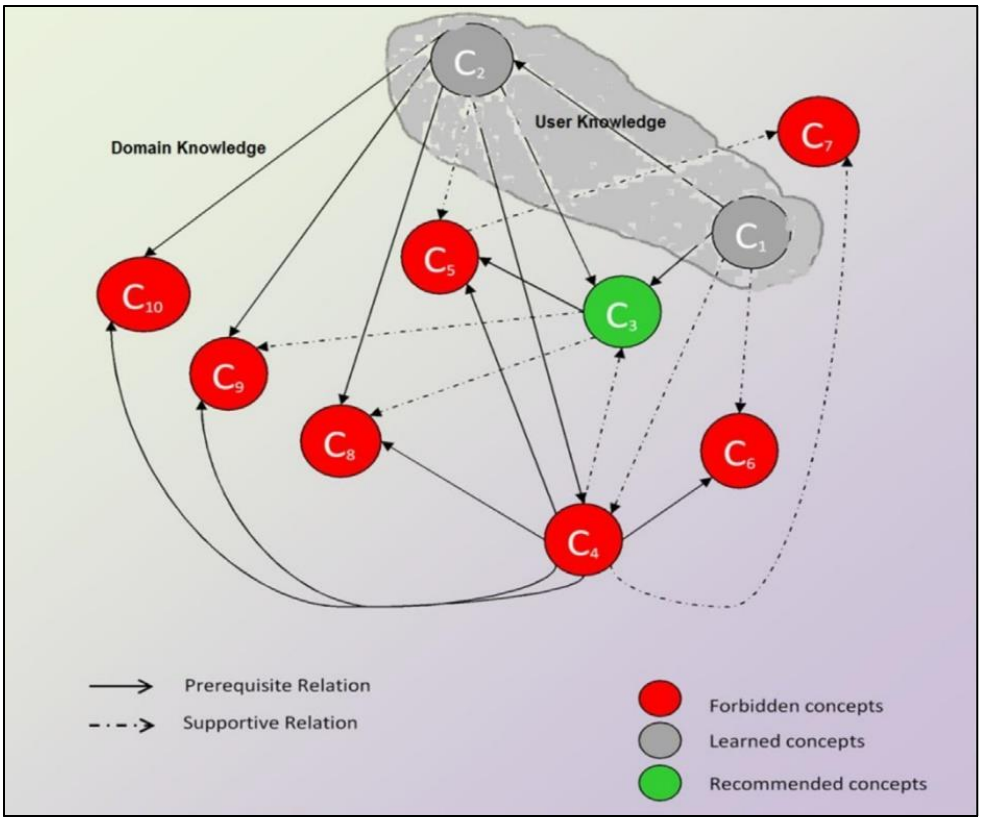


Figure 2.9 Concept map of the SQL course (Zafar and Albidewi, 2015)

The authors have run an experiment on two groups of students (experimental and control) groups with 30 students in each group. They have provided the students with their proposed system; adaptive version for the experimental group and the standard system for the control group. Firstly, the students in both groups took a pre-test to measure their pre-knowledge of the materials and took a post-test after using the proposed system. They have also used a questionnaire to take the students' opinions and feedback about the system. They have used quantitative and qualitative methods (questionnaire, pre and post-tests scores and the time-consumed in learning materials and a number of concept repetitions and steps). According to their results, it shows positive findings and overall satisfaction of the students who used the adaptive version of their proposed system.

Although the authors have provided an adaptation mechanism in their proposed system, it seems that their system is not providing recommendation concepts based on the student’s understanding level. However, their system recommends concepts based on the interaction of the learning objects via how many times the students review the concepts. In that case, it is not guaranteed that the students interact with suitable concepts based on their understanding levels. Despite using the pre-test and post-test in their experiment to identify the students' knowledge levels before and after using the proposed system, the authors did not include these tests into the adaptation mechanism they have used. They could use these tests to provide the appropriate concepts based on their performance in the test along with the interactions with the learning objects.

- Kirkpatrick and Layered Evaluation methods:

Fuzzy logic has also been used to determine and update student’s knowledge level of each domain concept, each time that they interact with the e-learning system (Chrysafiadi and Virvou, 2012). This research integrates fuzzy logic into the student model to evaluate the effectiveness of the system. They have used (Kirkpatrick, 1979) and (Brusilovsky et al., 2004) techniques to evaluate their system's student model. Kirkpatrick technique defines four levels of evaluation. Evaluation of reaction to examine the student's feeling about the system via questionnaire and evaluation of learning which assesses the student's knowledge and skills using quantitative measurements. Evaluation of behaviour to examine the changes that occurred during the learning process and evaluation of results to evaluate the effectiveness of the system and how the organisation gain benefits from the system. The layered evaluation framework (Brusilovsky et al., 2004) addresses two evaluation layers. The first layer is the evaluation of user modelling is used to determine user characteristics. The second layer is the evaluation of adaptation decision making and it is used to provide meaningful adaptation decisions to the student. Chrysafiadi and Virvou have used the evaluation of learner’s reaction, the evaluation of learner’s performance and evaluation of adaptation decisions. They have used fuzzy logic and overlay model integrated into the student model to represent the knowledge level of the student. Four fuzzy sets for defining student knowledge of a domain concept have been identified as can be seen in Figure 2.10.

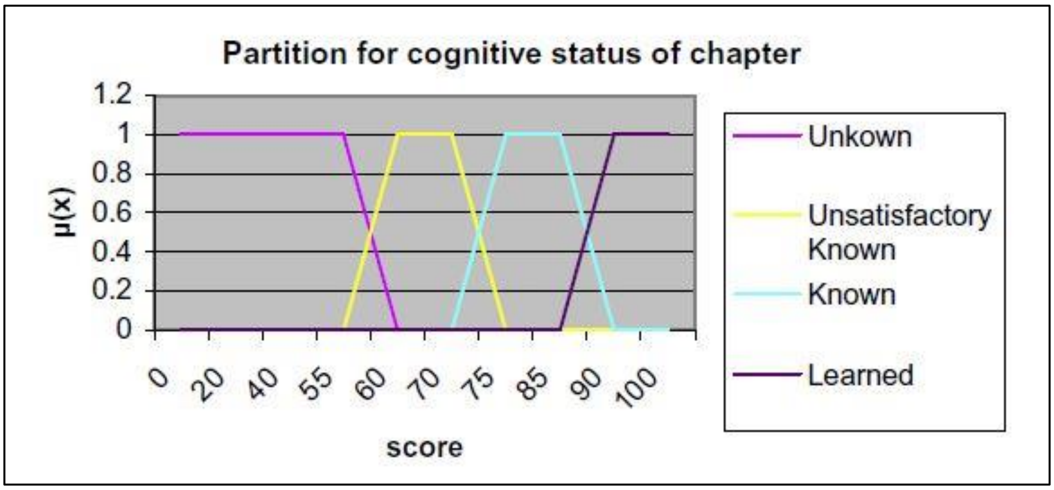


Figure 2.10 Partition for cognitive status of chapter (Chrysafiadi and Virvou, 2012)

The researchers do not justify the percentages of the degree of achievement in the domain concept, especially with "Unknown" notation, and this seems higher than would normally be expected. They have conducted an experiment on two groups of students (experimental and control) who used the system with the fuzzy student model for learning the C programming language. A test group of 53 students recorded their reactions about the system via questionnaires. The results of the experiment confirmed that the students were satisfied with the system and it helped them with adaptivity to make valid decisions. Although they examine the system using combinations of different evaluation techniques, they have only used a qualitative method to analyse the results. Not using a quantitative method such as test scores between the two groups to test the learner's performance is a clear disadvantage of this research.

- <u>MPRLS:</u>

Hsieh et al developed a personalized remedial learning system to support learners after taking an online test evaluation (Hsieh et al., 2013). Fuzzy logic theory is used to construct a proper learning path based on the learner's misunderstandings found through the chosen quiz. Their system selects the most suitable remedial contents for each learner based on the learning path for each learner in each concept regarding the learner's favourites. This system consists of five major components: The Learner Testing Component, Inference Module, Learning Style Analysis, and Learning Path and Remedial Materials Recommender. In the beginning, teachers can edit the learning style questionnaire and test items in the testing items repository through the Moodle-based personalized remedial learning system (MPRLS) interface. Then, the learners log into the system for learning and examination. For a novice, the system gives a learning style questionnaire to analyse their learning style using (Kolb, 2014) method such as converger, diverger, assimilator or accommodator. After the learners finish the whole testing process, the system analyses each learner's test results to recognize their misunderstandings and saves them in the student portfolio repository. Fuzzy logic is used by the Inference Module to indicate a proper learning path for each student's misunderstandings based on the received learning material from the internet provided by the tutor. Based on the produced learning path, the Learning Style Analysis Module then restores the relevant remedial materials that meet the learners' preferences from the internet and save them in the remedial materials repository. Finally, the goal of the Learning Path and Remedial Materials Recommender is to suggest both the most suitable learning paths and the most appropriate learning materials for each course unit based on the learners' misunderstandings and choices to promote more active learning for all the students. The learning path idea by Hsieh et al. is based on the student's misunderstanding about a particular topic, and is different from (Zafar and Albidewi, 2015) in the sense that the learning path of each learner is based on the difficulty level of each concept. Hsieh et al. study investigated to make their system use the features of teaching websites, including the learning styles, and obtained online teaching contents automatically instead of adding the materials manually. MPRLS system can offer the learners various appropriate educational materials immediately. Also, they have used a questionnaire survey that proved that the students were satisfied with the teaching materials supported by the system.

Although they have used learning styles and learning path based on the students' preferences and their results in the chosen test, the system has the disadvantage is that it does not show the students their knowledge level rather than only providing learning path. For example, when the students take a test on a specific concept, the system should give the students their knowledge level on that concept and the reason behind this is to let the students know about their abilities and then recommend them with a learning path to follow.

- <u>DEPTHS:</u>

Jeremić et al. have designed, implemented and evaluated DEPTHS (Design Pattern Teaching Help System) to present a student model (Jeremić et al., 2012). The student model in DEPTHS is a result of combining the stereotype and overlay modelling approaches. By using the knowledge assessment method based on fuzzy rules, which are a combination of production rules and fuzzy logic, the model of the student's understanding keeps updating during the learning process. As shown in Figure 2.11 they have used fuzzy logic with three input variables; test difficulty, duration and success to produce the degree of mastery of a concept in the subject area. A "Test difficulty" variable has been used to measure the difficulty level of each question in the chosen test. They have used the "duration" variable to measure how long the students spend answering each question, and they have used the "success" variable to measure how much the student knows about a particular concept. Each of these variables has a range of values which represent linguistic values (Figure 2.11). After calculation of these input values, "the degree of mastery" value is produced to represent a linguistic value for each concept in the domain. The student model in the DEPTHS system has concepts and processes similar to the student's learning path in remedial learning system that is presented by (Hsieh et al., 2013). DEPTHS is a web-based Intelligent Tutoring System (ITS) which teaches software design patterns. The gives students learning material which matches with their cognitive traits, knowledge, experience, and performance in their particular subject. DEPTHS consist of: domain model, pedagogical module, expert module, student model, and the presentation module. The domain module contains knowledge regarding software design patterns and associated teaching materials. The pedagogical module gives a base of knowledge to teach according to the student model. The pedagogical module offers a curriculum featuring a concepts plan, lessons plan, and tests plan. It decides on the presentation of the teaching material. It evaluates student performance and provides both summative and formative feedback to students. It uses an expert module for decision making related to curriculum sequencing, presentation planning, feedback provision, and evaluating and updating the student model.

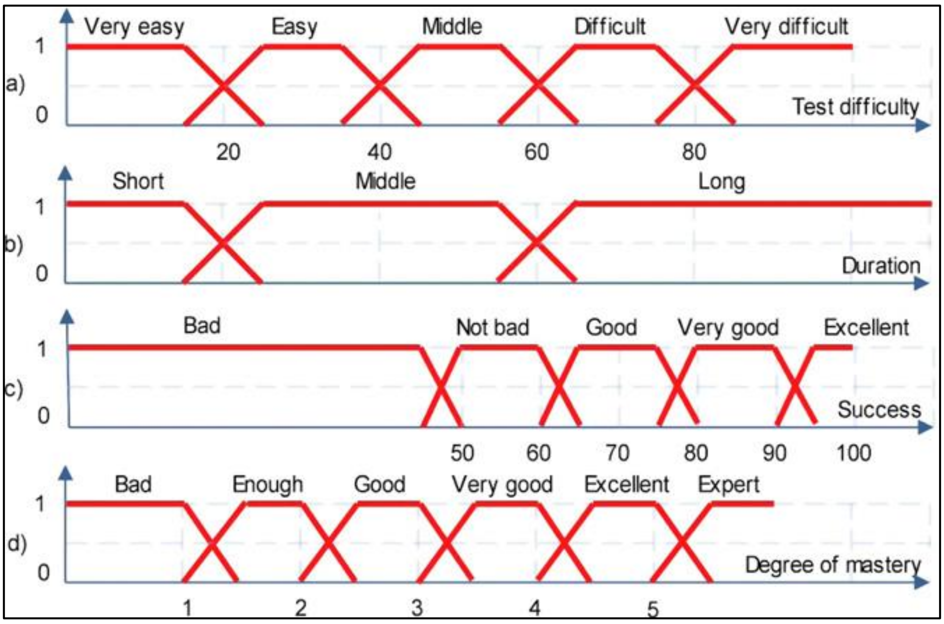


Figure 2.11 Fuzzy variables: (a) test difficulty, (b) duration, (c) success, (d) degree of freedom (Jeremić et al., 2012)

There are three fundamental student characteristic categories used for the student model in DEPTHS: personal data, performance data, and teaching history. When new students are registered onto the system, they choose a stereotype according to their self-assessed knowledge level of their particular subject. They are divided into beginner, intermediate or advanced.

Subsequently, the system generates a model for the student with default characteristic values for the determined stereotype. The lesson continues with the indicated stereotype until the first test is implemented and the first concept is learnt. On the basis of the test results and the initial system produced knowledge about the student, the system identifies the other characteristics' values needed for the overlay student model. The session is updated based on the new student achievement values. Jeremić et al. suggest upgrading their system through the support of a collaborative, project-based learning to allow student collaboration in DEPTHS system. The upgraded system integrates various current learning systems and tools, e.g. a Learning Management System, software modelling tool, different collaboration tools and other repositories of software Design Patterns (DPs) (Jeremić et al., 2009). These integrations assist students' learning effectiveness and performance by providing them with educational services promoting the collaborative learning process. They have run an experiment on two groups (experimental and control) using survey and test scores to evaluate their system and to analyse the results. However, they did not provide a statistical analysis of their experiment, they only provided a description of their experiment and mentioned that it was positive results. Also, small sample size has been a serious limitation for this study as they conducted their attempt on 14 students in each group.

- PeRSIVA:

PeRSIVA system is developed by Chrysafiadi and Virvou to attain validity, accuracy, and effectiveness of the intelligent e-learning system (Chrysafiadi and Virvou, 2013b). This evaluation method is a combination of different algorithms, such as the well-known Kirkpatrick assessment methodology (Kirkpatrick, 1979) and layered evaluation framework (Brusilovsky et al., 2004) to design and correct the assessment process of student model in an adaptive e-learning system. PeRSIVA method evaluates the student model by combining fuzzy logic and stereotypes techniques of e-learning system (Chrysafiadi and Virvou, 2013a). In PeRSIVA, student model links between an overlay model and a stereotype model and fuzzy logic techniques. The overlay model represents the student's knowledge as part of the domain model. The students' knowledge is determined when the students interact with the system each time. In fact, each time they finish the reading process of a domain concept, they have to complete a test, the results of which identify their knowledge levels and are the base for updating their overlay model. Subsequently, the information of the overlay model determines the stereotype category based on the learners' knowledge level.

There are eight stereotypes for representing the knowledge level of each learner starting from a stereotype one which represents the novice students to a stereotype eight which represents the expert learners. The development of a students' overlay model is based on the errors that the learners make in a test that they have to complete at the end of each instructional process, and on how they influence the knowledge level of past or following domain concepts. They have used the same fuzzy logic technique that has been applied in their previous research (Chrysafiadi and Virvou, 2012) to determine a student's knowledge level and the decision-making process about the instructional model for each student.

Chrysafiadi and Virvou performed an experiment on a group of students who used the system to learn the C programming language. They have used both quantitative and qualitative methods in the experiment. A test group of 53 students is utilized to save their responses and feedback about the system in its satisfaction, adaptation, validity and effectiveness. In general, the results of the experiment confirmed that the students are satisfied with using the system and it helped them with adaptivity to make valid decisions. However, Chrysafiadi and Virvou have also suggested making PeRSIVA framework more valid that has to be examined in various learning curriculums, such as other courses types, data structures, and database systems. Stereotypes could be suitable for well-structured subjects such as programming languages in PeRSIVA, but they may not fit to other subjects as the stereotype's classes do not exist at some point or do not meet the students' needs.

- FuzKSD:

Chrysafiadi and Virvou built on their previous work to develop an educational application module named Fuzzy Knowledge State Definer (FuzKSD) (Chrysafiadi and Virvou, 2015). It is implemented and evaluated for web-based education that performs individualized instruction in the field of programming languages (C Programming language). FuzKSD applies user modelling by dynamically classifying and updating a student's knowledge level of all the concepts of the domain knowledge. The procedure of FuzKSD is based on fuzzy cognitive maps (FCMs) that are used to design the dependencies among domain concepts. FuzKSD employs fuzzy sets to describe a student's knowledge level as a subset of the domain knowledge. Therefore, it incorporates fuzzy theory with the overlay model, and applies a new inference mechanism that dynamically updates user stereotypes using fuzzy sets. They have composed the overlay model and stereotypes for user modelling.

The authors have used FuzKSD system to perform and assess personalized instruction in the domain of programming language. As shown in figure 2.12, the hierarchy of the domain concepts and dependence relationships between them are represented in the domain knowledge. Hence, the domain knowledge of the FuzKSD is designed as a hierarchical structure in combination with Fuzzy Cognitive Maps (FCMs) based on the difficulty level of the domain topics and the sequence in which each topic must be taken first (Figure 2.13). The FCMs describe the dependence relationships among the domain concepts of the learning content concerning the influences of the knowledge level of a concept to that of another related concept.

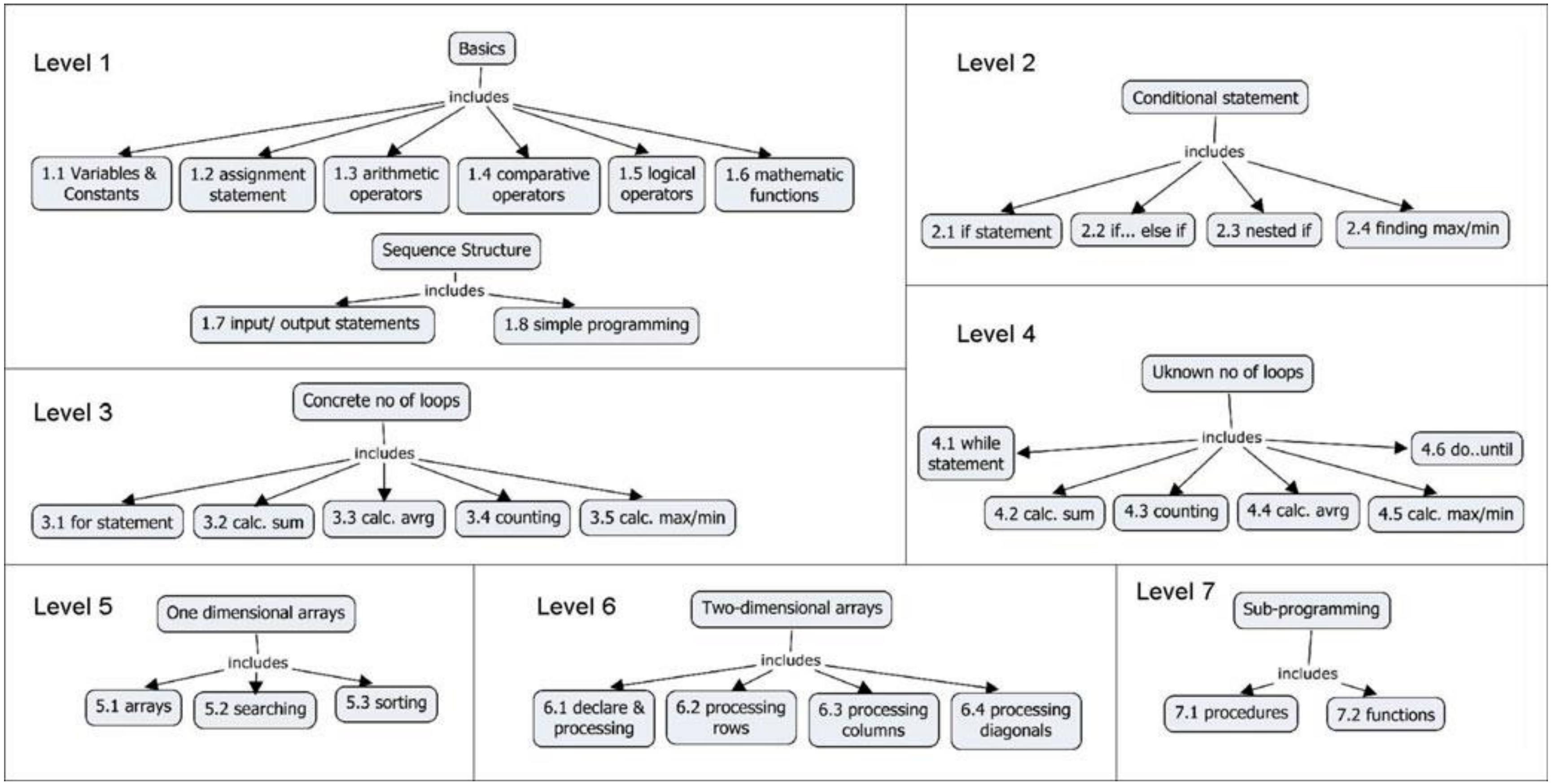


Figure 2.12 Analysis of the nodes of the hierarchical structure (Chrysafiadi and Virvou, 2015)

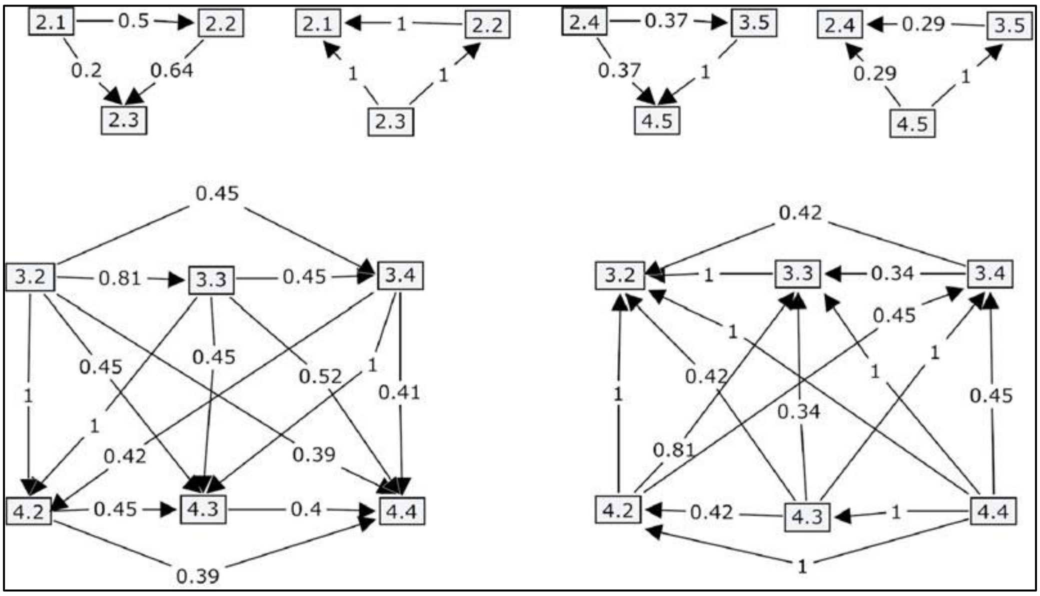


Figure 2.13 Fuzzy cognitive maps (Chrysafiadi and Virvou, 2015)

The FuzKSD system determines the knowledge level, misconceptions, and demands of learners in student modelling. A hybrid student model is used for expressing data through overlay and a three-dimensional stereotype model. The student model is formed of two layers: the student's knowledge of concepts and a 3-D stereotype model. The first layer is a depiction of student knowledge of concepts by using a weighted overlay model as a qualitative value (unknown, insufficiently known, known, learned) combined with a percentage ranging from 0 to 100. These percentage values show the weight of the concept's qualitative value used for each of the concepts representing their knowledge level. The second layer is a 3-D stereotype model. The first dimension is formed of eight stereotypes from the novice learner to expert learner and represents the knowledge level of the learner; the second dimension is formed of two stereotypes and changes the programming error type (logical or syntactic); the third-dimension involved preceding student knowledge in other programming languages. The overlay model and the first dimension of the stereotype model are representative of information regarding the learner's knowledge level. The second and third dimensions of the stereotype model assist the system with understanding and demonstrating the student's needs and misconceptions.

Every time learners interact with the system, they take a test consisting of four question types; true/false, multiple choice, fill in the gap and link parts to complete the programs, with the results identifying the learners' knowledge. Therefore, the overlay user model uses the new information about the learner in the stereotype category of the student model's second layer. In FuzKSD, the system chooses a stereotype level of a concept suitable for the learner in regard to their knowledge of that concept.

The authors have mentioned that FuzKSD system's evaluation showed that the incorporation of fuzzy sets with overlay and stereotype models contributes significantly to the adaptation of the learning process to the learning movement of each learner. Although they have provided their results and the students' performance in reading time, they did not provide a comparison between the groups and mean values in the test's results. FuzKSD system supports students that previously understood the aspects of computer programming to save time and effort through the learning process. In the system's evaluation process, a group of 53 students used the proposed system for learning the C programming language. This assessment was done during a postgraduate program in the department of informatics at the University of Piraeus, Greece. However, they did not provide statistical outcomes of their assessments.

Although they have used more than one adaptive technique, such as fuzzy logic, overlay model and stereotype, in this system to enhance adaptive and personalized e-learning, they have not given an overview of their system in general, such as a diagram, to understand how the educational process works through the graph. In addition, they did not provide which learning media they have used in their system such as text, images, animations, videos, etc. to the learners.

2.3.5 Expert System

An expert system is a computer program operated by human expertise based on knowledge and reasoning methods. It is used for solving problems and providing guidance in specific areas. It operates as an interactive system for answering questions, description queries, offers and recommendations, and supports the decision-making process. There are three primary components of an expert system to gain knowledge and experiential learnings. Firstly, the user interface permits users to interact with the expert system. Secondly, the inference engine which permits experts to use search methods to test different hypotheses to result in expert system results. This is a problem in the processing part and the expert system's control structure. The third component is the knowledge base – a set of facts and heuristics about the expert system domain. The expert system's power varies depending on its knowledge. Thus, it is vital that the knowledge base is complete, consistent and accurate (Liebowitz, 1995).

The expert system has been used to model students understanding of concepts using the pre-test, evaluations, and post-test which include planned questions (Hafidi and Bensebaa, 2013, Jadhav et al., 2013, ÖZyurt et al., 2013a). The expert system treats the knowledge base facts through the rules based on the inference engine instructions and concludes the skill level values of the learner for concepts covered in the given test. Rules express the way that an instructor evaluates a learner's answers (Hafidi and Bensebaa, 2013). The expert system is used in an e-learning process to make the system more adaptive. The learner's information can be filtered by the expert system to analyse the learner's wishes, preferences and understanding. Expert systems decide the contents and present them to the learner as well as they understand learners correctly and they can decide to choose a better approach to make the right decision about the leaner’s understanding (Kakoty and Sarma, 2011).

The expert system is used in an e-learning process to make the system more interactive by combining various tools or learning styles based on user profiles, such as visuals, animation, videos etc. to the e-learning environments. The expert system applications can be used to analyse the learner's wishes and preferences. The information-filtering agent, which is one of the applications of the expert systems, can filter the desired information, such as the contents and the learning styles by the learner, from undesired data to lessen the time and effort of searching large amount of data (Kakoty and Sarma, 2011). The function of filtering agents is to exclude data that does not meet the user profile. Each agent is a user profile that looks for learning style and contents that match the user profile and suggests these learning styles and contents to the user. The user can give feedback to the agent for the contents supported. User feedback modifies the adaptation of the profiles. If a user provides positive or negative feedback for a learning style or content, the adaptation of the profile that recovered the content or learning style is either improved or reduced. Hence, each agent determines and adapts during its continuation to the developing needs of the user (Liebowitz and Adya, 2000). Therefore, it could be concluded that the expert system determines the contents and learning styles which are given to the learner.

- Adaptive Intelligent Tutoring System (AITS):

Hafidi and Bensebaa have developed an adaptive and intelligent tutoring system which is offered by the expert system depending on the difficulty level of activities and the changing learning performance of each learner through the learning process (Hafidi and Bensebaa, 2013). In their system, they have used learners' skill level that is obtained from pre-test result analysis and they have used learners' multiple intelligences that is defined as learner’s characteristics which are obtained from questionnaire analysis to increase the individualized learning performance. Learners' multiple intelligences are included with learner model to determine the learning style and characteristics of the learner by a questionnaire. According to (Gardner, 2000), these multiple intelligences consist of eight things: logical/mathematical, linguistics, visual-spatial, musical-rhythmic, kinaesthetic, intrapersonal, interpersonal and naturalist. The expert system consists of a fact base which contains facts, such as student’s answers, learning styles identifications created from the problem data, and a rule base used by the inference engine to solve problems. Expert system includes pre-test, evaluation, and post-test which includes questions created by the expert system. Based on the student's answers to the test, the expert system can compute the skill level of each concept by converting the data collected from the student’s responses to identical facts. The expert system treats these facts through the rules based on the inference engine instructions. The expert system concludes the skill level values of the student for concepts included in the delivered test. Rules represent the way that a tutor evaluates the student's answers.

The researchers have conducted an empirical study on data from Algerian universities, and the target subject was the “Algorithmic" course. They used a t-test for two groups to measure the effectiveness of their system. They divided the students into a control group, which was a conventional adaptive intelligent tutoring system (O-AITS), and an experimental group, which was a personalized adaptive intelligent tutoring system (P-AITS), for the test strategy. From their experiment result, it shows that the experimental group (P-AITS) did better in their learning performance (Mean=85.71) than the control group (O-AITS) (Mean=80.00) in the post-test. However, they recommended extending the personalized mechanism to examine more complex individual traits and behaviours of the learner, and how to encourage the learners to learn while using their system.

- <u>Adaptive Test Generation and Assessment:</u>

User profiling and an adaptive test generation and assessment are developed using a rule-based technique to assess the knowledge level of the student and produce tests for them respectively by (Jadhav et al., 2013). They have used the expert system engine to decide the difficulty level of the test given to the students after completing their particular concept. The system consists of 5 personalized and adaptive modules which are: Learning Resources, Test Resources, Student Profiles, General Class, and Error Class. The Learning and Test Resources contain contents of many subjects to be studied and understandable by the learners. These subjects include sections that contain chapters, and the chapters have topics that include concepts followed by tests. General Class and Error Class modules have different sets of test questions for each concept that every learner should take after completing the learning contents. The difference between the General Class and Error Class is when the questions should be presented to the learners. General Class provides the questions when the learners finish understanding the concept, whereas Error Class provides the questions based on the learner's misunderstanding of the concept and it focuses on the errors that the learner has made in the previous test.

The learners have a choice to study a particular topic from various subjects, and they have an opportunity to explore the learning resources first or take an assessment directly before learning the contents. Once the learner completes studying the concept, the system transfers all the learner's skills and movements to Extraction Module. The Extraction Module processes the learner's data and decides an understanding level (Basic, Intermediate, Advanced). The extractor consists of two sub-modules which are: Unit Extraction Module and Fusion Model. The Unit Extraction Module maps the values of time (in seconds) needed by the learner to understand the whole concept, percent of content scrolled, and relational index on keywords per concept parameters. The Fusion Model uses a weighted average of these values to produce a value that leads to the understanding level of the learner. After calculation of the understanding level, the result is given to Test Generation system (TGS). TGS adapts a set of tests for the learners based on their understanding levels.

A learner can take a test without learning a concept; TGS provides the learner with an intermediate level test because the system does not determine the learner's knowledge level. When the learner makes an incorrect answer on the test, the system can immediately decide which error class does that choice and determine the mistake that the learner has made while answering the question. The Test Assessment System (TAS) identifies the achievement of the learner and decides whether it is satisfying performance or not. Based on the performance of the learner, the system sets an adaptive test to the learners based on their knowledge level. If a learner fails the test, the Test Remedial System (TRS) establishes another test which targets only the area of the learner's mistakes. Jadhav et al. have given the learners the choice of studying the concept first and then taking the test at the end of each concept or taking the test first before learning the contents of the concept. In addition, they classified the understanding level of the students by the Extractor into three categories (Basic, Intermediate, Advanced). However, the authors haven't conducted a study to test whether the system is valid. They could have used the system in a real classroom and apply the system to show the results and make improvements. They could have scaled the understanding level of the learners from words (Basic, Intermediate and Advanced) to a numeric rating 1- 10. The research would also have been more robust if the researchers had changed the Weighted-Mean approach for Fusion Model to Gaussian method or Bayesian theories to get actual outcomes.

- UZWEBMAT:

UZWEBMAT (Turkish abbreviation of Adaptive and Intelligent WEB based Mathematics Teaching–Learning System) was developed and utilized for teaching-learning in secondary schools using different levels of the learning styles VAK (visual, auditory, kinesthetic), specifically for the mathematics course (Özyurt et al., 2013b). This system determined the learning styles in three levels which are: primary, secondary, and tertiary learning styles. Learners can receive appropriate and most effective content learning style and other learning styles selected by the expert system.

In UZWEBMAT system, teachers and learners can log in and interact with the system. After registering for courses, learners have to take VAK learning styles scale, which are primary, secondary, tertiary learning styles, based on their prevailing learning style, and the only one who determines this scale is the teacher of the course, initially using the learning styles inventory (LSI). They must take the learning styles that their teacher determined first. They cannot select between these three learning styles based on their preferences. They only use the next learning styles if they are unable to achieve the learning objective of the topic or concept. Therefore, once the learners take their primary learning style, they are directed to their learning objectives and contents. An appropriate presentation tips and solution support is given to the learners based on their performance and guidance of learning objectives by the expert system. Therefore, learners can receive same primary learning style with different tips and solution support based on their performance. Hence, the adaptation process in this system is based on the learning objective.

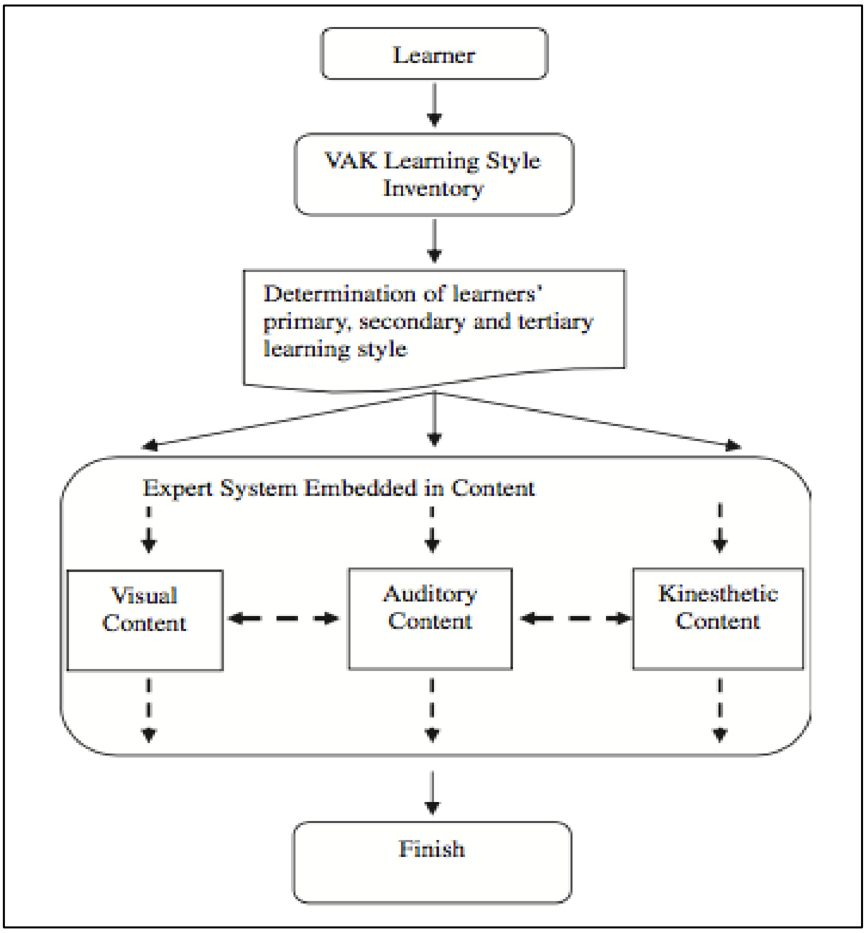


Figure 2.14 UZWEBMAT System Architecture (Özyurt et al., 2013b)

The expert system is designed and integrated within the content while developing the content (as shown in Figure 2.14). The expert system can present the content to each student, manage the improvement of students within Learning Objects (LOs), and select the content and solution support that students will gain based on learning knowledge and results of students within LO in UZWEBMAT. The expert system identifies the direction in which student will be directed to learn from other styles after obtaining the content of his/ her own Learning Style (LS). The expert system is not responsible for selecting the primary, secondary, or tertiary styles at first, while the only one who determines the learning style type is the teacher based on the initial inventory. The expert system makes a decision if the learner can take the next LO primary learning styles or take the same LO secondary learning style. The decision is based on the number of questions with correct answers and solution supports within learning objectives as shown in Figure 2.15. If the learner fails the present LO primary learning style, then he/she will be directed to learn LO secondary style. When he/she makes progress, the learner can take the next LO primary learning style. Therefore, when the learners progress a learning object, they can only take the primary learning styles for the next topic whether they progress the previous learning object using secondary or tertiary learning styles. However, if they fail the LO secondary learning style, the learners will take the same LO tertiary learning style with the same content. If they succeed with this LO tertiary learning style, the learner takes the next LO primary learning style. Otherwise, the teacher will change the contents based on the learner's performance.

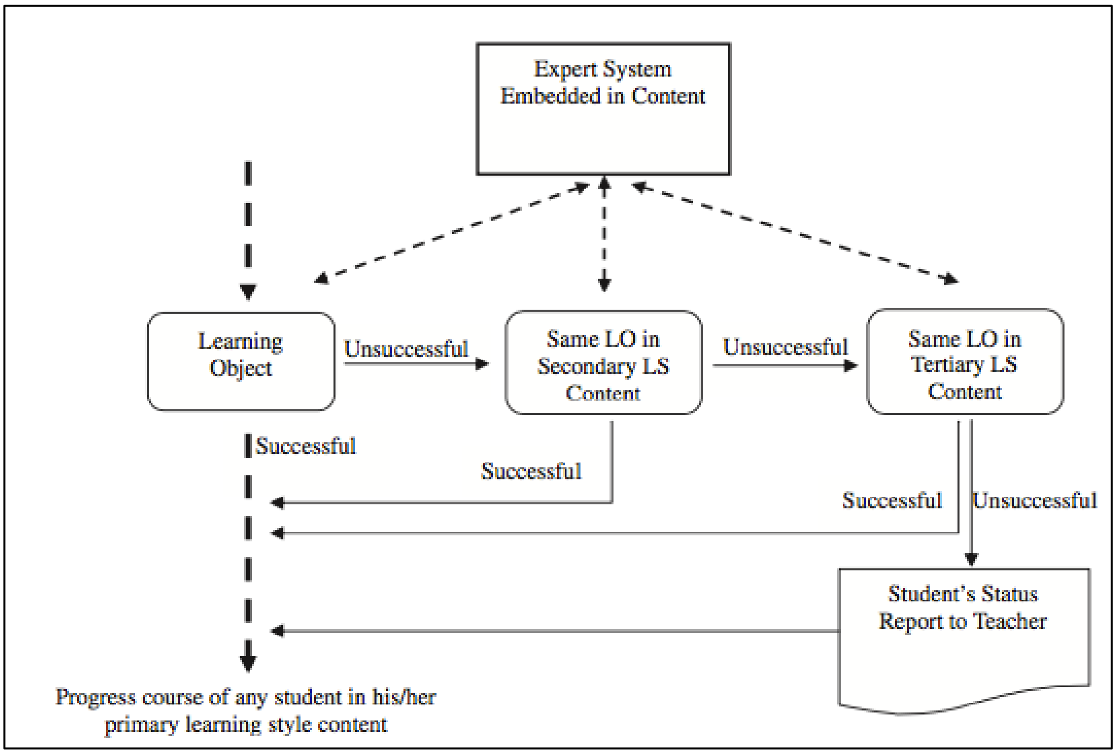


Figure 2.15 Expert system supported direction architecture within UZWEBMAT (Özyurt et al., 2013b)

UZWEBMAT system was tested with a dataset of 81 students from two high schools in a mathematics classroom. Qualitative and quantitative data was collected from students by making them answer the questions. Learners were satisfied using different learning styles, and it had a positive influence on their skills and helped their knowledge. However, they have only provided descriptive statistics of their questionnaires by using Likert-scales measurements. They could run their experiment on different groups and use more quantitative methods to evaluate their proposed system.

Although students can learn positively from various learning styles such as VAK, they cannot choose their learning styles initially in the UZWEBMAT system. Therefore, students should select the preferable learning styles to learn in combination with the expert system. In addition, learners can take VAK learning styles scale based on primary, secondary, tertiary learning styles, but when a student moves between concepts, he/she just uses the primary learning styles. For instance, if the learner prefers to learn the objectives and contents as visual, he/she should continue learning the next concepts with the same learning style or let the learners select their own learning styles. Matching different materials with different learning styles and observe if it affects the system is another way to further develop the system.

2.3.6 Bayesian Network

Bayesian networks (BNs), belief networks or a probabilistic directed acyclic graphical model, is a probabilistic graphical model that represents knowledge about an uncertain domain. Each of the nodes represents random variables, whereas the node edges represent probabilistic dependencies among the same random variables in the graph. Consequently, BNs combine opinions from graph theory, probability theory, computer science, and statistics (Ben - Gal, 2007). For example, a Bayesian network can represent probabilistic relationships, as found in the learner's understanding between prerequisite concept and concept in a learning process. The Bayesian network can be used to compute the probabilities of the appearance of various concepts. Bayesian networks help to understand the probability of a random variable in a given case when some other random variables' values are observed. They can be recommended to provide the best option for gaining new evidence (Olmus and Erbas, 2004, Cowell, 1998).

- <u>SITS:</u>

Hooshyar et al have used Bayesian networks to propose a Solution-based Intelligent Tutoring System (SITS) for managing uncertainty based on probability theory to increase the student's ability in computer programming (Hooshyar et al., 2016). A Bayesian network is used to offer a number of options to the students to choose their appropriate concept from flowchart development. Selection of a concept by the student is based on the knowledge level of the student. The concept may rely on another concept that the student should search before attempting the next concept. The suitable concept is designed by a Bayesian network using conditional probability distribution (CPD) of the learner's understanding.

In fact, all CPDs for the directed acyclic graph (DAG) are collected from a learner's pre-test results. Each concept has to be tested by questions and if the student answers the questions correctly, the concept is considered known. Solve- based ITS system can give different options (as shown in Figure 2.16): navigation support or menus to let the students track their paths between the concepts based on their level of knowledge, pre-requisite recommendations etc. For example, since the 'assignment' and 'IncreDecrementOperator' concepts are parent nodes of the 'for statement' concept in the graph, the system recommends both concepts to the student before continuing to the ‘for statement’ concept. Therefore, the students receive suggested concepts to be learned first and other concepts not to be learned until they understand the core concepts. Lastly, the flowchart development shows different coloured nodes to let the students know which topic they should learn first.

Another problem-solving technique that is used in this research is a multi-agent system, which is a computerized system consisting of multiple interacting intelligent agents within an environment. Multi-agent systems can be applied to solve problems that are complicated for an individual agent to solve. Intelligence may combine some methods, functional, algorithmic search or support learning. SITS system has used the knowledge base to be a repository for information about a particular subject, such as learning contents and quizzes. This system divided the knowledge base into two sections. The first section contains learning materials and sample exams with their solutions. Therefore, users can learn a new concept by presenting the learning materials, and a quiz is given to the users to determine their understanding of a particular concept. The second section includes a flowchart-based multi-agent system. The system provides two different flowchart development options: guidance and sorting. They are suggested to the students by the system based on the measured probability. The guidance option is utilized when the probability of the student’s understanding extends between 0-50% and shows which topics should be learned. The sorting option is advised for 50-100% probability, and it lists which topics should be learned next. SITS makes the students learn the concepts using drag and drop shapes method. For example, if the students manipulate shapes and most of them are incorrect, they should receive guidance option instead of receiving sorting option. However, if the students make most of shapes in correct positions, they receive list of sorting options.

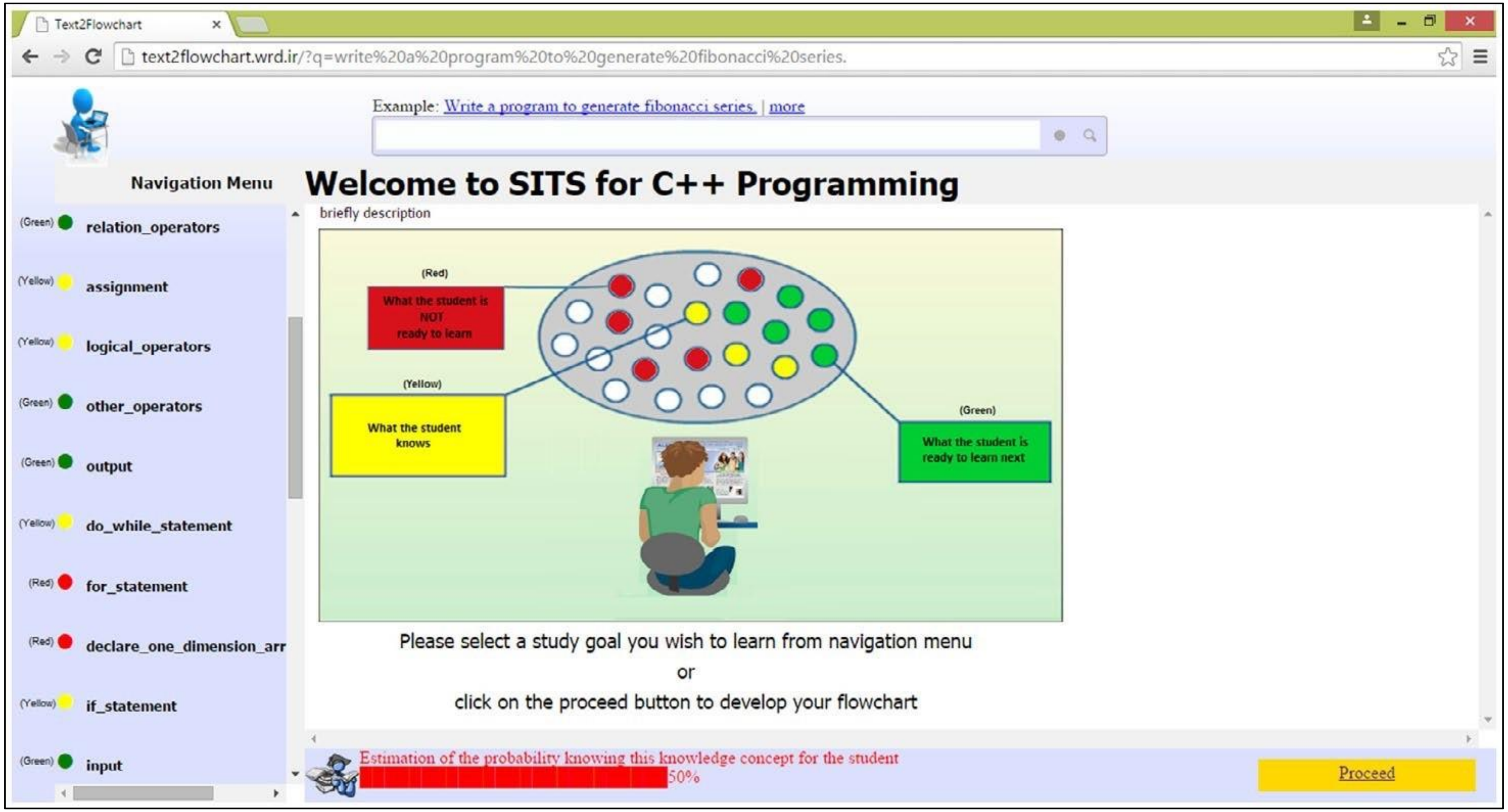


Figure 2.16 SITS Entry Page (Hooshyar et al., 2016)

The empirical study was conducted on 32 students who had taken their first introductory programming course. They were divided into two groups: the experimental group including 17 students, and the control group containing 15 students. The experimental group was required to practice the proposed solution based ITS, while the control group was offered traditional methods to learn. A set of tests were designed to measure the students' learning achievement by the experts, while a questionnaire was provided to evaluate students' learning perspective, learning interest and technology acceptance. According to the experimental findings, SITS had a positive influence on the experimental group's learning successes (Mean=4.80) over the control group (Mean=3.55) in the post-test. The study has a positive impact by using the pre and post-test as well as flowchart development for the given programming problem. SITS improved student attitude to the computer programming course along with their learning achievements. Also, the outcomes from technology acceptance and learning interest investigation revealed that most of the students in the experimental group confirmed the usefulness of the proposed SITS in developing their learning effectiveness.

ITS architecture can be extended to measure student's performance and interaction by creating new methods of modelling. SITS uses the learning style as textual, graphical and flowchart, but it could provide different learning styles based on the learner's preferences. In addition, it would be useful to apply this system to a large number of participants and implement it in different courses for an extended period.

- E-tutor:

A Bayesian network is used in a student evaluation model to determine the knowledge level of each student based on the answers to the questions (Chakraborty and Sinha, 2016). Two parameters are used in student evaluation model: guess and slip parameters. Guess is the probability that a student with a low level of knowledge gives correct answer on a hard question, while Slip is the probability that a student with a high level of knowledge gives incorrect answer on an easy question. Integrating these two parameters is useful for evaluating the knowledge level of each student as it avoids uncertainty about the student knowledge level.

According to the authors, student model determines the knowledge level of each student for each concept before starting the learning process. Therefore, this system makes the student login and pick the available courses, but before learning the chosen course, a pre-evaluation test is implemented to detect the student's knowledge level for each concept. Then, after finishing the pre-evaluation test, each student is provided with appropriate course contents by combining student model and the domain model. The calculated concepts have three levels: poor, good, excellent. For the final evaluation for each student, student evaluation model is created to calculate the concepts exercises and perform them by using Bayesian network to determine the knowledge level of each student. Bayesian network is used in the system based on the basics of Corbett and Anderson's knowledge tracing model (Corbett and Anderson, 1994) to calculate the probability of a student's current knowledge about a particular topic. Each question has a certain difficulty level (from 0-1). All the students get a grade to a particular intelligent level (from 0-1). Each student answers the question, either responding correctly or incorrectly. Students with lower knowledge level are more likely to give an incorrect answer, but they can answer correctly by making either a guess or cheating. However, students with a higher knowledge level can also answer incorrectly, due to a mistake or slip. Before responding to a question either correctly or incorrectly, the knowledge probability of a student is 0. This parameter will update with each response. Each student has a probability of learning a skill as well while answering a question. They have conducted an experimental study on 15 students, choosing 5 students from three levels of a certain concept. Combining the Guess and Slip parameters in a Bayesian network provided more effective percentage of answering questions to evaluate the student's understanding. Despite the effectiveness of their system, they have mentioned that they need to increase the number of conducting the experiment to receive more accurate results. Adaptive hypermedia systems are needed to include the study material support feature. Applying learning styles is one of the motivations approaches and it could be added to this study to assess the students based on their performance. Bayesian network can be improved to a dynamic Bayesian network which can increase the student's knowledge during the learning process.

- <u>ADOLS:</u>

An intelligent tutoring system is developed to provide an optimal learning track in each step of the learning process in (Kozierkiewicz-Hetmańska and Nguyen, 2011). The determination of each learning path relies on the student's preferences, learning styles, personal features, interests and knowledge state. During the registration procedure, the system has to gather information about the student, such as student's personal data, learning styles, the time taken for learning each lesson, learning results, etc. Each student is categorized into a group of students who are comparable to them. In this system, after registration, a new student is involved with the same category or class of other similar students. After each lesson, the system attempts to assess the student's knowledge adaptively. If the student has difficulty in reaching an appropriate score in a test, this means that the opening learning scenario is not sufficient for this student and the system will dynamically construct a Bayesian network based on collected data. By creating the Bayesian network, a graphical representation and assignment of probability tables to each node are used to evaluate the student's interaction with the system by observation. Therefore, the proposed system suggests modification of the opening learning scenario or determines a new learning scenario using Bayesian network based on the time of learning spent on each lesson, the most common version of lessons, the number of test failures, the test score for lesson, and the version of the lesson in case of selection of next topic. Kozierkiewicz-Hetmańska and Nguyen conducted a preliminary experiment on students and offered them a personalized learning scenario. The results showed that the students who supported personalized learning scenario did better rather than those who were given a universal learning situation. They have mentioned that they will further develop their system by focusing on student's preferences and learning style to increases the effectiveness of learning process. They have proposed a method that might be used in an e-learning system for handling training and supporting traditional learning in schools.

2.4 Summary

E-Learning systems are used in many different domains of the learning arena via solutions and the solving of an array of issues. These solutions improve learners' levels of understanding and engagement. However, standard e-learning systems have their own issues, as described in Chapter 1 and at the beginning of Chapter 2. E-Learning systems are adaptive and deliver appropriate learning materials based on their abilities and understanding levels. These adaptive e-learning systems make learning more effective and efficient and increase learner interactivity and engagement. This chapter has given an overview of adaptive e-Learning and definitions of adaptive e-learning from various authors. Adaptive e-learning techniques including concept maps, fuzzy logic, expert systems and Bayesian network were reviewed and discussed, and a there was a review of the objectives, advantages, barriers and challenges of these adaptive techniques as can be seen in Table 2.1. To understand each technique and their implementation level, a number of e-learning systems which explain the steps to implement such systems were also reviewed and investigated.

Despite the success of adaptive e-learning systems reviewed in this chapter, they still have shortcomings and drawbacks. These limitations suggest that the previous adaptive systems could be more effective in achieving both improved understanding and engagement levels for the learners. Although there are many different mechanisms by which adaptivity can be implemented the research reviewed in this chapter highlights some key aspects which are common to many of the reviewed works. For example, a structuring mechanism such as concept maps, overlay maps and module flowcharts are a common aspect of many systems although the way these structures are used is often different. Some researchers have used the concept map technique but did not provide the learners information on how much they (the students) knew about a concept by providing a map of their own understanding (Awati and Dixit, 2017, Violante and Vezzetti, 2015). They instead provided solutions on how to organise the objects regardless of the learner's knowledge level (Violante and Vezzetti, 2015) and construct a concept map of the hierarchy of the concepts that should be learned without letting the students know about their knowledge level for each concept (Awati and Dixit, 2017). Dogan and Dikbıyık have used the concept map to show the relationship between the concepts and pre-request concepts and show the learners' abilities in different categories (Dogan and Dikbıyık, 2016). However, they mention that their system needs to use one of the adaptive techniques such as data mining to provide more appropriate contents to the students.

Table 2.1 Summary of the previous studies in adaptive e-learning systems

Study Name	**Adaptive Technique**	**Objectives**	**Methods**	**Barriers**	**Recommendations**
Virtual 3D Objects	Concept Map	- Students motivation - Increase learning	Mixed method	- Lack of adaptivity (learner’s knowledge level)	- Provide an assessment to identify the learners understanding level.
AISLE	Concept Map	- Student’s knowledge level measurement	Quantitative method	- Not providing how much the students knew about a concept	- Provide an assessment to identify the learners understanding level about each concept.
OPCOMITS	Concept Map	- Show learner’s knowledge levels. - Recommend learning concepts.	Quantitative method	- Not providing a recommended concept based on the concept importance. - Not using an adaptive mechanism with the concepts map	- Using one of the adaptive techniques to make the system more effective. - Using different research approach such as including qualitative method to explore the students feeling and satisfaction about the system.
ELGuide	Fuzzy Logic	- Recommend learning path.	Mixed method	- Not including the tests (pre and post) into the adaptation mechanism. - Not showing the learners how much, they understand their knowledge levels of the subject area.	- Including these tests into the adaptation mechanism to provide the adaptation process automatically to the students. - Instead of just using the recommendation concepts to be learned, showing the understanding level could be included.

Kirkpatrick's model and the layered evaluation method	Fuzzy Logic	- To determine and update student's knowledge level.	Qualitative method	- Not justify the percentages of the degree of achievement in the domain concept - Not using the quantitative methods although using two groups.	- Using quantitative method to test the effectiveness of the system.
MPRLS	Fuzzy Logic	- Recommend learning path.	Quantitative method	- Not showing the learners how much, they understand their knowledge levels of the subject area.	- Instead of just providing learning path, this study could be improved by showing the understanding level for each in the subject area.
DEPTHS	Fuzzy Logic, stereotype and overlay modelling approaches	- Show learner's knowledge levels. - Recommend learning concepts.	Mixed method	- Not providing statistical information about their experiment. - Small sample size is used in their experiment	- Apply their system and run an experiment on large sample size to test the validity of their system.
PeRSIVA	Fuzzy Logic, stereotype and overlay modelling approaches	- To determine and update student's knowledge level.	Mixed method	- Stereotypes approach could be useful for one of the course's types, but for others.	- Apply their system and run an experiment on different course type to test the validity of their system.
FuzKSD	Fuzzy Logic, stereotype and overlay modelling approaches	- To determine and update student's knowledge level.	Mixed method	- Not providing statistical information about their experiment and how the system structured.	- Provide more information about their system and how it works as well as statistical information about their results.

AITS	Expert System	- Increase learning and performance based on learner’s preferences	Quantitative method	- Not focusing on engagement and motivation	- Needs extension of their system to examine more complex individual trials. - Encourage learners to learn by develop the engagement side of the system.
Adaptive Test Generation and Assessment	Expert System	- Identify the learner’s knowledge level. - Recommend learning path	-	- No experiment	- Running an experiment to test the validity of the system.
UZWEBMAT	Expert System	- Learning based on learning style	Mixed method	- Learners couldn’t choose their own learning style.	- Let the learners choose their own learning styles.
SITS	Bayesian Network	- Increase learning and performance	Mixed method	- Small sample size	- Run an experiment on large number size to test the reliability and validity of the system.
E-tutor	Bayesian Network	- Identify the learner’s knowledge level.	Quantitative method	- Small sample size	- Run an experiment on large number size to test the reliability and validity of the system. - Embedded learning styles to motivate the learners
ADOLS	Bayesian Network	- Recommend learning path	Quantitative method	- Lack of motivation and engagement	- Embedded learning styles to motivate the learners

Fuzzy logic also seems to be a key mechanism by which the variability of the information on the student's understanding can be translated into metrics for providing support information. The studies that have used the fuzzy logic technique to provide the adaptation to their systems, however, still have limitations in different aspects. For example, a study run by (Zafar and Albidewi, 2015) used a pre-test and post-test that are significant measurements to identify the knowledge levels of the learners, however, these tests did not include these tests in their adaptation mechanism. Instead this work used a measure of how many times the learners interacted with a specific concept of the subject area. Another research (Chrysafiadi and Virvou, 2012) used fuzzy logic, but only a qualitative method to analyse their result although they have two groups (experimental and control) that they could use a quantitative method such as test scores to make comparisons between these two groups to identify what the group has done better in these tests to prove the learning performance. Expert systems are also used in some research to provide the adaptation and learning services to the learners (Hafidi and Bensebaa, 2013, Jadhav et al., 2013, ÖZyurt et al., 2013a), but appear less effective. Despite research showing positive results, which are presented previously in this chapter, they have some shortcomings that affected the learning progress or the learners' performance. For instance, a study by (Hafidi and Bensebaa, 2013) is limited and still needs to extend their personalised system to examine more aspects of the learners' characteristics and behaviour and to how make the learners engage to their learning system. Some researchers who used expert systems with promising results did not, however, conduct experiments to evaluate their proposed system and make it valid (Jadhav et al., 2013). It is clear that from the previous research that there is a lack of connection between the knowledge or understanding level and engagement or motivation of the learners. From the previous research that has been done in the adaptive e-learning area, Bayesian networks and Expert systems do not appear to be as effective as fuzzy logic and concept maps techniques in the adaptive e-learning space.

In this research, the aim is to overcome the above-mentioned limitations by combining two adaptive techniques (fuzzy logic and concept maps). It is clear from the research reviewed in this chapter that both concept maps and fuzzy logic are effective mechanisms for improving adaptability in e-learning. However, little work has been done on combining these two mechanisms. The use of concept maps to provide not only the structure of the taught materials, but also as a mechanism for providing a display of the student's understanding of the topics, is a key component of the proposed research. This combines well with the use of fuzzy logic to provide the inference between test results and student understanding. The system proposed in chapter 3 uses this combination to ensure that the learners are provided with learning materials that are suitable to their learning performance and also to advise learners regarding their understanding levels of the subject area.

In the next chapter (Chapter 3) the conceptual model that will be utilized in this research to explore and analyse the key adaptive mechanisms that influence e-learning adaptation will be developed.

Chapter 3: Design and Development of CaFAE (an Adaptive E-learning System)

3.1 Introduction

As presented in Chapter 2, many adaptive e-learning techniques have been used to provide the adaptation of materials presented to the learners in order to increase their performance abilities and engagement. Chapter 2 has reviewed some limitations and shortcomings that the previous studies have. For example, some researchers did not identify the learners' understanding levels about a concept in the subject area and only provided recommendations as to which topics or concepts should be learned. Other researches did not conduct an experiment to evaluate their proposed systems or only used qualitative method although they could have used quantitative method or mixed method. Some studies only focused on increasing the learning performance or only concentrated on engagement and motivation of the learners.

A review of the work in Chapter 2 leads this research to propose a system titled ‘Concept-based and Fuzzy Adaptive E-learning (CaFAE)’, which it is postulated will provide better results by using a combination of concept map and fuzzy logic techniques to evaluate and show the learner's knowledge level for each concept in the domain and drive the presentation of learning materials. It will provide this via a Coloured Concept Map (CCM) and produce a Ranked Concept List (RCL) of learning materials to address misconceptions in the learner’s knowledge level. These two adaptive components (CCM and RCL) will contribute to increased learner understanding and engagement levels. This chapter discusses the design of this adaptive e-Learning system, its technical implementation, and a description of the adaptation mechanisms followed by Ranked Concepts List (RCL) process. This chapter also presents a simpler non-adaptive system that will be used as part of the system trials.

3.2 Adaptive System Architecture

This section describes how the adaptive e-learning system is structured and designed to identify the learners’ understanding level and provide the adapted content based on the learners’ performance.

Before describing the system components, first, there are three types of user in this system. Each has pre-defined functionalities:

- *Admin*: Responsible for initialising a course and adding students and teachers.

-*Teacher*: The teacher is responsible for course design and the primary concepts and topics as well as uploading the topic’s learning materials.

-*Student*: The students are the system's main users, because the system and the study are built with the perspective of the student in mind. The students interact with the system by browsing the coloured concept map and follow their ranked concepts list and associated learning materials.

3.2.1 System Structure

As shown in Figure 3.1, the CaFAE system consists of three main components: the fuzzy logic system, the coloured concept map (CCM) and the ranked concept list (RCL). First of all, the teacher creates a course and adds the main topics of the course to the system. Under each main topic there are one or more concepts related to that topic. Each concept in the subject area has three variables (Concept Number (C.No), Concept Name (C.Name), and Concept Weight (C.W)) and each concept could be a parent concept (Parent.C) to one or more concepts which represent the prerequisite concepts. Therefore, when the teacher finishes adding these topics and concepts, the course map (CM) is generated, so, that the students can browse that map before learning or taking actions. After that, the teacher adds the learning materials for each concept with different formats (text, image, video, etc). Also, when the teacher creates a test, whether it is a pre-test or post-test, the teacher defines the concept error value (CER) for each possible answer to each multiple-choice question. This CER represents how much the student knows about a particular concept in the subject domain. The general components of the adaptive system are described as follows:

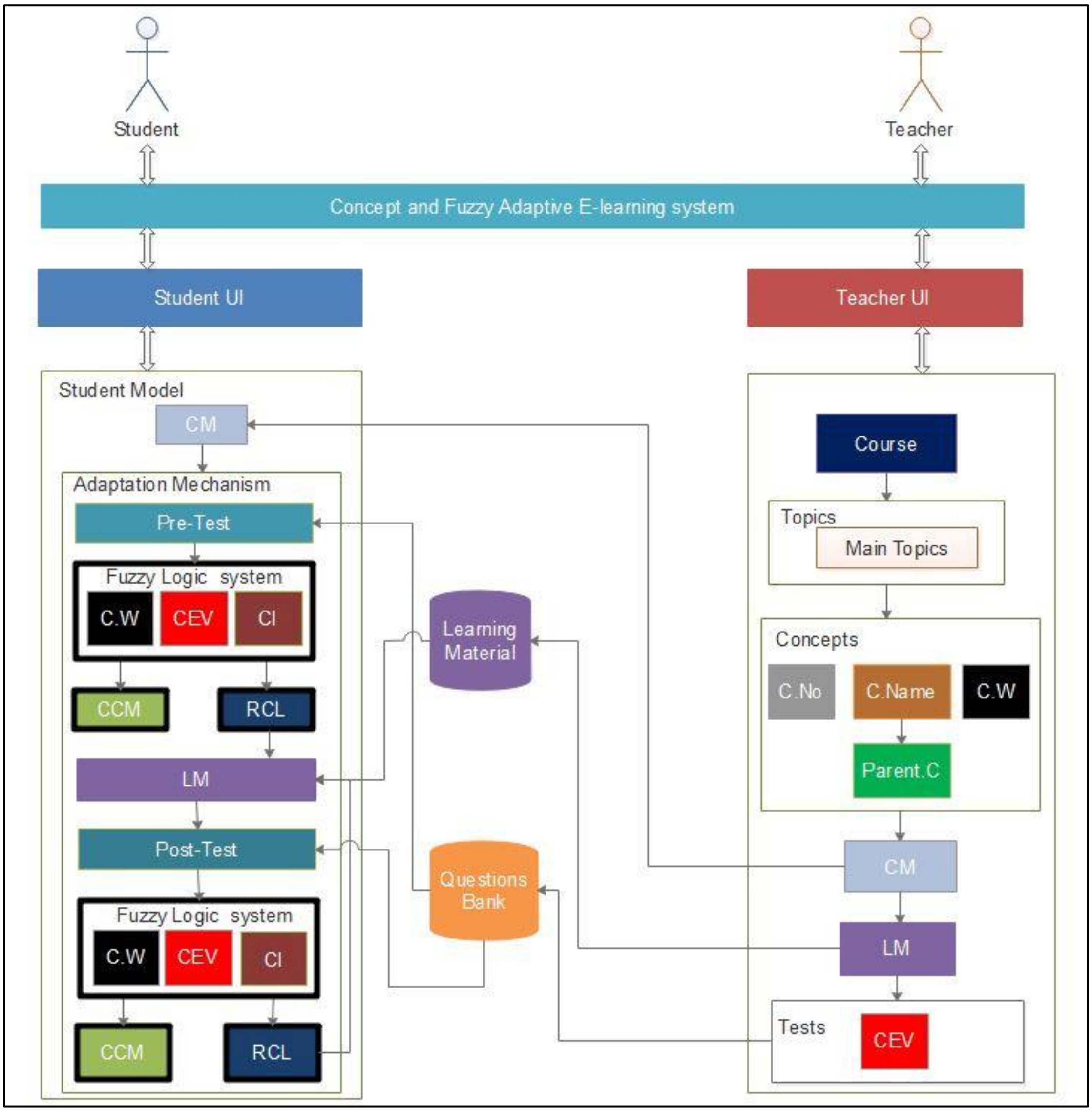


Figure 3.1 The architecture of CaFAE system

- *Course Map (CM):* When the students log in into the system and before taking any action, they browse the course map to have an overview of the course content and what concepts are covered. In addition, it shows the relationships between the concepts and how they are related to each other. This map is displayed to the students before the students take the pre-test.

- Pre-test: The purpose of this test is to identify the knowledge level of each concept in the subject area before learning is started. This test is a multiple-choice question type and covers the concepts that the students will learn in the course. The pre-test is evaluated using fuzzy logic technique.

- *Fuzzy logic system:* This technique is used to evaluate the pre-test or the post-test and produce the coloured concept map and ranked concepts list based on the results of these two tests.

- *Coloured concept map (CCM):* This map is generated after taking the pre-test or post-test to show the learners their understanding level based on their performance in these tests.

- *Ranked concepts list (RCL):* Is a bespoke list that contains ordered concepts based on the learner's performance in the pre-test and the post-test.

- *Learning Materials:* These materials are presented in different formats, such as texts, images, animations, or videos, based on the ranked concepts list order.

- *Post-test:* The purpose of this test is to identify the knowledge level of each concept in the subject area after learning the materials.

3.2.2 Adaptation Mechanism

The adaptive process works as sequential stages in this system as follows.

3.2.2.1 Pre-test and Post-test

The purpose of the pre-test and post-test is to assess the learner's knowledge level of the concepts for the module. To calculate both tests, two input variables are determined, Concept Weight (C.W) and Concept Error Value (CEV), and one output variable Concept Impact (CI). Concept weight is the first input variable and is considered the most important factor of the learning process environment as it determines the most important concept that must be understood before learning the other related concepts in the topic. For example, it is important for students to know the makeup of light sensitive cells in the eye before learning about colour sensitivity. Concept error value is the second input variable and is derived from the student's answers from the pre-test or post-test (in the beginning or at the end of learning the materials of the course). These pre- and post-tests are multiple choice questions type and unlike standard MCQ tests where there are 3 wrong answers and one right answer, these questions are written to have different values of correctness (Explained in more detail in section 3.2.2.2). Each answer for each question has a concept error value and this value represents the knowledge level of that choice (See Figure 3.3). The teacher of the course is responsible for providing these two input values in the process of creating the concepts and tests. The CI variable is used to give output values to be arranged in the ranked concept list (RCL) after submitting the pre-test or post-test. The teacher can create an unlimited number of multiple-choice questions. Each question is related to one concept in the topic to determine the knowledge level of the students as shown in Figure 3.2. The students are allowed to choose only one answer for each question. Each choice of a question can be one of the knowledge level categories (*Learned, Known, Unsatisfied known, and Unknown*).

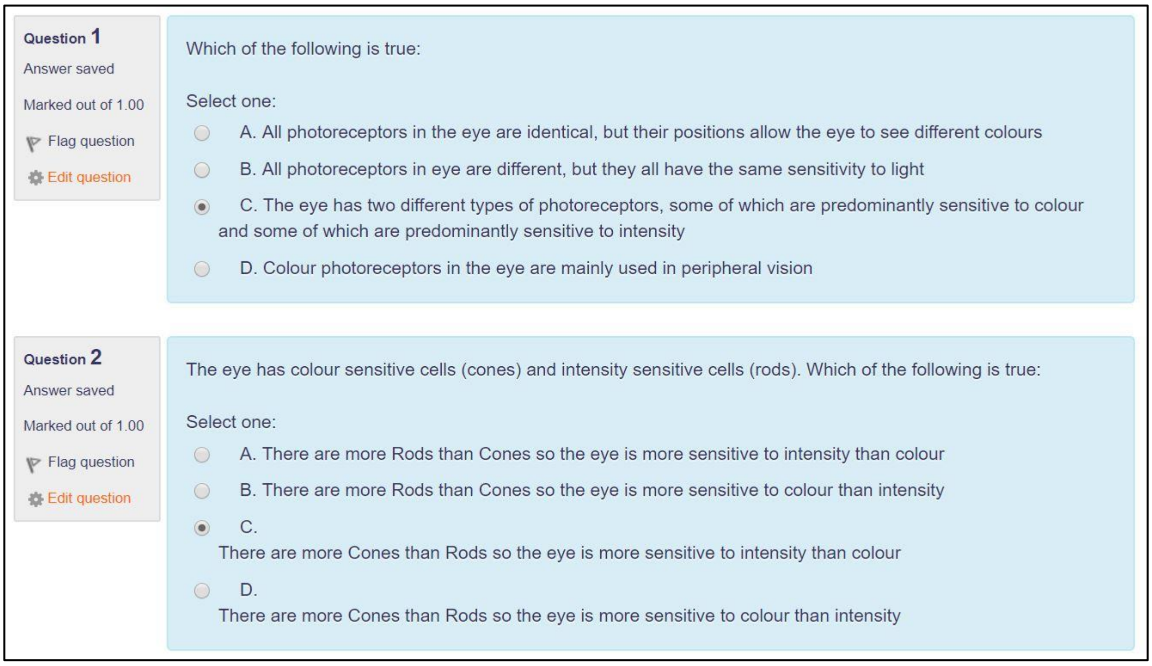


Figure 3.2 Pre- and Post-Tests Multiple Choice Questions

Each choice has its own error value determined by the teacher in the Feedback section (see Figure 3.3). After submitting the pre-test or post-test, students receive two major components (CCM and RCL) in this system. They can display their coloured concept map to discover their knowledge level for each concept in the domain and can follow their ranked concept list based on the results of the pre-test (Explained later in this chapter and shown in Figures 3.9 and 3.10).

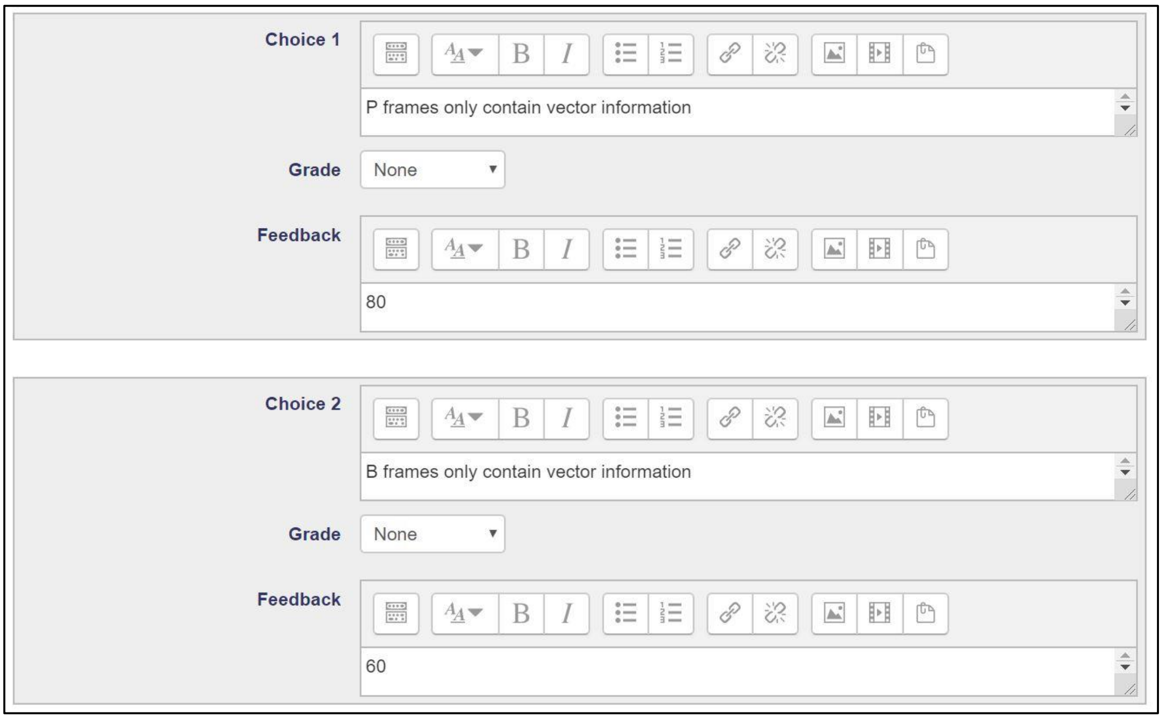


Figure 3.3 Defining Concept Error Value (CEV) for each choice to each question

3.2.2.2 Fuzzy Logic System

In this system, fuzzy logic is used to assess the learner's knowledge level for each concept in the domain and recommend suitable learning materials. To build the fuzzy logic system (Negnevitsky, 2005), the problem and the input and output variables need to be specified. Each variable has a range of values termed a fuzzy set, and each fuzzy set represents linguistic variables. These variables have their own linguistic values. In this research, they are determined by experts in the courses in which they were asked to define and estimate the ranges of values. These fuzzy sets need to be determined, and then fuzzy rules are constructed, and fuzzy inference is performed. Based on these tasks, the following steps are followed:

1) Specify the problem and define the linguistic variables:

For this system, there are three main linguistic variables: concept weight, concept error value, and concept impact. The linguistic variables are shown in Figure 3.4.

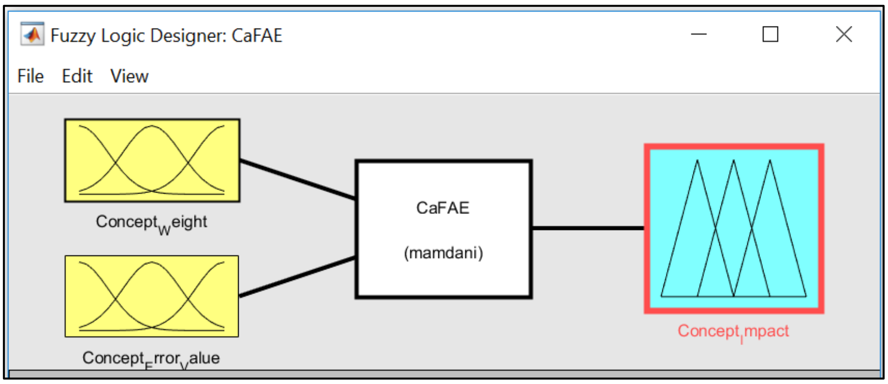


Figure 3.4 Linguistic variables of CaFAE system

Concept Weight (C.W):

In this system, each concept has its own weight which is determined by the expert of the course. The concept weight ranges from 0.0 to 1.0. When the concept weight reaches the value of 1.0, the concept becomes the most important amongst related concepts in the topic. Conversely, when the concept weight has a smaller value than the others, it becomes a less important concept amongst the related concepts. For this study, in the fuzzy logic system, there are three linguistic values, *Small, Medium,* and *Large*, and each linguistic value has its range of fuzzy values (0.0 to 0.4), (0.3 to 0.8) and (0.7 to 1.0) respectively, to show the importance of learning a specific concept (see Figure 3.5).

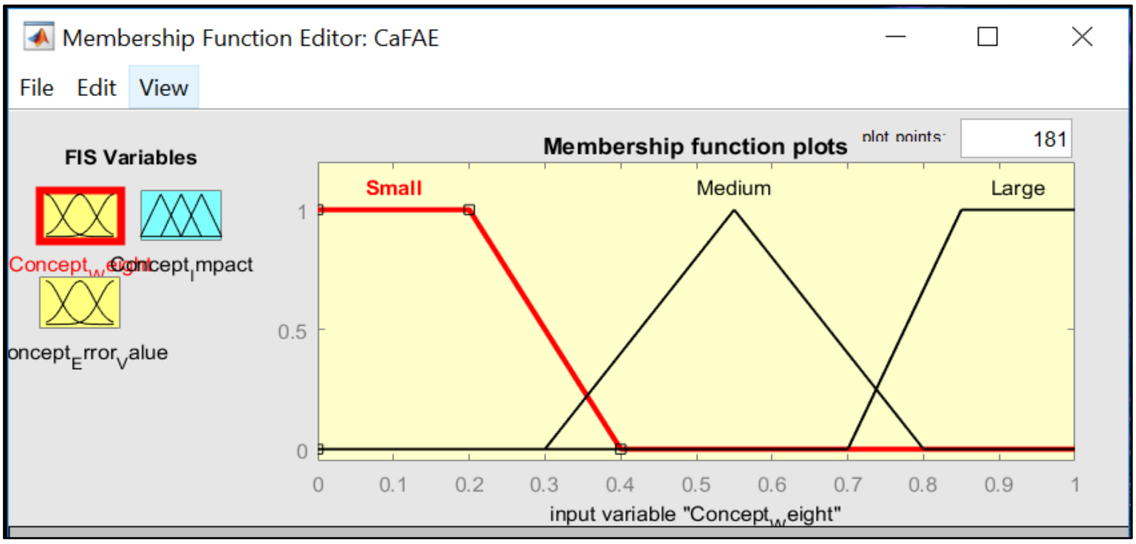


Figure 3.5 Fuzzy Set for Input Variable (Concept Weight) with three different fuzzy levels

<u>Concept Error Value (CEV):</u>

The CEV has four linguistic values in order of level of understanding *Learned*, *Known*, *Unsatisfied Known*, and *Unknown*, and each linguistic value has its own range of fuzzy values (0 to 25), (20 to 50), (45 to 75) and (70 to 100) respectively to determine the knowledge level of each concept in the domain for each student (see Figure 3.6).

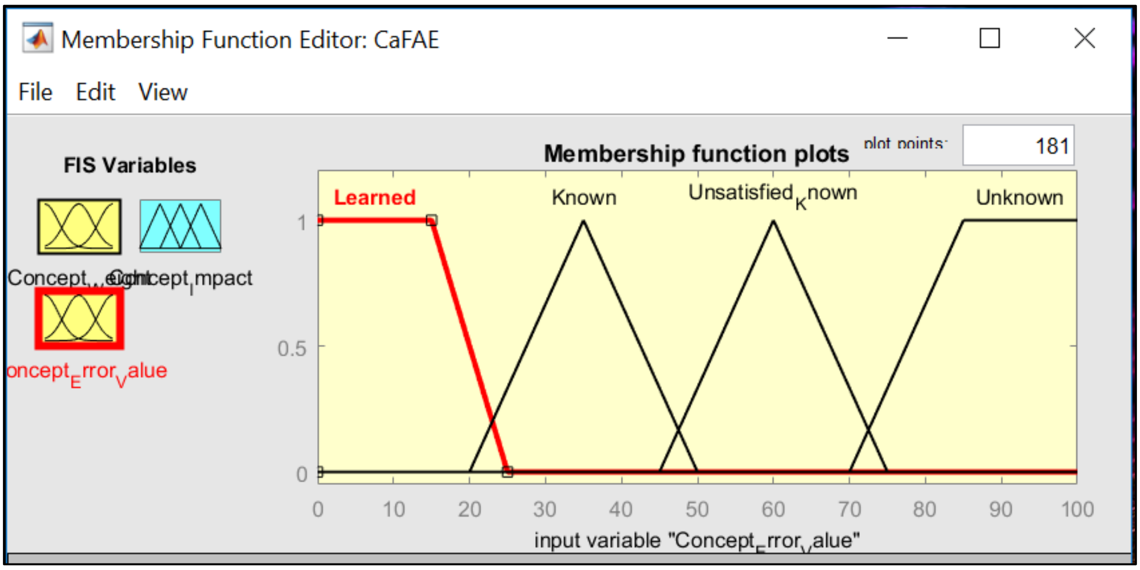


Figure 3.6 Fuzzy set for Input Variable (Concept Error Value) with four different fuzzy levels

<u>Concept Impact (CI):</u>

The concept impact value is an output variable and is calculated using MATLAB Fuzzy Logic Toolbox from the MathWorks (Negnevitsky, Michael, 2005). This value is obtained for each question. All these values are arranged into the ranked concepts list in orderly way. We categorise the output values based on MATLAB Fuzzy Logic Toolbox result. CI has three linguistic values: *Small*, *Medium*, and *Large*; each linguistic value has its range of fuzzy values

(0 to 35), (25 to 70) and (60 to 100) respectively to be arranged in the ranked list from which students can learn the appropriate related concepts in a topic (see Figure 3.7).

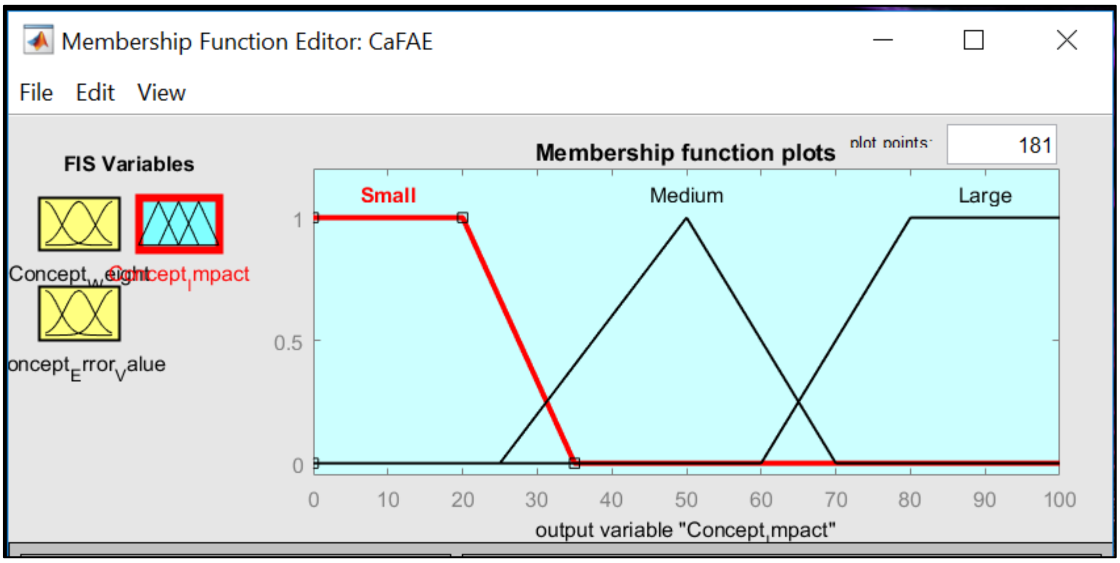


Figure 3.7 Membership functions for Output Variable (Concept Impact) with three different fuzzy levels

2) Determine Fuzzy Sets:

A fuzzy set is a set of objects with fuzzy boundaries, such as low, medium or high for concept's level of understanding. To assign a fuzzy set, the proposed system represents it as a function and then maps the elements of the set to their degree of membership. The ideal example in fuzzy sets in the proposed system is an unknown concept. The elements of its fuzzy set "unknown" are all weak or unknown concepts, but their degrees of membership are based on their levels. Normal membership functions applied in fuzzy expert systems are triangles and trapezoids (Negnevitsky, Michael, 2005).

3) Construct Fuzzy Rules:

After defining the input and output variables with their fuzzy sets, the proposed system addresses the fuzzy rules as in Figure 3.8. Fuzzy rules are used to take personal knowledge of a situation or status such as long, short or known and unknown. "A fuzzy rule is a conditional statement in the form (IF x is A, THEN y is B), where x and y are linguistic variables, and A and B are linguistic values defined by fuzzy sets" (Negnevitsky, Michael, 2005). Therefore, there are three concept weights and four concept error values which produce 12 possible rules (as shown in Figure 3.8). For example, IF the concept weight is *Medium* AND the concept error value is *Known* THEN the impact of the concept is *Small.*

1. If (Concept_Weight is Small) and (Concept_Error_Value is Learned) then (Concept_Impact is Small) (1)
2. If (Concept_Weight is Small) and (Concept_Error_Value is Known) then (Concept_Impact is Small) (1)
3. If (Concept_Weight is Small) and (Concept_Error_Value is Unknown) then (Concept_Impact is Large) (1)
4. If (Concept_Weight is Small) and (Concept_Error_Value is Unsatisfied_Known) then (Concept_Impact is Small) (1)
5. If (Concept_Weight is Medium) and (Concept_Error_Value is Learned) then (Concept_Impact is Small) (1)
6. If (Concept_Weight is Medium) and (Concept_Error_Value is Known) then (Concept_Impact is Small) (1)
7. If (Concept_Weight is Medium) and (Concept_Error_Value is Unsatisfied_Known) then (Concept_Impact is Medium) (1)
8. If (Concept_Weight is Medium) and (Concept_Error_Value is Unknown) then (Concept_Impact is Large) (1)
9. If (Concept_Weight is Large) and (Concept_Error_Value is Learned) then (Concept_Impact is Small) (1)
10. If (Concept_Weight is Large) and (Concept_Error_Value is Known) then (Concept_Impact is Medium) (1)
11. If (Concept_Weight is Large) and (Concept_Error_Value is Unsatisfied_Known) then (Concept_Impact is Large) (1)
12. If (Concept_Weight is Large) and (Concept_Error_Value is Unknown) then (Concept_Impact is Large) (1)

Figure 3.8 Fuzzy rules inference using MATLAB fuzzy Logic Toolbox

4) Performing the Fuzzy Inference:

The process of expressing the mapping from one specific input to an output by using the fuzzy sets theory is known as fuzzy inference. There are four steps involved in this process: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs, and defuzzification (Betito, 2004).

Step 1: Fuzzification

Initially, the crisp inputs (concept weight and concept error value) are taken and it is determined to what degree these inputs belong to each relevant fuzzy set. At this stage, the degree of membership for the linguistic values of C.W and CEV is calculated. The C.W and CEV values are determined by the teachers when creating the tests and concepts. The teachers can provide numbers between 0.0 and 1.0 which are representative of the concept weight. Additionally, they give numbers between 0 and 100 to represent the concept error value for each of the choices during pre-test or post-test creation. After the crisp inputs C.W and CEV are obtained, they are fuzzified against the appropriate linguistic fuzzy sets. Thus, each input is fuzzified over all the membership functions used by the fuzzy rules (Negnevitsky, 2005, Vargas, 2010).

Step 2: Rule evaluation or inference step

Next, the fuzzified inputs are taken and applied to the antecedents of the fuzzy rules, as displayed in Figure 3.8. Each fuzzy rule has multiple antecedents, and the fuzzy operator (AND) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is subsequently applied to the consequent membership function. The fuzzy inference in this system uses AND operation between Concept Weight (C.W) and Concept Error Value (CEV) (as input linguistic variables) in the IF antecedents' part, and Concept Impact (CI) as an output is used in the linguistic variable in the THEN consequent part. For evaluation of the conjunction of the rule antecedents, the AND fuzzy operation *intersection* is applied with min method as in (Equation 3.1):

Equation 3.1 Fuzzy Rules Process

$$\mu A \cap B(X) = min[\mu A(x), \mu B(x)]$$

Based on (Equ 3.1), rules were examined using rule number 6:

IF x is A	IF concept weight is medium (0.5)
AND y is B	AND concept error value is known (30)
THEN z is C	THEN concept impact is small (14.9)

$\mu C(z) = \min[\mu A(x), \mu B(y)] = \min[0.5{,}30] = 14.9$

Twelve rules are employed, which are based on the combinations possible for the two linguistic terms and the two fuzzy input variables. Every fuzzy inference rule is defined by the prior knowledge of the domain expert. Rule output variables are defined as fuzzy output variable CI, the concept impact, which includes *Small*, *Medium,* and *Large*, as its three associated linguistic terms. The last three output variable values represent the concept impact levels.

Step 3: Aggregation of the rule outputs:

Aggregation is the unification output process of all rules. Rule consequent membership functions are combined into a single fuzzy set. Therefore, the aggregation process input is the list of consequent membership functions, and the output is one fuzzy set for each of the output variables.

Step 4: Defuzzification

The final stage in the fuzzy inference process is defuzzification. Fuzziness evaluates the rules; however, the final output of a fuzzy system must be a crisp number which is produced as a result of a calculation decided by the fuzzy inference regarding which fuzzy membership function is suitable for this value. The defuzzification process input is the aggregate output fuzzy set, with a single number as the output.

3.2.2.3 Coloured Concept Map (CCM)

The knowledge level category is represented via a colour representation of the concept map (Figure 3.9) based on student responses to the pre-test and post-test. Students browse their own learning level in regard to concepts via this map. Knowledge level concepts are indicated as “Learned” with green, “Known” with blue, “Unsatisfied known” with orange, and “Unknown” with red.

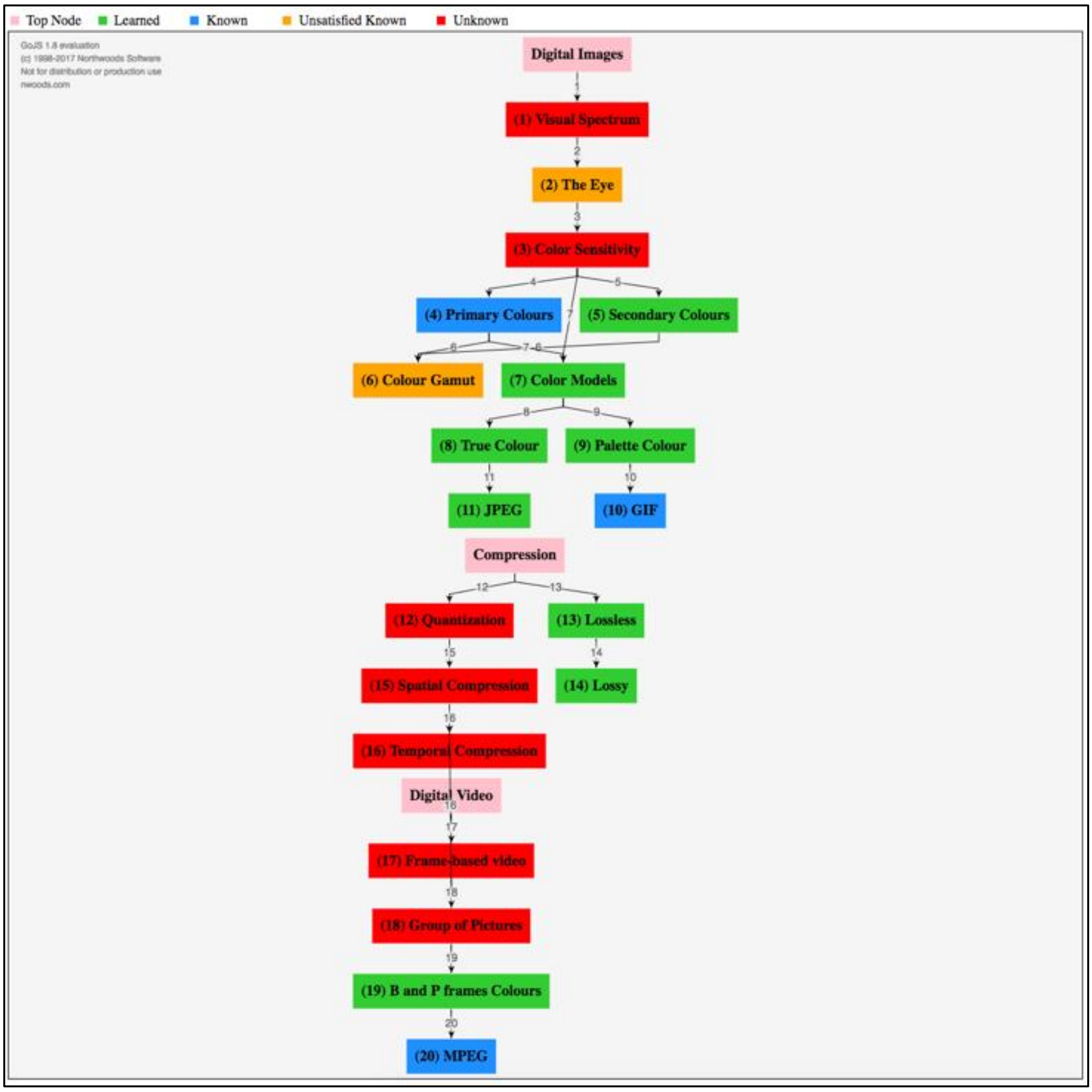


Figure 3.9 The Coloured Concept Map for pre-test or post-test

3.2.2.4 Ranked Concepts List (RCL)

Students must follow their ranked concept list based on their pre-test or post-test results after completing each test (see Figures 3.10). They will learn the learning material based on the order provided by the ranked list, concept by concept, until they complete all the concepts in the topic. After this, they can take a post-test to evaluate their knowledge level of each concept in the topic.

Pre Test Result

Ranked Concepts List

Rank	Concept No.	Topic Name	Concept Weight	Color Code	Knowledge Level	Concept Impact
1	3	Color Sensitivity	Large		Unknown	Large
2	12	Quantization	Large		Unknown	Large
3	15	Spatial Compression	Large		Unknown	Large
4	17	Frame-based video	Large		Unknown	Large
5	18	Group of Pictures	Large		Unknown	Large
6	16	Temporal Compression	Medium		Unknown	Large
7	1	Visual Spectrum	Small		Unknown	Large
8	4	Primary Colours	Large		Known	Medium
9	20	MPEG	Large		Known	Medium
10	2	The Eye	Medium		Unsatisfied Known	Medium
11	6	Colour Gamut	Small		Unsatisfied Known	Medium
12	11	JPEG	Large		Learned	Small
13	7	Color Models	Medium		Learned	Small
14	10	GIF	Medium		Known	Small
15	5	Secondary Colours	Small		Learned	Small
16	13	Lossless	Small		Learned	Small
17	8	True Colour	Small		Learned	Small
18	9	Palette Colour	Small		Learned	Small
19	19	B and P frames Colours	Medium		Learned	Small
20	14	Lossy	Large		Learned	Small

Figure 3.10 Ranked Concept List after taking the pre-test

Figure 3.10 shows a ranked concept list which consists of the rank number, concept number, topic name, concept weight, colour code, knowledge level, and concept impact. After completing the pre-test or post-test, students receive their concept impact values derived from the answers to the questions. To arrange the ranked concepts list (RCL), the priority to be at the top of the list and learned first is the highest Concept Impact (CI) value. However, if two or more Concept Impact values are the same, the following algorithm works to solve this problem. The arrangement of the ranked concepts list works based on the highest value for each variable.

Ranked Concepts List (RCL) = Concept Impact (CI) ➔ Concept Weight (C.W) ➔ Concept Error Value (CEV) ➔ Concept Number (C.No)

Therefore, if two or more variables have the same value, the priority to be learned first is the next variable's highest value and so on as can be seen in the equation below. Figure 3.11 shows the algorithm that works as the process of the equation above.

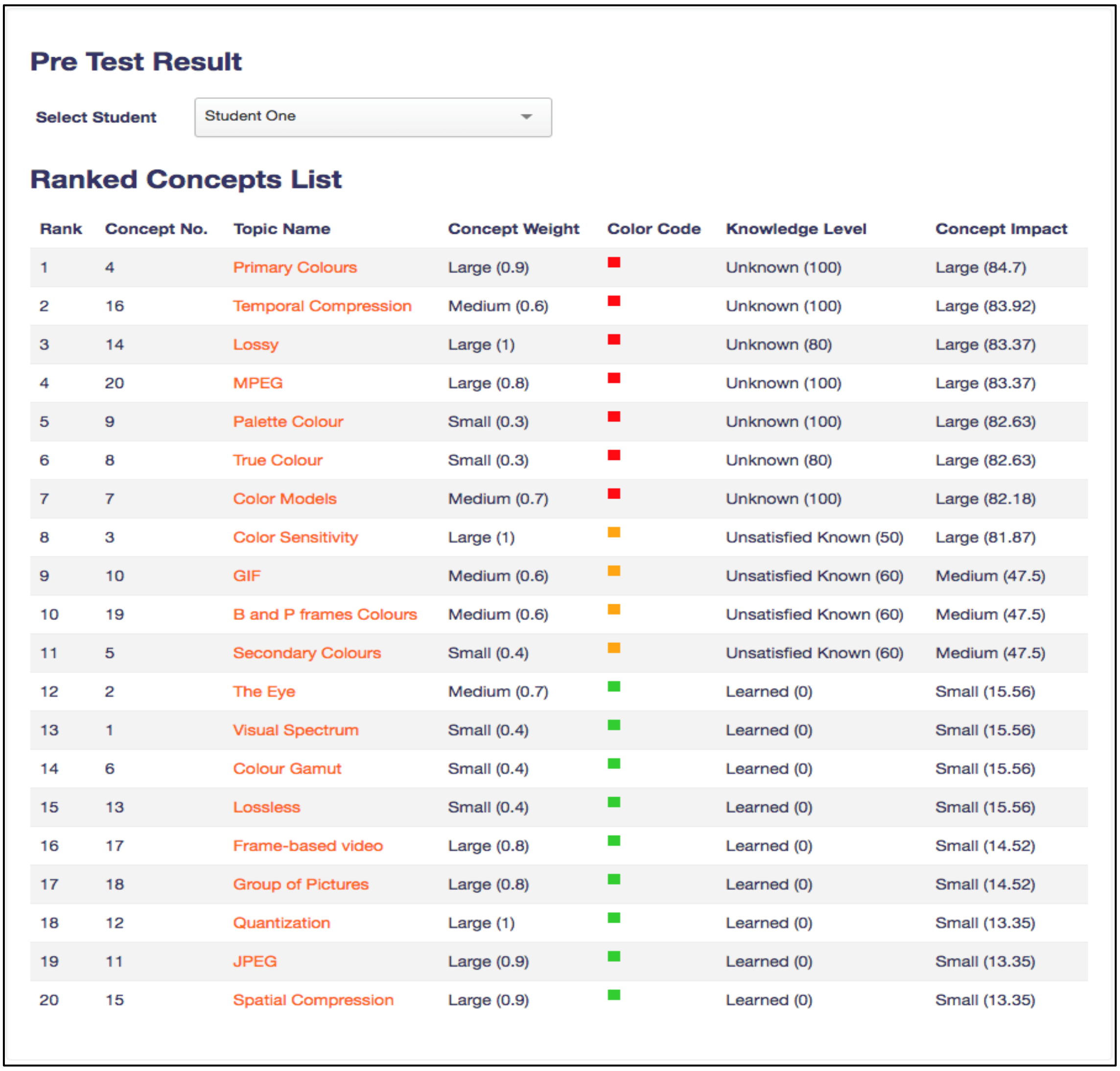
Ranked Concept List arrangement:
Input: Concept Impact (*CI*), Concept Weight (*C.W*), Concept Error Value (*CEV*), and Concept Number (*C.No*)
Output: A suitable ranked concept list (*RCL*)
Process:

1) ***RCL*** = {0}
2) Find the highest concept impact value (*CI*) from the ranked concept list (***RCL***) values.
3) Add the highest ***CI*** into first place in ***RCL.***
   While (***CI*** value < highest ***CI*** value) {
   Find the next highest (***CI***) value to the head of the ***RCL***
   Add the next highest ***CI*** into the next place in ***RCL***
   If (***CI*** value == highest ***CI*** value)
   Do {
   Find the highest concept weight ***C.W*** from the concepts that have the same ***CI*** values
   Add the highest ***C.W*** into the next place in ***RCL***
   While (***C.W*** value < highest ***C.W*** value) {
   Find the next highest (***C.W***) value to the head of the ***RCL***
   Add the next highest ***C.W*** into the next place in ***RCL***
   else
   If (***CI*** value == highest ***CI*** value) and (***C.W*** value == highest ***C.W*** value)
   Do {
   Find the highest concept error value ***CEV*** from the concepts that have the same ***CI*** values and ***C.W*** values
   Add the highest ***CEV*** into the next place in ***RCL***
   While (***CEV*** value < highest ***CEV*** value) {
   Find the next highest (***CEV***) value to the head of the ***RCL***
   Add the next highest ***CEV*** into the next place in ***RCL***
   else
   If (***CI*** value == highest ***CI*** value) and (***C.W*** value == highest ***C.W*** value) and (***CEV*** value == highest ***CEV*** value)
   Do {
   Find the first concept number (*C.No*) in the RCL
   Add the first *C.No* into the next place in ***RCL***
   } until (***CI*** value ≠ highest ***CI*** value) and (***C.W*** value ≠ highest ***C.W*** value) and (***CEV*** value ≠ highest ***CEV*** value)

   } until (***CI*** value ≠ highest ***CI*** value) and (***C.W*** value ≠ highest ***C.W*** value)
   } until (***CI*** value ≠ highest ***CI*** value)
   }
   else Add ***CI*** to ***RCL***
4) Return ***RCL***.

Figure 3.11 The process of Algorithm in the Ranked Concept List

In this algorithm, the priority to be learned first is the highest concept impact value, followed by the smaller values. However, if there are two or more concept impact values that are equal, we compare the concept weights (C.W) of these equal concept impact values, and the concept with the highest concept weight value will be the priority to be learned first. However, if two or more concepts have equal concept impact values and equal concept weight values, we compare the concept error values of these equal concept impact values and equal concept weights, and the concept with the highest concept error value will be the priority to be learned first. Finally, if two or more concepts have equal concept impact values, equal concept weight values, and equal concept error values, then the priority to be learned first is based on the concept number (C.No) in the ranked concepts list (RCL) (see student example in Figure 3.12).



Pre Test Result

Select Student: Student One

Ranked Concepts List

Rank	Concept No.	Topic Name	Concept Weight	Color Code	Knowledge Level	Concept Impact
1	4	Primary Colours	Large (0.9)		Unknown (100)	Large (84.7)
2	16	Temporal Compression	Medium (0.6)		Unknown (100)	Large (83.92)
3	14	Lossy	Large (1)		Unknown (80)	Large (83.37)
4	20	MPEG	Large (0.8)		Unknown (100)	Large (83.37)
5	9	Palette Colour	Small (0.3)		Unknown (100)	Large (82.63)
6	8	True Colour	Small (0.3)		Unknown (80)	Large (82.63)
7	7	Color Models	Medium (0.7)		Unknown (100)	Large (82.18)
8	3	Color Sensitivity	Large (1)		Unsatisfied Known (50)	Large (81.87)
9	10	GIF	Medium (0.6)		Unsatisfied Known (60)	Medium (47.5)
10	19	B and P frames Colours	Medium (0.6)		Unsatisfied Known (60)	Medium (47.5)
11	5	Secondary Colours	Small (0.4)		Unsatisfied Known (60)	Medium (47.5)
12	2	The Eye	Medium (0.7)		Learned (0)	Small (15.56)
13	1	Visual Spectrum	Small (0.4)		Learned (0)	Small (15.56)
14	6	Colour Gamut	Small (0.4)		Learned (0)	Small (15.56)
15	13	Lossless	Small (0.4)		Learned (0)	Small (15.56)
16	17	Frame-based video	Large (0.8)		Learned (0)	Small (14.52)
17	18	Group of Pictures	Large (0.8)		Learned (0)	Small (14.52)
18	12	Quantization	Large (1)		Learned (0)	Small (13.35)
19	11	JPEG	Large (0.9)		Learned (0)	Small (13.35)
20	15	Spatial Compression	Large (0.9)		Learned (0)	Small (13.35)

Figure 3.12 Ranked Concepts List for the teacher or admin using fuzzy logic method – with additional numerical values

3.2.2.5 Learning Materials (LM)

Teachers can add the learning materials and store them in the LM database once they create the course. Learning materials can be provided in different formats (text, audio and video). Students can learn with their preferable learning style and can choose from these different formats as shown in Figure 3.13. They cannot choose any concept in the course to learn without first taking the pre-test. Learning materials are provided to the students based on their concept understanding and ranked concept list; they are forced to go through the ranked concepts list and learn the materials in bespoke order.

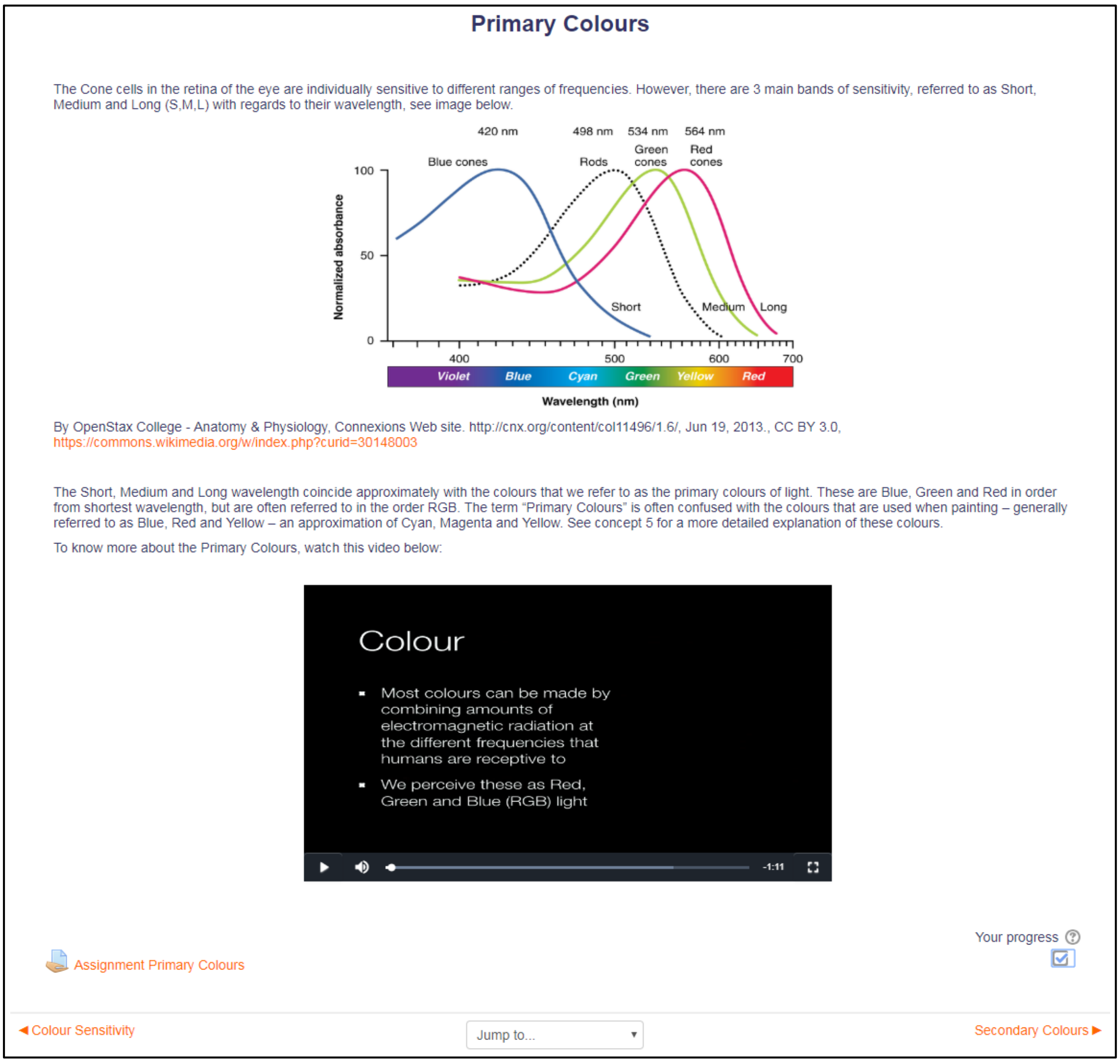


Figure 3.13 Learning Materials in different formats

3.3 System Software

In this section, the proposed system is implemented as explained in these two following sections:

3.3.1 System Design

Open source Moodle 3.3 LMS has been used to design and develop the proposed system (Moodle, 2019a). Moodle is adopted for designing the proposed system as it is open source and it can be developed as it is well supported by detailed documentation and guidelines, and also templates for programming and incorporating new features (Alkhuraiji, 2016). The system features, such as online course materials and resources, course calendars, discussion forums, online self-assessment modules, communication tools, access control tools, search ability, file storage, wiki/blogs etc., already exist in the Moodle LMS platform. The fuzzy course admin block has been built to make this system more effective and adaptive as compared to the traditional learning environment.

3.3.2 System Framework

The system is web-based and does not need a special application at the client end, aside from a browser. This permits easy access from devices, including tablets and mobile devices to make the application system independent and accessible. The system is developed using a PHP 7 framework which is a compatible with the Moodle structure. GoJS library (GoJS, 2018) is used for the concept map. The database used is MySQL (MYSQL 5.6). It is a popular database used in web applications (Alkhuraiji, 2016). This database creates and manages the course materials and student activity history. MySQL ‘structured query language’ is used to execute database queries and to edit, delete and modify the data, execute SQL queries, and create new tables.

3.4 Sample Course

A sample course has been used to illustrate of how the system works. The proposed system has two different interfaces, one for the teacher or tutor, and the other one for the student. The two interfaces are explained in detail below.

3.4.1 Teacher Interface

At the beginning of using the system, teachers can log into the system using this interface, and create courses, main topics and related concepts of each topic, add learning materials (LM), and store this in the Learning Material database. For example, as shown in Figure 3.14, Multimedia Design and Applications course is created with three main topics: Digital Images, Compression and Digital Video. Each of these main topics has related concepts and some of these concepts are parents for each other.

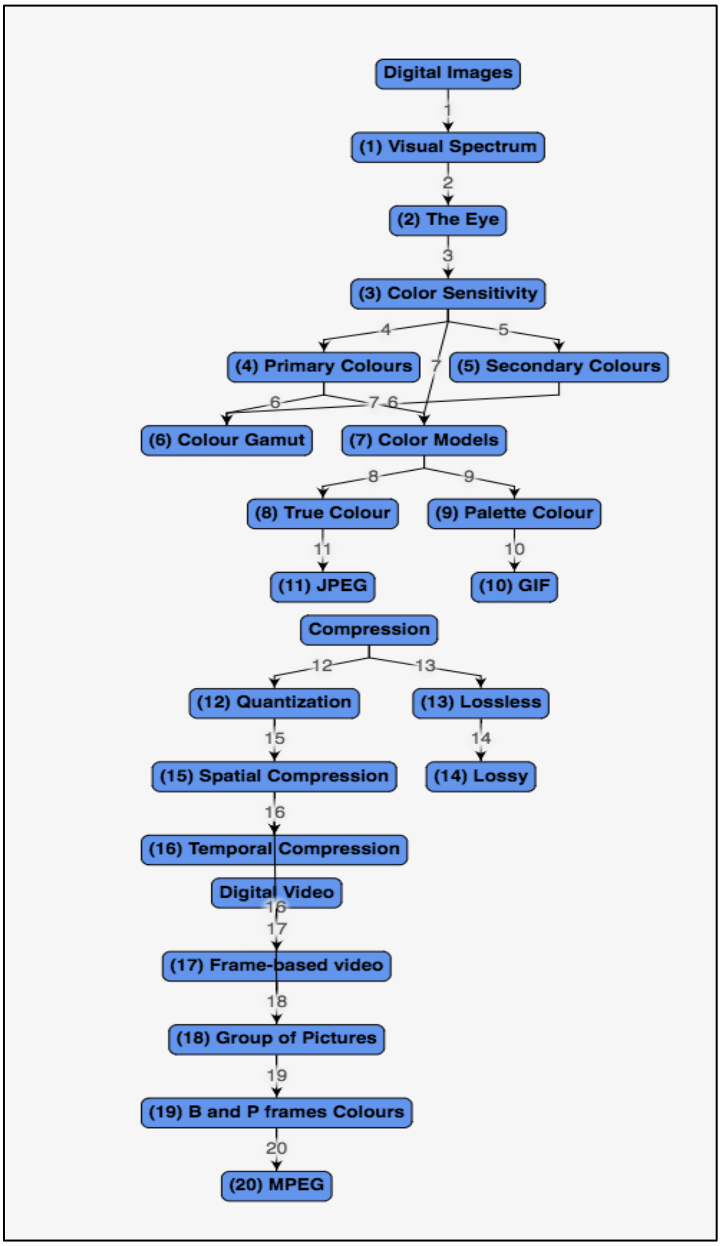


Figure 3.14 The Concept Map of the Multimedia Design and Applications course created by the teacher

To construct a concept map (CM) of the course, as shown in Figure 3.14, teachers are able to determine the concept number (C.No), concept weight (C.W) , concept name (C.Name) and parent of the concepts (Parent.C) if needed (see Figure 3.15). They can also create the pre-test and post-test to evaluate the learner's understanding level of each concept in the topic and store it in the Questions Bank database. To do so, concept error values (CEV) as shown in Figure 3.3 earlier, must be specified for each possible answer when the teacher create the tests.

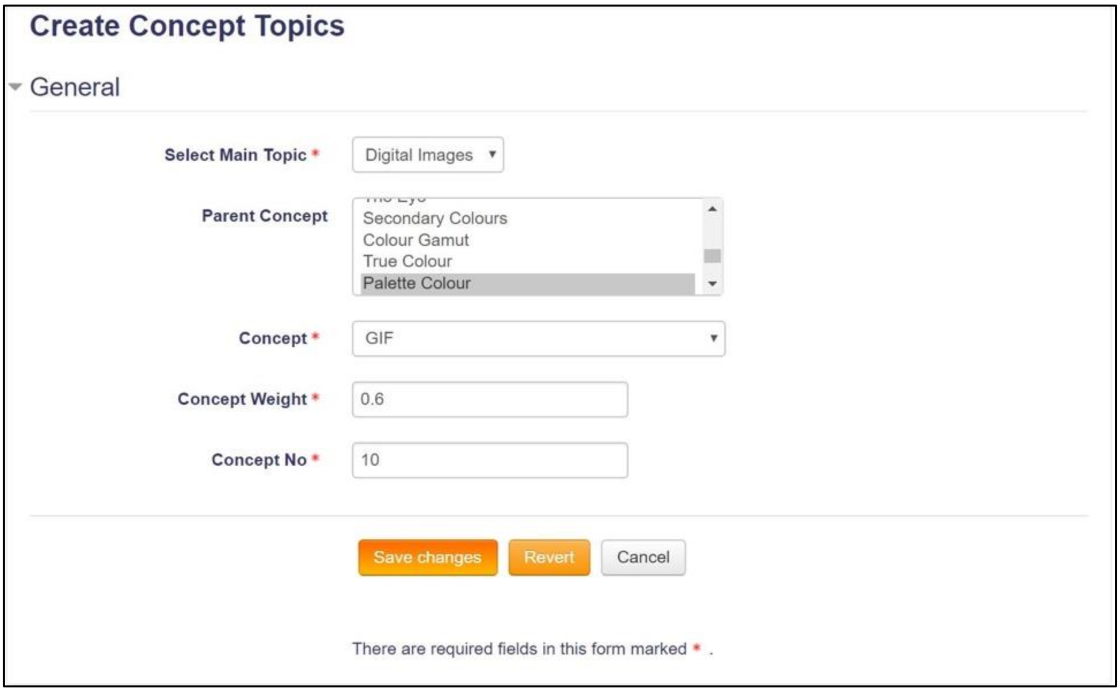


Figure 3.15 Concept Topics Creation by the teacher

The most important part of the system is the course admin block which is considered as a novel contribution of designing the proposed system for both teachers and students.

Course Admin Block for the teacher: There are three components in this block which the teacher can deal with (see Figure 3.16).

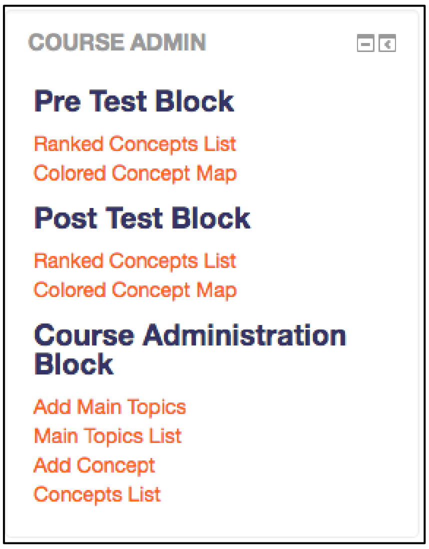


Figure 3.16 Course Admin Block for the teacher

Pre-Test Block: Consists of the ranked concept list and coloured concept map. The teacher can display the ranked concept list or coloured concept map for each student who takes the pre-test.

Post-Test Block: Consists of ranked concepts list and coloured concept map. The teacher can display the ranked concept list or coloured concept map for each student who takes the post-test.

<u>*Course Administration Block:*</u> This block includes four functions:

- Add Main Topics: The teacher can add a new main topic for the course.
- Main Topics List: The teacher can display, edit or delete existing main topics.
- Add Concept: The teacher can use this function to add a new concept and determine its parameters, such as concept name, number, main topic, parent concept (see Figure 3.15).
- Concepts List: Used to browse, edit or delete existing concepts (see Figure 3.17).

Concept Topic List

S.No.	Concept No.	Topic Name	Link
1	1	Visual Spectrum	✕ ⚙
2	4	Primary Colours	✕ ⚙
3	2	The Eye	✕ ⚙
4	3	Color Sensitivity	✕ ⚙
5	13	Lossless	✕ ⚙
6	16	Temporal Compression	✕ ⚙
7	17	Frame-based video	✕ ⚙
8	18	Group of Pictures	✕ ⚙
9	20	MPEG	✕ ⚙
10	19	B and P frames Colours	✕ ⚙
11	11	JPEG	✕ ⚙
12	12	Quantization	✕ ⚙
13	7	Color Models	✕ ⚙
14	14	Lossy	✕ ⚙
15	15	Spatial Compression	✕ ⚙
16	10	GIF	✕ ⚙
17	5	Secondary Colours	✕ ⚙
18	6	Colour Gamut	✕ ⚙
19	8	True Colour	✕ ⚙
20	9	Palette Colour	✕ ⚙

Figure 3.17 A sample concept topic list after adding the concepts by the teacher

3.4.2 Student Interface

In this model, first, learners follow the navigation menu in the left side of the interface as can be seen in Figure 3.18, and then they are able to see the concept map of the course to have a better understanding of the course structure (See Figure 3.14). After that, learners take an initial pre-test before learning the materials to evaluate their knowledge level of each concept in the topic (See Figure 3.19). A fuzzy logic system is used in the pre-test evaluation to evaluate the learner's knowledge level for each concept in the domain and construct a coloured concept map (CCM) (See Figure 3.20) to show the learners their knowledge level and produce a ranked concept list (RCL) of learning materials (LM) to address their misconceptions (See Figure 3.21). Learners have to follow their ranked concept list to learn the material in different formats (text, audio and video) and can display their coloured concept map using course admin block (see Figure 3.22). After using the system to learn the materials, they take a post-test to measure their abilities of understanding the concepts and are presented with a revised coloured concept to show their understanding level of each concept.

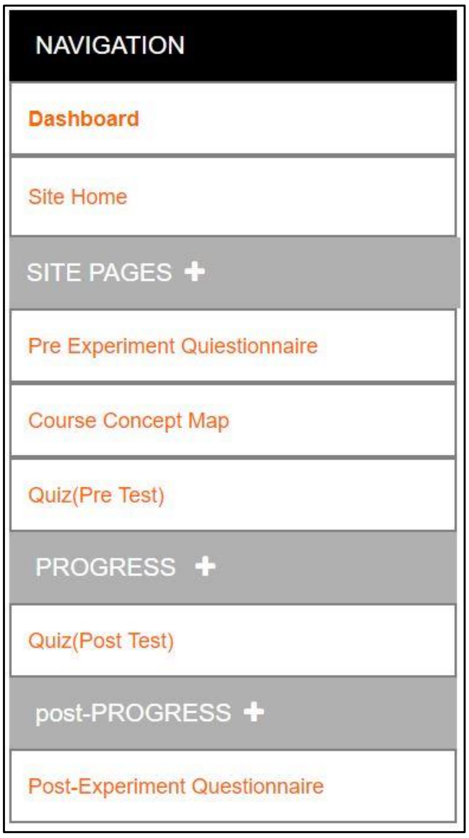


Figure 3.18 Navigation Menu for the student

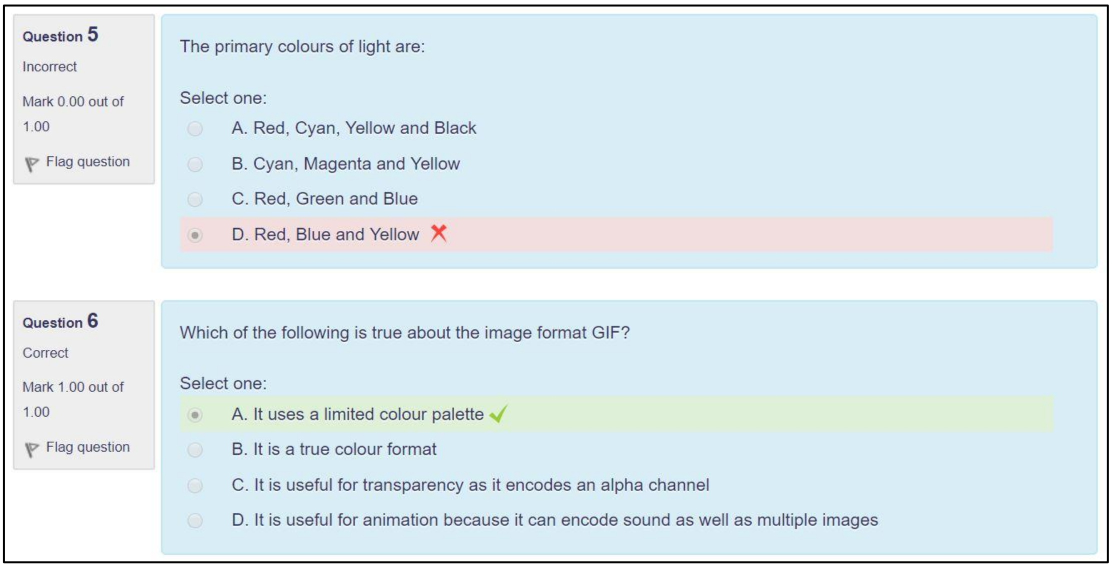


Figure 3.19 Student Pre-test Result Feedback

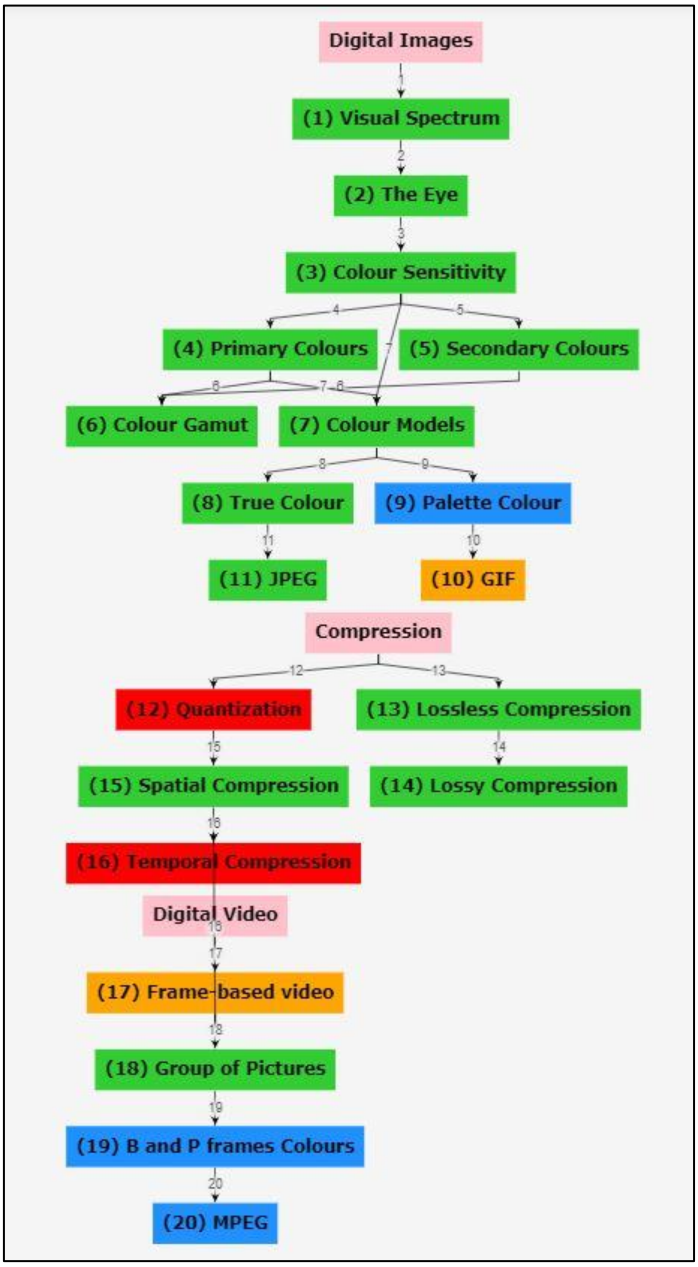


Figure 3.20 Student Coloured Concept Map (CCM) after pre-test

Ranked Concepts List

Rank	Topic Name	Color Code	Knowledge Level
1	Temporal Compression		Unknown
2	Quantization		Unknown
3	Frame-based video		Unsatisfied Known
4	MPEG		Known
5	GIF		Unsatisfied Known
6	B and P frames Colours		Known
7	Palette Colour		Known

Figure 3.21 Student Ranked Concepts List (RCL) after pre-test

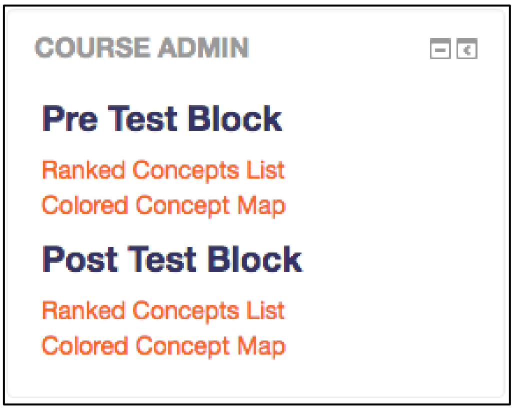


Figure 3.22 Course Admin Block for the student

Course Admin Block for the students: There are two components in this block with which the students can interact.

- *Pre-Test Block:* Consists of the ranked concept list and coloured concept map. The students can display the ranked concept list to follow their learning path, start learning the materials, and browse their coloured concept map to explore their knowledge level for each concept after taking the pre-test.
- *Post-Test Block:* Consists of ranked concept list and coloured concept map. The students can display the ranked concepts list to follow their learning path, start learning the materials, and browse their coloured concept map to find their knowledge level for each concept after taking the post-test.

3.5 Non-Adaptive System Architecture

The architecture of the non-adaptive (standard) system (shown in Figure 3.23) has the same general structure as the adaptive architecture except the adaptation mechanisms is removed. The non-adaptive system initially uses a pre-test and the results from this are utilized by a standard evaluation module/block to determine the understanding of the user of the concepts. Students are then provided with all the learning materials in different formats regardless of their knowledge level and without any specific order. Once the learning materials have been studied by the students, they are tested (post-test) again to identify their current level of knowledge.

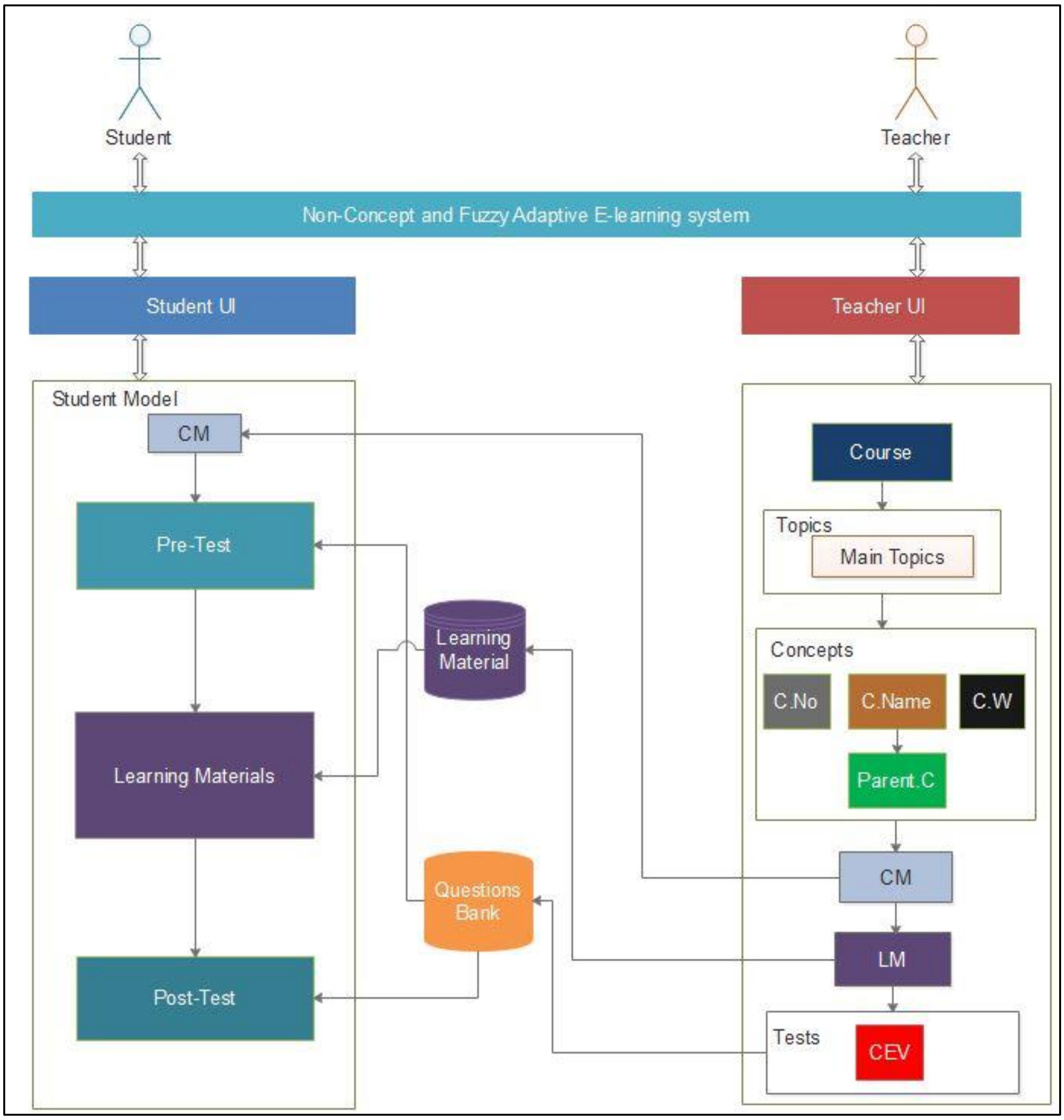


Figure 3.23 The non-adaptive system architecture

3.6 Summary

This chapter has described the design and development of a novel adaptive e-learning system. The general components of the system are explained in detail along with the adaptive mechanism used. This includes the evaluation methods (pre-test and post-test) of the learners to identify their understanding level. As a result of that, both coloured concept map and ranked concepts list are generated using the fuzzy logic technique. The fuzzy logic process is explained with its steps and the addressed variables.

Chapter 4: Methodology

4.1 Introduction

The overall aim of this thesis is to determine the effectiveness of the adaptive e-learning system; Concept-based and Fuzzy Adaptive E-learning (CaFAE). This system uses a coloured concept map and ranked concepts list to illustrate the learner's knowledge level for each concept in a given topic; it also recommends a bespoke ordered list that contains the most appropriate concepts to be learned. This provides an extension of the additivity concept of learning to increase engagement, performance and understanding of learner through the use of ranked concepts list and coloured concept maps. Based on the literature review and the rationale of this study, this study aims to answer one main research question: **Can an adaptive learning system enhance learners' understanding and make learning more effective?** Participants' performance relative to the adaptive e-learning system was examined though a number of variables such as: the student test scores that measure learning effectiveness; time taken to learn the concepts and time taken to answer questions and questionnaires.

Overall, this thesis followed an experimental mixed design approach, where data and variables were scored pre and post the application of the adaptive e-learning system. The adaptive group (experimental group) were exposed to the adaptive system and the non-adaptive group (control group) were exposed to a similar system, but without the adaptive mechanism. This allowed the researcher to test outcomes before and after (pre/post-test) applying the system and between the two groups (adaptive vs. non-adaptive). In light of the literature review and previous research this thesis hypothesises that:

H1: The pre-test will show no significant difference in knowledge level between the two groups (adaptive vs. non-adaptive).

H2: Post-test, the adaptive group will significantly out-perform the non-adaptive group in knowledge level.

H3: Comparison of scores pre-test and post-test will reflect significant differences in performance between the two groups each and combined, i.e. both the post-tests in the both groups will show improvements.

H4: Less time will be taken to learn the concepts and answer post-test questions by those using the adaptive e-learning system than by those using the non-adaptive e-learning.

H5: Students will find the system engaging with good usability

These hypotheses were examined following two studies, a pilot study and a full study. Both studies follow the same approaches and procedures using different samples (British students for the pilot study and Saudi Students for the full study). To avoid repetition, procedures for both studies are embedded together in this chapter. Also, it should be noted that both studies are discussed in more details in separate chapters.

Following the brief introduction, this chapter (methodology) aims to illustrate and explain all the methods used to test the research hypotheses specified earlier. Firstly, this chapter will provide a brief explanation of the research approach used, followed by the research design, sampling and participants, materials used, the data collection procedure. Furthermore, this chapter will also explain ethical considerations and the type of tests used in this study to confirm/reject the research hypotheses.

4.2 Research Approach

This study followed mixed methods (quantitative and qualitative methods) to collect data and answer the research questions. This approach is used for the participants' test scores, the time it takes them to learn concepts and to answer questions and by the pedagogical system. as well as some questions in both pre and post-experiment questionnaires. This chosen approach is inspired by earlier research in the field (Alzahrani, 2015; Aslam, 2014; Dare, 2011; Özyurt et al., 2013b). Following a similar approach to similar previous studies enables the researcher to compare results and relate to previous research findings.

Matveev describes the quantitative approach as a way of generating reliable data because of the researcher's controlled observations, laboratory studies/experiments as well as other types of quantitative data collection tools (Matveev, 2002). Furthermore, the quantitative approach considers a specific research problem and seeks to arrive at an objective outcome. It should be highlighted that the quantitative research stems from a positivist research philosophy, which believes that knowledge is objective and that such knowledge and experiences can be quantified and understood numerically (Creswell and Creswell, 2017). Typically, quantitative approaches are also deductive in their nature, i.e. the researcher constructs their reasoning from the general to the specific (top-down approach). This allows the researcher to search earlier studies and check earlier theories and introduce new hypotheses as a result of such hypotheses and then tests, i.e. the process of theory leading to hypotheses, followed by observation and lastly confirmation (Bryman, 2016). Quantitative data is often generated using closed-ended questions within a questionnaire. Such quantitative data will enable the researcher to answer the research hypotheses. The quantitative approach allows for reliable and descriptive outcomes, cost-effective procedures and generalisability (from a small sample to the bigger population). It is seen as the ideal choice for this study that seeks quantitative data from questionnaires (test results of knowledge) as well as computerised observed data (e.g. time).

Despite these advantages, like any other approach, the quantitative approach and the data collection tools have their disadvantages. The quantitative approach is viewed as abstract and not detailed and assumes that individuals have similar experiences of a phenomenon. This is where the qualitative approach is seen as advantageous; it aims to generate subjective inductive knowledge, i.e. assumes that individuals have different views and experiences, and their experiences and knowledge are constructed and built based on their own individual experiences (Cohen et al., 2011). This approach, through the use of qualitative data collection tools (e.g. interviews), offers deeper knowledge and perhaps knowledge that is new to the researcher that questionnaires might miss.

The researcher acknowledges that this study is deductive and aims to answer a set number of research hypotheses, however open-ended questions were introduced to participants to further generate information that might not be reflected in the questionnaire. The introduction of these open-ended question does not change the approach. In this research, a mixed method is used to reach the aims and provide answers to the research question and hypotheses by using various methods of collecting data (qualitative and quantitative). This approach investigated the research significance through analysis of the experimental results in various aspects, such as testing increases in student performance and how they feel about the system. Such different data collection methods are reflective of the effectiveness, validity and reliability of the system.

4.3 Research Design and Variables

Experimental research designs are often concerned with measuring and impact or a relationship between variables after manipulating a main variable (an intervention), differences or correlations are often expected. According to (Cook et al., 2002) an experiment is "a study in which an intervention is deliberately introduced to observe its effects" (p. 12). These authors went on to elaborate that there are typically two types of experiments: randomized experiments and quasi experiments. The main difference between both is the way participants are assigned to the experimental conditions; randomised experiments expect participants to be randomly selected for the study's conditions. Lack of random selection to the conditions leads to a Quasi-experimental design. Random assignment to the conditions makes sure that research participants will be equal in their expectation on what is asked of them.

This study will utilize a two-condition experimental design, i.e. between groups (two groups) and over time (two times), for the two studies (the pilot study and the full study). Participants were randomly assigned to the conditions and equal instructions were given to all. In this study the researcher utilises the Concept-based and Fuzzy Adaptive E-learning (CaFAE) and applied among the experimental group of students. Students were provided with two modules, one for each study; Multimedia Design and Applications course (pilot study) and Algorithm and

Data Structure course (full study) after 7-weeks of beginning of term. Students were randomly chosen to participate in:

Adaptive e-learning condition: In this part of the experiments all students followed a Concept-based and Fuzzy Adaptive E-learning (CaFAE). The previous chapter (3) included more details about this system.

Non-adaptive e-learning condition: Students here were not provided with the CaFAE, instead they were simply provided with the non-adaptive (standard) system.

All students are subjected to measurements before and after the experiment, following either the adaptive or the non-adaptive conditions. As explained in the introduction, this study includes five hypotheses; these hypotheses are designed based the researcher's expectations of the proposed system (Concept-based and Fuzzy Adaptive E-learning (CaFAE)). It is generally expected that those who participates in the CaFAE system condition are more likely to improve knowledge the module they are studying. Also, it is expected that students' knowledge level at pre-experiment phase will be different from the post-experiment knowledge (CaFAE group). To confirm these hypotheses (see introduction) a number of variables were considered the following independent and dependent variables:

Independent Variables (IVs):

The independent variables in this experiment are the variables that the researcher is manipulating, i.e. impactful variables.

1. Group type is the first variable were participants participated in either: Use of the adaptive e-learning system for adaptive content presentation or Use of the non-adaptive e-learning system (adaptive vs. non-adaptive); this is considered a between subject's variables, as it looks at two independent groups.
2. The second variable is considered Time/Phase, which follows a repeated measures design (Pre-experiment and Post-experiment). This reflects the two points of data collections.

Dependent Variables (DVs)

Dependent variables are those the researcher observes during the experiments and believes to be potential sources of useful information. It is expected that these variables will be affected by the IVs.

1. Students' test scores; this test reflects students' level of knowledge and how much the Concept-based and Fuzzy Adaptive E-learning (CaFAE) system has helped them
2. Time spent on learning the concepts: This reflects time spent online learning the concepts introduced

3. Time spent answering questions: time spent between the start of an answer to the completion of an answer

4.4 Sampling Participants:

Like any other empirical study, choosing participants is challenging. A sample is considered as smaller collection of units/individuals from a population, the sample is used to determine and examine how truthful the outcomes are about the population (Field, 2005). Research has pointed to two main approaches in sampling, one is randomised sampling and the other is non-randomised sampling (Groves and Fowler, 2004). Randomised sampling is an ideal approach, each member of the targeted population has the same/identical chance of being chosen to participate; this is achieved through various methods such as systematic, stratified and cluster sampling. It should be acknowledged that achieving random sampling is challenging, expensive and time consuming.

On the other hand, the research has also proposed non-randomised sampling methods that are often used. The non-randomised sampling approach reflects the fact that some participants have more chance of being chosen than others (i.e. not identical chances). One of the main advantages of this approach is that it is relatively cost effective, and easy to implement. According to (Groves and Fowler, 2004) the two main sampling methods used are Purposeful and Convenience sampling. Purposeful sampling is one the researcher chooses a person/participant as a result of their suitability to the study; they might have particular knowledge of what the researcher is seeking. Convenience sampling, although similar, is an approach when the researcher approaches the participants based on his own convenience and the convenience of the participant. In light of the above sampling methods, the researcher utilised a mix of both. Firstly, the purpose was to experiment among students' population, and then students were chosen based on the convenience of the researcher, participants (groups) who agreed first were recruited. This was the case for the pilot study and the full study. In the pilot study this mixed sampling selection allowed the researcher to seek Post-graduate and Under-graduate students at the University of Sussex Informatics Department in Falmer/UK. Student were then assigned to conditions (adaptive vs. non-adaptive) based on their surnames. A similar strategy was followed for the full study where participants were taken from a cohort of undergraduate students from the Prince Sattam bin Abdulaziz University in Alaflaj/Saudi Arabia (for the purpose of the full study). Participants were placed into groups in and alternate way based on surname (adaptive then non-adaptive).

A total of 41 participants were conveniently selected by the researcher in the pilot experimental study, which was conducted before the full study (main study) and was based on the school's available modules providing learning materials. This made uploading existing lectures to the system easier. The sample was collected using self-selected sampling from participants available during the term who were studying the module and were willing to participate. Students wishing to take part signed a consent form (Appendix A.2). As for the main study (full study) among the Saudi Student's sample, students were conveniently selected. A total of 100 agreed to take part (July 2018). Students' understanding of the adaptive and non-adaptive learning systems was essential, so a tutorial section was available to help students understand how the system operates. Participation was completely voluntary and based on participants' convenience, they were told of the main aim of the experiment and the time they need to dedicate (see Appendix A.1 for experiment's instruction sheet). To enhance their motivation for participation the researcher highlighted the importance of the study and the great contribution they are making. Students were told that use of the system (adaptive or non-adaptive) in the experiment is not part of their assessment (to keep it neutral to all). Participants were either assigned to a control group (non-adaptive system group) or an experimental group (adaptive system group) were they receive the adaptive e-learning system; this was done randomly on alternate fashion. Participants were told that they will be tested, pre-post experiment.

4.5 Materials used:

This section provides a list of all materials used to for this study. As explained in the previous chapter where the CaFAE system is fully described; this study seeks to find how effective it could be when used among students. This intervention is considered of great importance and could also be considered as materials for this study. This is a computer-based study and for the collection and recruitment of participants the researcher utilised the following:

Firstly, Recruitment Email: this was an email sent to all participants to explain the research's aim, provide all information concerning the experiment, and outlines the experiment's schedule. Contact information is included to allow participants to ask any questions about the experiment (see Appendix A.1). Secondly, Information Sheet: this sheet explains why the study is taking place, which is to evaluate the learning experience and satisfaction level of participants using the system during participation in adaptive and non-adaptive e-learning systems. It also includes the inclusion criterion of access to this module's online lectures, meaning that, only students enrolled on the Multimedia Design and Applications and Algorithm and Data Structure modules could participate, as well as providing all information needed by participants before the experiment begins (See Appendix A). Thirdly, Consent Form: this followed the information sheet, it was essential that students read the information sheet as well as the consent form which highlights their voluntary participation, their assured confidentiality and anonymity and their right to withdraw at any given time should they choose to do so (See Appendix A.1). Fourthly, Pre- and Post-Experiment Questionnaires: these questionnaires were designed to take students' background and experience at pre- experiment stage and take their opinions and feedback at post-experiment stage (see Appendix B and respectively).

4.6 Data Collection Procedure:

This section explains in detail the process of data collection in this study. The procedure is best described as follows (see chapters 5 and 6 for more details). Participants were recruited from the University using a convenience sampling method. Participants were politely approached, and the aims of the study were explained; they were told that their experiment will take 2 hours after 7 weeks of the taught material at which point the system is testing their understanding of what they have learnt so far and trying to address any deficiencies in their understanding. Participants were told that this research study is about Concept-based and Fuzzy Adaptive E-learning (CaFAE) and were initially asked to carefully read the information sheet, a copy of which they could keep for their records; the main aim of the is to evaluate their learning experience using a novel adaptive e-learning system (CaFAE), and take note of their satisfaction level during your participation in the use of the system. All participants were told that this system will be assessed using Multimedia Design and Applications and Algorithm and Data Structure modules. A module that is ran for a whole term, taking approximately 7 weeks for both pilot and full studies.

Further information was given that the aim here is to measure their understanding level of a selection of topics and recommend to them a suitable set of learning materials to improve their understanding of the module. All participants were asked to provide their informed consent if they voluntarily accept to take part. They were also told that they could withdraw at any given time should they choose to, without the need to provide a reason. It was also stressed that this module bares no impact on their university grades (not part of their study). Expectations were set, participants were told to expect that they will complete the following during the 2 hours experiment period:

- **Use the system for a period of 2 hours:** it is important that participating students sufficiently and appropriately use the system for 2 hours for both studies.
- **Pre-experiment questionnaire:** this evaluated users' experience with online learning and adaptive e-learning systems to build an idea of the type of students who are using the system (Appendix B.1). Participants were told they could review the questionnaire before choosing to complete it.
- **Pre-test and post-test results (Knowledge):** A multiple choice quiz is used to evaluate users' understanding of each concept in the topic before learning the material (either adaptive or non-adaptive) (Appendix B.2).
- **Time spent in learning the concepts and answering the questions:** Measures time spent on learning the materials after taking the pre-test, and time spent answering the questions (pre and post-test).

Students were assured that the procedure followed strict ethical guidelines based on voluntary participation, informed consent, confidentiality and anonymity. Participants were aware that the data provided will only be used for the purpose of this study only, and that their data will be accessed by the researcher (and supervisor). Participants were told that they have the right to withdraw from the study at any given time and consult with the researcher in case of any inconvenience caused. Participants' identifying information were removed (e.g. no names or ID numbers were kept). Also, the data provided was kept securely (with a password) on the researcher's computer. All participants were given the contact details of the researcher in case they wish to know more about the study or its findings in the future. Ethical considerations are further elaborated below.

4.7 Ethical Consideration

This study followed the ethical guidelines set by the University of Sussex. The study was ethically approved (ethical review) before commencing with data collection. Research have touched upon many ethical issues in research. It is essential that each researcher adhere to the highest ethical standards. To simplify ethics and what they stand for, (Hammersley and Traianou, 2012) have summarized ethical issues into five main principles. Firstly, minimising and reducing harm or potential harm caused participants, e.g. financial, physical, psychological etc. Also, it is important that the study does not cause harm to others too (non-participating individuals), even harm to researchers too. Secondly, respecting autonomy, participants need to be assured of their autonomy and freedom in participating, they are in charge of this, i.e. avoid deception. Thirdly, protecting privacy, making sure that they are aware of their own privacy and what of the research would be made public and shared with others. Confidentiality and anonymity are essential. Fourthly, offering reciprocity: participants' give some of their own time, and convenience to participate, this could disrupt their routine. They should be aware of what to expect in return, e.g. inceptive. Finally, equal treatment, participants have the right to be treated equally with no favouritism or discrimination.

Although there are other ethical considerations, the researcher feels that these five principles summarise the main issues. Hence this study sought to meet all these principles by informing participants of what to expect from the experiment/study (information sheet) followed by an agreement to participate, i.e. consent. Following the experiment participants were debriefed too. The study's information sheet, consent form, details of the experiment, recruitment email, and pre- and post- questionnaires (see Appendix B) were subjected to ethical review.

4.8 Pilot Study

Previous paragraphs explained the various methods used for both the pilot study and the full study. Both followed similar procedures. This section talks about the benefits of the pilot study. A pilot study is a term often used in empirical (data-based research); a pilot study could be explained as a feasibility study; a small version of the full study or a trial of the methods used prior to commencing the full study (Polit and Beck, 2006). A pilot study could also refer to trying-out or testing a particular instrument within a proposed study (Baker, 1994). There are a number of advantages of a pilot study, clearly it allows the researcher to get advance warning of how the study could fail, how successful the research protocol or procedure is, the appropriateness of the methods/instruments and their complications (De Vaus and de Vaus, 2001). A pilot study checks whether or not the sampling method works, difficulties in recruiting participants, what logistical issues exist and whether or not a research instrument works (Van Teijlingen and Hundley, 2002). Van Teijlingen and Hundley further elaborated by explaining that it is also essential to understand that pilot studies could have their limitations too. Pilot studies often rely on small samples, and hence the outcomes should be treated with caution, this increases the chances of inaccurate predictions or expectations. Indeed, some issues with a study are only apparent when using a larger sample. Some researchers also argue that the pilot study results should not be included in a full study, especially if modifications in the instruments or the procedures were shaped or changed after the pilot study.

The pilot study's main purpose is to ensure a functioning system and to obtain feedback on the system before beginning the full study. The Moodle learning management system was the e-learning platform used to run the experiment. The pilot study was carried out at the University of Sussex, Falmer, United Kingdom. There was no need for the pilot study to exceed that number, as its purpose was only to provide a test of the technology. Sample participation was voluntary and was drawn from postgraduate and undergraduate informatics students. The module lasted for twelve weeks; however, these 7 weeks were the key weeks for the topics covered by the system.

It should be noted that the pilot study is considered a small version of the full study, hence the study followed a pre-determined procedure set by the researcher. The aim was to test the functionality of the system, potential issues with participants, difficulties, time and recruitment. Furthermore, the results from the pilot study were analysed to give an indication of what the results might look like after the full study. The study was conducted over 7-weeks, using pre-post experimental design, under either adaptive or non-adaptive conditions. Hence differences between the two groups and the difference between the two main times (pre and post intervention) was also examined. In short, the pilot study sought to practice the experiment and also answer the main research questions as well: Are students' understanding, knowledge, engagement and motivation improved by the proposed adaptive e-learning system? Do the students express their satisfaction with the engagement provided as a more active learning process by an adaptive learning system? Are students' learning needs met by the system without need for additional tools? The pilot study is discussed in length in Chapter 5 and the full is discussed in Chapter 6.

4.9 Analysis Techniques:

As explained previously in the design section and based on the research hypotheses for the full study and the pilot study it is crucial to take measurement at baseline (pre-experiment) and after experiment (post-experiment) for both the adaptive and non-adaptive groups. Data was coded into SPSS (statistical Package for Social Science). This statistics tool is well used in educational research and is relatively easy to use to generate statistical outcome. After gaining data from the pilot study and the full study the results were analysed using descriptive and inferential statistics:

Descriptive statistics: Descriptive statistics are generally used to describe sample characteristics, i.e. their demographic details, their questionnaire answers, knowledge etc. the descriptive statistics used in this study are:

- Frequency: represents the total number of participants answering a particular answer
- Percentage (%): this reflects the proportion of individuals (out of the all the sample) who answered a particular answer.
- Mean: this reflects an average score on a given scale.
- Standard Deviation (std.): This statistic illustrates deviation from the mean.
- Median: This is a measure of central tendency that reflects the middle score of range of ordered scores (ascending/descending order).

Inferential statistics: inferential are different from descriptive statistics as they seek to answer the research hypotheses and generalise the outcome generated from the sample to the bigger population. This study adopted a repeated measures design (measuring differences between pre and post-experiment outcomes), and also between subjects' design (measuring difference between the adaptive group (experimental group) and the non-adaptive group (control)). This design was followed in line with the research hypotheses.

Tests are used to analyse the results with significance level set as $\alpha = 0.05$ to obtain 95% confidence levels that the differences are due to Independent Variables employed (i.e. group type, and pre-post conditions). To test the hypotheses two main inferential tests were used:

Two related samples (Repeated) Measures t-test: This is a test that shows if scores from two times for the same participants significantly differ ($p<0.05$). This test allows the researcher to answer whether or not students' scores different between pre-experiment questionnaire and post-experiment questionnaire. This test displays the t-value and the significance level of the difference between the two times, by checking them and the mean scores the researcher will be able to determine if the hypotheses can be accepted or rejected. This test is used when the data (for the dependent variables) is normally distributed, i.e. the mean reflects a good central tendency measure (majority of scores scattered around the mean). If the data is not normally distributed the researcher could use **Two-Related-Sample Test Wilcoxon Signed-Rank test**, it is used when the data is not normally distributed, or when using ordinal/ranking scales. The Median is considered a good indicator of central tendency here.

Independent samples t-test: These tests parametric test dealing with data (dependent variables) that have a normal distribution and follow an interval scale. This tests whether two independent samples are significantly different from each other. This will demonstrate whether the experimental group (adaptive e-learning) and the control group (non-adaptive learning) significantly differ from each other; difference is determined based on the t-value and the significance level ($p<0.05$). An alternative test is the **Two-Independent Sample Test using Mann-Whitney U**, this is considered a non-parametric test, often used when the data does not justify normal distribution, i.e. the frequency of scores (for a given variable) does not follow a bell shaped distribution which means that the mean does not reflect a good measure of central tendency. Using the median scores this test provides the U statistics and the significance level too.

It should be noted that the pilot study utilized the non-parametric tests, while the full study utilized the parametric test. The small sample of the pilot study, the distribution of the results did not meet the parametric assumptions stated above. However, the full study did, hence parametric tests were used for the full study.

Likert Scales: The Likert Scale analyses data from a number of Likert-Type items to produce a single composite score or value which provides a quantitative measure for the research question to which an answer is required (Clason and Dormody, 1994). The majority of scales used in the current research instruments were Likert Scales and this allows descriptive analysis to incorporate mean and standard deviations.

Weighted averages show tendencies represented by composite scores, with the following entered into SPSS to represent item weights on a 5-point Likert Scale: Strongly agree=5, Agree=4, neutral=3, Disagree=2 and Strongly disagree=1. The results are interpreted by computing a weighted average, performed by dividing the distances between scale values (representing the data range) by the number of values. In 5-point Likert scales, distances are 4 since the first distance is between 1 and 2, the second is between 2 and 3, the third is between 3 and 4 and the fourth is between 4 and 5. As the number of values in the scale is 5, the period length would be 4/5= 0.80 and this is the value used in computing weighted averages.

Qualitative analysis: A number of open-ended questions were analyzed using simple form content analysis, this is a qualitative data analysis technique aims to finding patterns/themes within textual data. Although very few participants answered the open-ended questions, the researcher looked at creating themes based on a thematic-analysis procedure (Braun and Clarke, 2006).

4.10 Summary

This chapter has described the methodology and design used in this research study and how they have influenced data collection. It first introduced the research hypotheses and the general aim of the study, followed by explaining the quantitative approach as the preferred approach for this study. The design of the experiment is considered experimental. Using the Concept-based and Fuzzy Adaptive E-learning (CaFAE) system as an intervention, the researcher followed a mixed approach to enable studying group differences (adaptive group vis the non-adaptive group) while also being able to measure potential differences between students' level of knowledge pre-experiment compared to post-experiment. The methodology here was written to explain the full study and the pilot study as both followed similar methods. Both studies followed an ethical procedure using a questionnaire, knowledge and system-related statistics to assess the functionality of the Concept-based and Fuzzy Adaptive E-learning (CaFAE). The pilot study to understand the research procedure and potential issues with the design was conducted with 41 students (UK). This was followed by the full study among Saudi participants (n= 100). Using appropriate statistical techniques (in the following chapters), the researcher will examine if the research hypotheses were accepted or rejected. In line with the research methodology, design and procedure, the following chapter will report and discuss the findings related to the pilot study. The following chapter (5) will discuss the findings from the pilot study.

Chapter 5: Pilot Study

5.1 Introduction

The previous chapters presented an adaptive e-learning system, CaFAE, that uses a coloured concept map and a fuzzy logic system to enhance student performance and understanding. This chapter provides details of the pilot study performed using CaFAE for a small number of participants. The primary purpose of the pilot study was to ensure that the system was usable and to allow testing of the experimental methodology. Although the results for learning were positive, they were not statistically significant. Overall, this pilot study looked at third-year undergraduate and postgraduate students from the University of Sussex. The participating students were assigned randomly to two groups: an adaptive group and a non-adaptive group, both as part of the "Multimedia Design and Applications" course module. This chapter presents the quantitative data analysis of the pilot study taking into account students' knowledge scores (pre-test and post-test), time spent in learning concepts, and time spent in answering the questions in the post-test. Qualitative data was also generated from pre-experiment and post-experiment questionnaire findings, along with our observations regarding the number of students that generate the ranked concepts list and coloured concept maps. These results generated evidence concerning the usability of the system and validity of the experimental methodology; they also showed the advantages of adaptive methods over non-adaptive techniques. The following subsections provide details about the participants, the location of the evaluation, objectives of the experiment, the data analysis approach, and the hypotheses. The experimental results are discussed at the end of the chapter.

5.2 Sampling Participants

The target participants were postgraduate students from second and third-year undergraduate students enrolled at the University of Sussex. In particular, students who registered for the 'Multimedia Design and Application' module offered by the School of Engineering and Informatics, and volunteered for the experiment, were included. Participants were recruited based on a convenience sampling strategy. The researcher approached a total of 77 registered students, however, only 41 students agreed to participate (53%) and completed the questionnaire at the pre-experiment stage. The participants were: 29 third-year undergraduate students and 12 postgraduate students (MSc). All participants attended the 'Multimedia Design and Application' laboratory sessions; they used and accessed the extended e-learning environment (Moodle) based CaFAE system, where they could take a pre-test and learn the concepts depending on their groups, and then take the post-test to evaluate their understanding level of the concepts in the subject area.

The sample size is crucial. A small sample size is not sufficient to test system usability to avoid pitfalls in the main study. The project is low risk, and the findings were anonymised (see ethical approval documents in Appendix A).

5.3 Experiment Location

The participants accessed the online CaFAE in the school labs in the Chichester 1 building, University of Sussex, Falmer, UK. Each lab was equipped with more than 50 desktop computers. All computers were running Windows 10 and connected to the Internet. Each group was assigned to do the experiment at different times. All students registered using the CaFAE system. They logged into the system by using their username and password.

5.4 Objectives of Experiment

The main reason for the pilot study was testing usability of the CaFAE system and to understand how the system is received by students before launching the full study. This pilot study intends to modify the system based on findings (or critical findings or limitations) before running the full study. In addition, the experiment (pilot study) aimed to test the hypotheses (given in Section 4.2) by measuring performance, learning speed and efficiency of each student. When averaged over each of the two groups, these measurements would allow comparison of the effectiveness of the adaptive learning system with non-adaptive system. Also, this experiment would demonstrate the adaptivity of the proposed system by providing suitable ranked concepts lists and coloured concept maps to the students enrolled in this group, and indicate if an improvement in performance, engagement and understanding of the concepts is likely as compared to the non-adaptive group.

5.5 Experiment Procedures

Students taking part in the experiment were divided into two groups, as explained in Section.4.2.1. The students signed a consent form before beginning to use the system, as shown in Appendix A.2. The system procedures for each group were explained to students who consented. The functionalities of the system were explained to the students, including how to take the pre-experiment questionnaire, how to take the pre-test, how to display the coloured concept map and follow the ranked concept list for the adaptive group, how to learn the concepts, how to take the post-test, and how to take the post-experiment questionnaire at the end of the experiment. Students logged into the CaFAE system using their given username and password. The system asked the students to fill in the pre-experiment questionnaire to evaluate if the students had previously used an adaptive e-learning system, and if so, their experience with using such an adaptive e-learning system. Next, a pre-test on the concepts covered in the module was presented, and its results were collected. After that, the learning content was presented to the students according to their assigned group. In the adaptive group, concepts were presented according to the ranked concept list along with the coloured concept map. The students in this experiment group were presented with a map of their understanding of the concepts and then they can learn and acquire knowledge following their ranked concept lists based on their performance in the pre-test. However, the students in the non-adaptive group were just give their test results and could learn the learning content after taking the pre-test without any ranking of the concept or orderly way to present the content. After learning the concepts, students in both groups were able to take the post-test to evaluate their abilities for each concept in the topic. Finally, the system asked the students to fill in the post-experiment questionnaire that contained questions related to their experience with the proposed system (for the adaptive group). The student's knowledge acquisition was measured according to: the pre-test and post-test results, and the time spent learning the concepts, and the time taken in answering the questions in the post-test.

5.6 Pilot Study Findings

This section tests the system functionalities by describing the questionnaire results at the pre-experiment and post-experiment stages. When analysing the questionnaire, the results of the close-ended questions are quantitatively evaluated, using descriptive and inferential statistics through IBM SPSS (IBM SPSS Software, Ver. 24). The results of the open-ended questions are evaluated qualitatively.

It should be noted that the study assumes differences between pre-experiment and post-experiment stages in student performance (as per hypotheses suggested). To test the hypotheses, it was originally intended to use Independent Samples t-test as well as Paired-Sample t-test; however, due to the small number of students who participated in this study (n = 41) and the skewed data (not normally distributed), non-parametric tests were chosen to analyse the experiment results. Hence, it was necessary to use the Two-Independent Samples Mann-Whitney U test and the Two-Related-Samples Test Wilcoxon Signed-Rank test (Field, 2013). Both tests were used for analysing the results with significance level set as $\alpha = 0.05$ to obtain 95% confidence level that the differences are due to Independent Variables employed (i.e., group type, pre-test, and post-test conditions). Mann-Witney U test was conducted to measure the differences between the two scenarios (adaptive vs non-adaptive), while the Wilcoxon Signed-Rank test was conducted to measure the differences between pre-experiment and post-experiment. Significance or probability of less than or equal to 5% (0.05) assumes significant differences (Field, 2013). By utilising SPSS, descriptive statistics and the two tests previously mentioned, the following sub-sections will report the results obtained at Pre-Experiment level, Hypotheses testing and Post-Experiment level.

5.6.1 Pre-Experiment Questionnaire

The pre-questionnaire (pre-experiment) evaluated students' previous experience with using standard online learning systems (non-adaptive) as well as experience with using adaptive e-learning systems in education. The results from the questionnaire are described below; these reflect general information about students' preferred learning methods, their use of online learning environments, opinion about online compared to traditional lectures, ways to improve understanding and the use of adaptive e-learning.

Table 5.1 Results for Closed-End Questions for Pre-Experiment Questionnaire

Questionnaire Item	Measure	Percentage
Preferable learning Method	Online lecture	38.5%
	Traditional	46.2%
	Other	15.3%
The use of online learning environment	Yes	46.2%
	No	53.8%
Time spent using online learning	Less than 2 hours	26%
	Between 2 and 4 hours	21%
	Between 4 and 8 hours	15%
	More than 8 hours	38%
Online learning compared to traditional lecture	Superior	64%
	Inferior	28%
	Similar	8%
Online learning improves understanding	Yes	92%
	No	8%
The use of adaptive e-learning	Yes	8%
	No	92%

As can be seen from Table 5.1, the majority of students (46%) preferred to learn with the traditional method. However, 38.5% of the students preferred to learn using online learning tools, while 15.4% of them preferred learning using exercises, labs, or both learning methods together. Although more than half of the students (54%) have not previously used online learning for personal study, the majority of the students (92%) agreed that online learning improves their understanding. Table 5.1 also shows that the majority of the students (92%) have not used an adaptive e-learning system before. It can be concluded that although many students have previously used traditional and e-learning methods, a significant proportion of them (92%) showed no use of adaptive e-learning methods. These findings further justify the case for adaptive e-learning within universities.

5.6.2 Hypotheses Testing

This study utilized a number of hypotheses (See Chapter.4, section 4.1) to test the functionality of the system. The descriptive and inferential statistics and variables are explained in Chapter 4, section 4.9 and have been used to test the hypotheses. Mainly, this study assumed that the adaptive group (using CaFAE system) will show improvement compared to the non-adoptive group after the experiment. No differences in knowledge are assumed at pre-experiment level. Using Mann-Whitney U test and Wilcoxon Ranked test, the following sections aim to accept or reject the proposed hypotheses.

5.6.2.1 Differences Between Conditions: Pre-Experiment

Differences between the pre-test results of the adaptive group and the non-adaptive group were measured using Mann-Witney U test. This test was utilised with the following hypothesis:

H1: At pre-test level, there will be no significant difference in knowledge level between the adaptive and the non-adaptive groups.

To test the above null hypothesis, a Mann-Whitney U test was used to check whether the two groups were significantly different from each other in the knowledge level (based on students' subject area). The results given in Table 5.2 show that there is no significant difference between the two groups as p is greater than 0.05 (U = 152, p = 0.282) at pre-experiment level. This accepts the null hypothesis assumed above, i.e. the students in each of the two groups reflected similar background knowledge within their subject area. The median for the adaptive group and the non-adaptive group was 6.50 and 5.25 respectively.

Table 5.2 Results of Mann-Whitney U Test for Differences between the Mean Pre-test Scores of the two Groups

Variable	Group	N	Mean	Std. Deviation	Median	Mean Rank	Sum of Ranks	U-Value	P-Value
Pre-Test	Adaptive Group	19	6.21	1.25	6.50	22.00	418.00	152.00	.282
	Non-Adaptive Group	20	5.82	1.81	5.25	18.10	362.00		

5.6.2.2 Differences Between Conditions: Post-Experiment

Similar to the analysis in previous sub-section, this part is concerned with differences between both groups (adaptive and non-adaptive) at the post-experiment stage. Hence a Mann-Whitney U test was used to test the second hypothesis:

H2: Post-test, the adaptive group will significantly out-perform the non-adaptive group in knowledge level

Mann-Whitney U test was used to check whether the two groups were significantly different from each other in the knowledge level (based on students' subject area) in the post-test. The results shown in Table 5.3 illustrate that there is no significant difference between the two groups as p is greater than 0.05 (U = 39.5, p = 0.705) at post-experiment level. This rejects the alternative hypothesis assumed above, i.e. the students in the adaptive group reflected a better background knowledge within their subject area as compared to the non-adaptive group. The mean rank for the adaptive group and the non-adaptive group was 10.56 and 9.59 respectively.

Table 5.3 Results of Mann-Whitney U Test for Differences Between the Mean Post-Test Scores of the Two Groups

Variable	Group	N	Mean	Std. Deviation	Median	Mean Rank	Sum of Ranks	U-Value	p-Value
Post-Test	Adaptive Group	8	8.31	1.25	8.50	10.56	84.50	39.50	0.705
	Non-adaptive Group	11	7.77	2.11	8.50	9.59	105.50		

5.6.2.3 Differences Between Pre-Experiment and Post-Experiment

This part of analysis assumes that there would be significant difference between participants' knowledge level at pre-experiment and post-experiment. The hypothesis is:

H3: In each of the groups, separately and combined, the post-test scores will be significantly higher (better) than pre-test scores.

This hypothesis was tested through Wilcoxon Signed-Rank test which examines differences between two conditions for the same sample (pre vs post) using a significance level of $p = 0.05$ with 95% confidence level. This hypothesis was tested for the adaptive group and the non-adaptive group separately and combined.

For the combined group knowledge test (adaptive plus non-adaptive), there was a statistically significant difference ($p < 0.05$) between pre-experiment and post-experiment conditions ($Z = 3.21$, $p = 0.001$). This clearly illustrates that there is a significant improvement in the post-experiment knowledge (Median = 8.50) compared to pre-experiment condition (Median = 6.00).

For the adaptive group knowledge test, there was a statistically significant difference ($p < 0.05$) between pre-experiment and post-experiment conditions ($Z = 2.55$, $p = 0.011$). This demonstrates that there is a significant enhancement in the post-experiment knowledge (Median = 8.50) compared to pre-experiment condition (Median = 6.50).

For the non-adaptive group knowledge test, there was a statistically significant difference ($p < 0.05$) between pre-experiment and post-experiment conditions ($Z = 2.18$, $p = 0.029$). This shows that there is significant development in the post-experiment knowledge (Median = 8.50) compared to pre-experiment condition (Median = 5.25).

Table 5.4 Results of Two-Related-Sample Test Using Wilcoxon Signed-Rank Test to Compare Two Test Means Pre- and Post-Scores within the Same Group

	Variable	N	Mean	SD	Median	Z-Value	p-Value

Combined	Pre-Test	39	6.01	1.55	6.00	3.214	0.001
	Post-Test	19	8.00	1.77	8.50		
Adaptive Group	Pre-Test	19	6.21	1.25	6.50	2.555	0.011
	Post-Test	8	8.31	1.25	8.50		
Non-adaptive Group	Pre-Test	20	5.82	1.81	5.25	2.185	0.029
	Post-Test	11	7.77	2.11	8.50		

Overall, it can be concluded that post-experiment knowledge scores were significantly higher than pre-experiment knowledge scores. Looking at the Z-score, it is clear that the difference was bigger among the adaptive group as compared to the non-adaptive group.

5.6.2.4 Differences in Time Spent

Further to the previously tested hypotheses, this sub-section is concerned with the time consumed in each of the two experimental conditions. The hypothesis is:

H4: Less time will be taken to learn the concepts and answer post-test questions by those using adaptive e-learning than by those using non-adaptive e-learning.

For this hypothesis, the participants who completed the study in a one-time period (not occasionally) for both groups were analysed to guarantee that they were active and manipulate with the learning materials during the experiment. To examine this hypothesis, Mann-Whitney test was conducted to find whether the two groups were significantly different from each other with regards to the time spent on learning the materials, answering the pre-test questions, and answering the post-test questions.

For time spent answering the pre-experiment questions, the results show that there is no significant difference between the two groups as p is greater than 0.05 (U = 182, p = 0.822). Similarly, for time spent learning the materials, it can be concluded that there is no significant difference between the two groups (U = 21, p = 0.247). For time spent answering the post-experiment questions, the results indicate that there is no significant difference between the two groups (U = 43, p = 0.934). This shows that the fourth hypothesis is rejected.

Table 5.5 Results of Mann-Whitney U Test for Differences in Time Spent in Learning Materials Between the Two Groups

Variable	Group	N	Mean	Std. Deviation	Median	Mean Rank	Sum of Ranks	U-Value	p-Value
Pre-Test Answering Time	Adaptive Group	19	19.68	9.80	16.00	20.42	388.00	182.00	.822
	Non-Adaptive Group	20	19.25	10.96	18.00	19.60	392.00		
	Adaptive Group	8	49.25	23.18	39.00	9.88	79.00	21.00	.247

Learning Time	Non-Adaptive Group	8	30.12	25.39	26.50	7.13	57.00		
Post-Test Answering Time	Adaptive Group	8	10.37	9.31	7.50	9.88	79.00	43.00	.934
	Non-Adaptive Group	11	21.54	34.13	8.00	10.09	111.00		

By looking at the median scores and the mean scores of the time consumed in each of the two groups, it was clear that there are similarities in time spent at pre-test stage. However, in the learning time, the adaptive group has shown to take more time (Median = 39.00) compared to the non-adaptive group (Median = 26.50). At the post-test stage, the non-adaptive group consumed more time (Median = 8.00) compared to the adaptive group (Median = 7.50).

Even though the hypothesis is rejected, spending less time to learn concepts is not necessarily an advantage. This may mean that students are internalising the concepts more strongly, are engaging better with the material or are motivated to try harder to ensure they understand the content. Hypothesis H2, even if rejected, and H3 which is accepted in previous sections indicate that despite students spending more time learning in an adaptive group, they performed better and spent less time answering in post-tests than the non-adaptive group.

5.6.3 Post-Experiment Questionnaire Findings

Only the students in the adaptive group were asked about their attitude and inclination towards using the adaptive e-learning systems. This is one of the limitations of this pilot study that was found and forced us to prepare a post-questionnaire for the non-adaptive group for the full study. Due to the small number of students who completed this part (9 out of 20 students) in the adaptive group, the data is illustrated descriptively.

The first section in the post-test questionnaire study aimed to evaluate the usability of the system, user satisfaction, and the impact of the core functions (coloured concept map and ranked concepts list) in the system. There were 26 scaling questions related to different factors of the system on a 5-point Likert scale (Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree). To simplify the analysis, the answers were combined as Agree (Agree and Strongly Agree) and Disagree (Disagree and Strongly Disagree).

Table 5.6 Results for the System Usability Factor

Item Statement	Agree	Neutral	Disagree
The e-learning system was easy to use.	6	0	3
The instructions provided to use the tools within the site are clear and precise.	6	2	1
Whenever I make a mistake using the system, I recover easily and quickly.	7	0	2
I would imagine that most students would learn to use this system very quickly.	5	4	0

The System Usability Factor was measured using four items to evaluate the adaptive e-learning system. It is clear from Table 5.6 that most students agreed that the system usability was a reliable factor in their learning process through providing their good impressions, satisfaction and their positive attitudes toward using the system, although improvements for the main study could be made.

Table 5.7 Results for the Learning Material Factor

Item Statement	Agree	Neutral	Disagree
The material provided by the e-learning system is easy to understand.	6	3	0
The e-learning system made it easy for me to find the material I need.	4	4	1
I have no problems accessing and going through the materials.	5	1	3
The e-learning system provides sufficient material.	5	1	3

The Learning Material Factor was another metric used to measure the reliability of the system. As can be seen form Table 5.7, the majority of the students were satisfied regarding the learning materials and how easy they were to use.

Table 5.8 Results for the User Satisfaction Factor

Item Statement	Agree	Neutral	Disagree
I feel I learn more in this system.	4	5	0
I feel comfortable using this system.	6	2	1
I believe I became productive using this system.	3	6	0
This system has all the functions and capabilities I expect it to have.	6	1	2
The activities/quizzes provided in the course enhanced my learning.	6	2	1
Overall, I am satisfied with this system.	5	3	1

The User Satisfaction Factor was used in this questionnaire to improve the system functionalities and other parts in the full study based on students' responses and feedback. As evident from Table 5.8, most of the students were satisfied with the system except for the productivity criteria which will be discussed in more detail in Chapter 7.

Table 5.9 Results for the Adaptation Factor

Item Statement	Agree	Neutral	Disagree
I feel the adaptive e-learning approach can substitute for or enhance the normal online learning approach.	4	4	1
The e-learning system provided material that exactly fitted my needs.	6	0	3
The e-learning system enabled me to learn the material I need.	6	3	0
The e-learning system enabled me to control my learning progress.	6	2	1
The e-learning system recorded my learning progress and performance.	8	0	1
The e-learning system was more adaptive than I thought.	5	1	3
The feedback from activities/quizzes helped me to locate where I am having difficulties.	8	1	0
The responses to the pre-test helped me understand where I am having difficulties.	7	1	1

Adaptation is one of the most important factors used in this questionnaire. The aim of measuring this factor is to receive student feedback regarding their attitudes to the adaptation process in the system. It is obvious from Table 5.9 that the majority of the students agreed that the adaptation factor had a high contribution in increasing their performance and determining their understanding level.

Table 5.10 Results for the Coloured Concept Map Effectiveness Factor

Item Statement	Agree	Neutral	Disagree
I found the coloured concept map is more helpful and helped me understand my knowledge level.	7	1	1
The coloured concept map showed information that exactly fits my understanding level.	7	1	1

Coloured Concept Map Effectiveness Factor was used to measure one of the adaptation components of the system (Coloured Concept Map). As seen from Table 5.10, most students agree that the coloured concept map was a helpful tool to show their abilities and to enable them to understand their knowledge levels.

Table 5.11 Results for the Ranked Concepts List Effectiveness Factor

Item Statement	Agree	Neutral	Disagree
The ranked concepts list helped me to locate where I am having difficulties.	7	2	0
I can follow the ranked concepts list easily.	6	2	1

The last factor used in this questionnaire was the Ranked Concepts List, and it was used to measure the effectiveness of the list and how it was suitable for student's understanding level of the subject area. It is clear from Table 5.11 that most students agreed that the ranked concepts list was easy to follow and helped to identify their weakness in the topic area.

Table 5.12 Results for Closed-End Questions for Post-Experiment Questionnaire

Questionnaire Item	**Yes**	**No**
Ranked concepts list matched understanding	8	1
Ranked concepts list helped for better understanding	8	1
Coloured concept map determined knowledge level	8	1
Ranked concepts list importance for improve understanding	9	0
The system answered the problems that the students faced in learning	8	1
Ranked concepts list increasing learning	9	0
The system making the learning process more fun	7	2
Ranked concepts list and Coloured concept map helped to solve problems	8	1

Table 5.12 shows that the students were asked about the effectiveness of both the coloured concept map and the ranked concepts list, and how they helped their understanding level and provided them solutions and recommendations to improve their performance.

Most of the students responded positively to open-ended questions and believed that these two methods (coloured concept map and ranked concepts list) helped them to identify their understanding levels and topics they should improve themselves in. One student remarked:

"The failed ones and the ones I almost got right were presented to me. I wasn't aware there were topics I had "almost" understood, and it was good to see this"

Another student elaborated on the coloured concept map and how it showed him the required areas that needed to be improved:

"*It showed which areas needed to be worked on and the required topics on top of them to understand in order to work on them"*

Some students felt that these two techniques provided by the system were clear, concise and motivational for them, which helped them to learn more. For example, one student said:

"The ranking was well made for me and the information was concise enough that it didn't feel dull learning"

However, one of the students who participated in the post-questionnaire gave negative responses to all the questions and appeared not to understand the nature of the system, how it is structured, and the procedures followed. Of course, these responses were taken into consideration, although all the students were provided initial instructions on how to use the system.

Another question was asked related to the ranked concepts list's contribution in developing better understanding of the topic area. Generally, most students provided positive responses in different ways. One student believed that the ranked concepts list filled the cognitive gaps in their knowledge that they encountered during learning. Another student said that this ranked concepts list shows the relationships between the concepts. A student also believed that this list was a good repetition of the materials, while other students answered with a 'yes' without explanation. As a whole, students expressed their opinions positively to this question.

The students were asked whether the ranked concepts list was an important factor in improving their level of understanding, and in increasing their learning of the subject area. In general, most of them agreed that the ranked concepts list played a significant role in increasing the knowledge level. Most of the responses attributed the importance of this ranked concepts list to showing their abilities and knowledge levels of the subject area. One student remarked:

"Being able to quickly learn about subjects that I had apparently got wrong and wouldn't have known about was a big help"

Another student commented:

"It showed me where I was doing well and not doing well"

The rest of the positive answers consisted of just one or two words, such as *“clear and helpful”*, without any detail or reasons.

Additionally, students were asked whether both methods (coloured concept map and ranked concepts list) and the system itself helped them to solve problems they had faced during their learning. Some of the students who responded to this question positively believed that this system helped them to know their abilities and supported them in reminding the important parts of the failed concepts so that they could improve their performance. One student stated:

"Very, by showing the key areas I got wrong rather than just the questions that I got wrong it changed how I would go about learning the subject."

Other students believed that this system solved the problems they had faced by providing them with a good interface with various learning materials, such as YouTube videos and short paragraphs. One student declared that this system was good for memorization as it allows revision of the learning material that they had a weakness with. Only one of the students gave a negative answer to this question by asking why the correct answers are not presented immediately after the pre-test to identify the weaknesses and learn from the test mistakes. It appears that this student was not engaged by the structure of learning in the CaFAE system. Overall, most of the students had a positive attitude towards using this system, and they expressed their satisfaction about interacting with the system and using the adaptation methods.

The students were also asked whether the system made the learning process more fun. Most of them agreed that the system was a good tool to provide fun while learning the material. One of the students considered that the system was concise, while another student believed that it was more engaging. A student remarked that the coloured concept map could be more gamified and has functionalities to make the learning process more fun and interactive. In general, it can be concluded that most students agreed that the system made the learning process more fun and engaging in different aspects.

From the results above, it is clear that the students found the system, including the coloured concept map and ranked concepts list, a very helpful tool in their learning compared to other tools. These results are also supportive of H5 showing a good level if usability for the system

5.7 User Data

In this section, the obtained information from the system will be presented, such as the total numbers of users, pre- and post-questionnaire responses, pre- and post-test scores, and the total number of coloured concept maps and ranked concepts lists generated by the students. The user data was collected from the experiment, and the following information was recorded:

Users: Registered users in the database totalled 80, amongst whom 77 were students. Of those who had enrolled for the 'Multimedia Design and Applications' course, 41 had volunteered at the start of the study to test the system.

Pre-Experiment Questionnaire: The questionnaire was uploaded to the system so that the students could respond to the questionnaire using the system. All the students who participated in the experiment answered the questionnaire. Therefore, the total number of records was 41 from both groups.

Pre-Test: When the students had taken this test, the coloured concept map and the ranked concepts list were generated automatically only in the adaptive group. All the students who volunteered in both groups (39) had taken this test, and two students completed only the pre-questionnaire in the whole experiment. Therefore, the pre-test results were 39 records and were used to analyse the hypotheses.

Post-Test: When the students had taken this test, the coloured concept map and the ranked concepts list were generated automatically only in the adaptive group. Amongst the students who completed the pre-test (39) in both groups, only 19 of them had taken this test. Therefore, the post-test results were 19 records and were used to analyse the hypotheses.

Coloured Concept Map and Ranked Concepts List: After taking each test, 27 coloured concept maps and 27 ranked concepts lists were generated by the adaptive group in the system (pre-test:19 coloured concept maps and ranked concepts lists; post-test: 8 coloured concept maps and ranked concepts lists).

Post-Experiment Questionnaire: This questionnaire was also uploaded to the system. Only 9 students from the adaptive group responded to this questionnaire.

In general, this study was successful in both technical and methodological aspects, and in obtaining positive feedback from students regarding system usage. In fact, there were some issues encountered when conducting this study; these will be discussed in detail in Chapter 7. Nevertheless, through this experience, there were many lessons learnt which led us to develop and refine the system further to reach satisfactory results in the main study of this research. One of the lessons learnt from this experience was to make the system clearer and improve navigation to enable the students to follow the instructions more easily. Another lesson was to take into consideration the timing of the experiment so that the students were not under any stress, such as assignment submission or exams.

5.8 Summary

This chapter presented and analysed the results of the pilot study. The aim of this study was to test the system functionalities and to make sure the experimental methodology is effective. The pilot study was conducted very smoothly; the students firstly responded to the pre-experiment questionnaire followed by the pre-test to test their abilities before learning the materials. In the adaptive group, students followed the ranked concepts lists to learn the materials according to that list, while in the non-adaptive group, students started to learn the materials without a list or any guidance. Both groups took the post-test to determine their achievement in the course. Finally, some students responded to the post-experiment questionnaire to share their ideas and perceptions about the system in different areas.

Based on the post-test and pre-test scores of both groups, it is clear that the students found the CaFAE system useful in increasing their performance. Although there were no statistically significant differences in some hypotheses findings, some students revealed their satisfaction with the system and how the system improved their ability and performance in the post-experiment questionnaire. Based on the pilot study findings, the experimental methodology was further refined to address issues that were identified in this study. In addition, the students' feedback was taken into consideration in the next phase of development of the adaptive e-learning system before running the full study.

Chapter 6: Full Study

6.1 Introduction

This chapter introduces a discussion of the full study carried out to investigate the research hypotheses (given in Section 1.5) and the technical contributions described in Section 1.6. The full study has similarities with the pilot study. However, changes were made to both the experimental procedures and the proposed system based on feedback and analysis obtained in the pilot study (provided in Chapter 4).

6.2 Participants

The target participants of this full study were undergraduate students from the Department of Computer Science at the Prince Sattam bin Abdulaziz University during the summer term 2018. Specifically, male students who enrolled for the Algorithm and Data Structure module and volunteered for the experiment were included. In total, 100 students participated in this experiment and were divided into two groups; 50 students belonged to the adaptive group, and 50 to the non-adaptive group. All the participants were assigned randomly to the groups.

All the participants attended the Algorithm and Data Structure Lab and used CaFAE system. They could take a pre-test and learn the concepts depending on their group, and then take the post-test to evaluate their understanding level of the concepts in the subject area.

6.3 Location of Experiment

The participants accessed the online CaFAE system in the labs at Prince Sattam bin Abdulaziz University, Alaflaj, Saudi Arabia. Each lab was equipped with more than 25 desktop computers. All computers were running Windows10 and were connected to the Internet. Both groups were assigned to do the experiment in different sections. All students were registered on the CaFAE system. Students logged into the system by using their username and password.

6.4 Experiment Aims

The experiment aimed to test the hypotheses mentioned in Section 4.2 by measuring the performance, the learning speed, the efficiency of each student, and by qualitatively measuring their experience. When averaged over each of the two groups, these measurements allowed the comparison of the effectiveness of adaptive e-learning with non-adaptive.

6.5 Experiment Procedures

Each student was required to sign a consent form prior to starting use of the CaFAE system. Subsequently, the system procedures for each group were explained to the students. The students were given an explanation of the system functionality, including: how to take a pre-experiment questionnaire, how to take the pre-test, how to display the coloured concept map and follow the ranked concept list for the adaptive group, how to learn the concepts, how to take the post-test, and how to take the post-experimental questionnaire after the experiment. Once the study gained ethical approval (See appendix A), students entered the system with their username and password. The system asked the students to complete the pre-experimental questionnaire which evaluated their prior experience regarding using an adaptive e-learning system to discover if they had used adaptive e-learning systems in the past. Next, a pre-test was presented, and its results were collected. After that the learning content was presented to the students according to their assigned group. In the adaptive group, concepts were presented according to the ranked concept list along with the coloured concept map which showed the students their abilities and understanding level as a result of their pre-test. The students in this experiment learned and acquired knowledge using their ranked concept lists that could be changed according to student achievements in the course. However, in the non-adaptive group, the students could learn the learning content after taking the pre-test without any ranking of the concept or orderly way to present the content. After learning the concepts, students in both groups were able to take the post-test to evaluate their abilities for each concept in the topic. Finally, the system asked the students to fill in the post-experiment questionnaire that contains questions regarding their experience with the use of the CaFAE system for the adaptive group. The knowledge acquisition of students was measured according to: the time spent learning the concepts, the time spent in answering the questions in the post-test, and the pre-test and post-test results.

6.6 Full Study Findings

Both questionnaires and hypotheses were tested and statistically analysed. The results of the closed-ended questions were quantitatively evaluated using IBM SPSS Software (Ver. 24) for questionnaire analysis. The results were qualitatively evaluated.

For testing the hypotheses, the Independent Samples t-test and Paired Sample t-test (Trochim, 2000) with significance level α =0.05 to obtain 95% confidence level was used. Thus, the probability of wrongly rejecting a hypothesis (Type 1 error) would then be equal to α, or 5 times out of 100. The results presented in the following sub-sections were analysed using the 'SPSS' statistical analysis software package (V24.0). These two statistical tests helped to examine whether or not the means of the two groups were likely to be equal. After all the results from the questionnaires and hypotheses are analysed, they are discussed with regard to their contribution to the research outcomes.

6.6.1 Pre-Experiment Questionnaire Overview

Previous experiences of students using adaptive e-learning systems and other online learning systems were evaluated using the pre-questionnaire, which contained two open-ended and seven closed-ended questions (Appendix B.1). Each question was split into one of four domains: learning preferences, online learning experience, time spent on learning, and adaptive e-learning experience. The questionnaire results provided information regarding users' backgrounds in e-learning and their past experience with using adaptive e-learning systems.

The pre-experiment questionnaire was analysed for both groups (adaptive and non-adaptive) to quantify if students in different groups had similar pre-experience.

6.6.1.1 Pre-Experiment Questionnaire Findings

Every student volunteering for the experiment responded to the pre-experimental questionnaire. Here, the questionnaire data, along with the discussion and data analysis, is presented.

Table 6.1 Pre-Experiment Questionnaire Closed-Ended Questions Combined for Both Groups

Questionnaire Item	Measure	Percentage
Preferable learning Method	Online lecture	15%
	Traditional	27%
	Both	52%
	Other	6%
The use of online learning environment	Yes	34%
	No	66%
Time spent using online learning	Less than 2 hours	45%
	Between 2 and 4 hours	43%
	Between 6 and 8 hours	7%
	More than 8 hours	5%
Online learning compared to traditional lecture	Superior	16%
	Inferior	34%
	Similar	50%
Online learning improves understanding	Yes	54%
	No	46%
The use of adaptive e-learning	Yes	5%
	No	95%

6.6.1.1.1 Learning Method

Table 6.1 shows that more than half the students (52%) preferred using both online learning and traditional lecture. Around 27% favoured attending the traditional lectures, while 15% preferred online learning, and only 6% favoured other types of learning methods including attending labs, practical sessions, and mixed learning types, such as online with lab or traditional with lab.

The results indicate that both online learning and traditional lectures are more commonly preferred as compared to just online learning or traditional way of learning. It is clear that the students who preferred both ways, although they had used the online learning before, still needed the traditional lectures for different reasons.

6.6.1.1.2 Online Learning Experience

The next question asked the students whether they had used the online learning environment for personal study before. Table 6.1 illustrates that almost two-third of students (66%) had not used an online learning system before for personal studying while 34% had used online learning systems. When the students were asked which e-learning system you had used, some students who answered “yes” stated different learning management systems, such as Udemy (Udemy, 2019), Code (Code, 2019), Duolingo (Duolingo, 2019), Coursears (coursears, 2019), Misk (Foundation, 2019), Rwaq (Rwaq, 2019), Doroob (Doroob, 2019), etc.

6.6.1.1.3 Time Spent using Online Learning for Personal Learning Each Week

The students were questioned about time spent using online learning for studying. The results indicate that most students spent fewer than 4 hours using online learning weekly. As evident from Table 6.1, 45% students spent fewer than 2 hours per week using online learning. Additionally, 43% of students spent 2-4 hours a week utilising online learning. This implies that most students (88%) did not use online learning for over four hours per week.

6.6.1.1.4 Student Opinion about Online Learning compared to Traditional Lecture

As shown in Table 6.1, the students were questioned in regard to if they found the online learning experiences similar to, or superior or inferior to, traditional learning. The results show that half of the students (50%) found both learning methods to be similar. Moreover, 34% students found online learning to be inferior compared to the traditional learning, and only 16% found the online learning to be superior compared to the traditional learning. This result was expected as almost two-third of the students (66%) had not used an online learning system for personal study before, and this highlighted the need for improvements in online learning as provided by the proposed CaFAE system.

The students who preferred online learning over traditional lecture stated different factors that influenced their preference. The following percentages are based on the students’ comments (whether positive or negative). Thirty one percent of students believed that the online learning system is considered as backup and supportive of their study in case of missing information as one of the student stated *“When I miss some information in the lecture, it is easy for me to recap and find what I miss”*. Some of them thought that online learning is valuable especially for doing the exercise, practice, details and examples. One of the students declared: *“If I don't understand a specific point in the lecture, I can look back online and search to find it with different explanation or media type”.* Some 19% students suggested that they could learn better, when they find the materials anytime using the online learning. Another 19% considered that the online learning system is more flexible that makes them learn depending on their ability. One of the students said: *"They are better, they allow you to study at your own pace"*. Likewise, 19% students remarked that one of the advantages of using the online learning system is repeatability, which makes you rewind and pause to take notes. One of the students mentioned: *"easy to pause and replay to take notes"*. Only 13% students indicated that they could access the learning material anytime and anywhere.

The students who chose traditional learning over online learning indicated various aspects that affected their views. Some 21% of the respondents deemed that using the online learning is easy to get distracted. A growth in popularity of using social networks make the students to not pay attention and not concentrate on their study while using online learning. The majority of the participants (47%) revealed that the online learning has a lack of interaction as the students cannot ask questions and get the answers directly. One of the students stated: *"I prefer the traditional lecture because if I want to ask the teacher, I can get the answer from the tutor"*. Another student mentioned: *"If you have a question, you can't ask immediately"*. Therefore, online learning needs to be more interactive that does not make the students ask the tutor without help from the online learning. Another negative aspect of using online learning, as confirmed by 16% students, was lack of motivation. They believed that the traditional lecture provided them more motivation by practicing and discussing with each other. Some 11% of the students indicated that online learning is not trustful regarding the quality and integrity of the materials. One student stated that the online learning is not support for all the material. He said: *"Participation is important especially for the programming language, and the online learning doesn't provide good materials or methods"*.

The students who selected both online and traditional learning expressed their preference based on the following factors:

- <u>Accessibility:</u> Online learning can be accessed from any location.
- <u>Availability:</u> Online learning materials are available at any time.
- <u>Repeatability:</u> Online learning can be repeated multiple times.
- <u>Interaction:</u> By asking questions and sharing ideas with other students using online learning such as chatting rooms and discussion groups.
- <u>Flexibility:</u> Online learning makes the students work at their own pace depending on their performance.
- <u>Engagement:</u> Traditional learning engages the student with the learning process.
- <u>Motivation:</u> By practicing and participating with each other in traditional lecture.
- <u>Full knowledge:</u> By using both learning methods.
- <u>Supportive:</u> Online learning can be used as backup for traditional lecture.

These are some of the responses of the students:

"Both as you can pause and replay when you don't understand something in the lecture and traditional lecture when you have questions".

"Sometimes online learning helps you understand more but you need to attend the traditional lecture in case if you want to participate".

"Online learning is more accessible and convenient as being able to re-read / rewind and the traditional lecture is good for engagement. I like them both".

"I am using them both; the traditional lecture to fully understand the topics and online learning for support or if I miss some information from the lecture".

6.6.1.1.5 Student Opinion about Online Learning Improving Understanding

Although 66% students had not used any online learning system before, more than half of the students (54%) agreed that online learning is a good way of improving understanding. More than two-third of students (65%) who answered this question, indicated different factors that improved understanding. Based on the responses, 68% students answered positively to this question. Additional support, good for practicing, providing different learning materials, repeatability, flexibility, accessibility, and availability are the factors commonly mentioned in their responses. Some of their responses are listed below.

"It really does because if I did not understand the lecture in class, I can return to online learning website"

"I think it's good for practicing and doing some quizzes"

"In some cases, such as using different content and styles"

"Using online learning makes you review the materials repeatedly"

"Saving your time and learning in everywhere."

"They are available, so you can learn anywhere anytime ".

However, 32% students responded negatively to this question due to factors, such as lack of interaction and motivation, less communication, easy distraction. Here are some of the views of the students:

"I don't think so because when I have a question, I need an answer from the teacher"

"You don't know about your progress"

"Could be, but not every time especially for practical courses"

6.6.1.1.6 Student Opinion about Adaptive e-Learning

The findings showed that 95% students had not used an adaptive online learning system before.

The students mentioned some learning management systems with their opinions:

"Edx, it was good, it provided me recommendation exercise in maths"
Edx is an open online learning system and is considered one of the Massive Open Online Course (MOOC) systems (edX, 2019). This system provides the students with exercises after each topic without any recommendations what the students should learn based on their understanding level.

"Khan academy, they provide list of videos and they start with easy lessons to the hard ones, it was beneficial"

Khan Academy is an online learning website that suggests practice exercises, list of videos, and a personalized learning profile that allow learners to study at their own pace and it is considered as an adaptive technology that identifies knowledge levels and learning gaps (KhanAcademy, 2019).

"Qiyas, this was a website for measuring the ability in maths and it gave me recommendations for my weaknesses"

Qiyas is an online measurement and evaluation system of the students' abilities after graduation from high school in Saudi Arabia (Qiyas, 2019). However, in this example, this student misunderstood the adaptive meaning because this type of measurement is not considered as an adaptive system. In fact, it is just an online test without recommendations.

"Doroob, showed me many courses depending on my field".

This website (Doroob, 2019) has a similar structure and design of Edx system but with Arabic version. It provides many courses and topics with different exercises after each topic.

The responses were very similar to the pre-questionnaire for both groups as they had the same background of online learning.

6.6.2 Hypothesis Analysis

An independent sample test was used to verify the differences between the two groups, the adaptive group and the non-adaptive group, after the participants finished the pre-test and completed the post-test. In addition, this test was applied to identify if there were statistically significant differences between the two groups for the time spent in learning materials and the time spent in the post-test.

The 'Paired' samples t-test was used to identify whether there were 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 analysing 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, it 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- α) % confidence level. This would be evident for rejecting the null hypothesis that there is no statistically significant difference in the means, in favour of the alternative hypothesis that there is a statistically significant difference. In the evaluation, three different confidence levels were taken which are: 0.05 meaning that 95% confidence level is obtained, 0.01 meaning that 99% confidence level is obtained, and 0.001 meaning that 99.9% confidence level is obtained (Trochim, 2000).

6.6.2.1 Hypothesis H1: "The pre-test will show no significant difference between the two groups"

Firstly, an independent sample t-test is used to check whether the two groups had significant differences in the means of their pre-test scores. Table 6.2 shows that the p-value is 0.774, 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 two groups. In that case, this indicates that the H1 hypothesis was satisfied and that the students in each of the two sample groups are not likely to have had a different background knowledge level.

Table 6.2 Results of Independent Sample t-test for Differences between the Mean Pre-test Scores of the two Groups

Variable	Group	N	Mean	Std. Deviation	T	p
Pre-Test	Adaptive Group	50	3.8092	1.02222	-0.288	0.774
	Non-Adaptive Group	50	3.8736	1.20852		

*p < 0.05, **p < 0.01, ***p < 0.001

6.6.2.2 Hypothesis H2: "Post-test, the adaptive group will significantly out-perform the non-adaptive group"

To examine this hypothesis, an independent sample t-test was performed to find the differences between the mean scores of the two groups in post-test scores. Results are shown in Table 6.3 where it can be seen that the p-value is 0.000 ($p < 0.001$), which is less than $\alpha = 0.001$.

This indicates 99.9% confidence level that there was a statistically significant difference between the two groups in the post-test scores. This also indicates that hypothesis H2 is accepted.

Table 6.3 Results of Independent Sample t-test for Differences between the Mean Post-test Scores of the two Groups

Variable	Group	N	Mean	Std. Deviation	T	p
Post-Test	Adaptive Group	50	8.3125	1.27525	8.563	0.000***
	Non-Adaptive Group	50	6.2898	0.86345		

*p < 0.05, **p < 0.01, ***p < 0.001

6.6.2.3 Hypothesis H3: "In each of the groups separately and combined, the post-test scores will be significantly higher (better) than pre-test scores"

To test this hypothesis, the 'Paired Samples t-test' was performed to find out if there was a statistically significant difference, to a 95%, 99% or 99.9% 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 6.4 where it may be seen that:

For both groups, adaptive and non-adaptive, the mean post-test score was 7.22 which is greater than the mean pre-test score of 3.84. The t-test gives a value which was significant at t (99.9) =19.10, p=0.000 ($p < 0.001$); Therefore, it can be inferred that the difference between these two means is statistically significant.

For the adaptive group, the mean post-test score was 8.15 which is greater than the mean pre-test score of 3.80. The t-test gives a p-value of 0.000 which is less than $\alpha = 0.001$. Therefore, it can be inferred that the difference between these two means (pre-test and post-test) is statistically significant to a 99.9% confidence level.

For the non-adaptive group, the post-test score was 6.28 which was greater than the mean pre-test score of 3.87. The t-test gives a p-value of 0.000, which is less than $\alpha = 0.001$. Therefore, the difference between these two means (pre-test and post-test) is statistically significant to 99.9% confidence level. Based on the above tests of significance, the hypothesis H3 is accepted.

Table 6.4 Results of Paired-Samples t-Test to Compare Two Test Means Pre- and Post- Scores within the Same Group

Group	Test	N	Mean	Std. Deviation	T	p
Both	Pre-Test	100	3.8414	1.11405	19.106	0.000***
	Post-Test	100	7.2223	1.43257		
Adaptive Group	Pre-Test	50	3.8092	1.02222	19.367	0.000***
	Post-Test	50	8.1548	1.27525		
Non-Adaptive Group	Pre-Test	50	3.8736	1.20852	12.362	0.000***
	Post-Test	50	6.2898	0.86345		

*p < 0.05, **p < 0.01, ***p < 0.001

6.6.2.4 Hypothesis H4: "Less time will be taken to learn the concepts and answer post-test questions by those using adaptive e-learning than by those using non-adaptive e-learning."

In this hypothesis, an independent sample t-test was performed to find the differences between the mean time spent in answering the pre-test, the time spent in learning materials, and the time spent in answering the post-test of the two groups. As can be seen from Table 6.5, the p-value is 0.003, which is less than $\alpha = 0.01$. This indicates, to a 99% confidence level, that there was a statistically significant difference between the two groups in time spent answering the pre-test. It can be seen that the p-value is 0.001 for learning time, which is less than $\alpha = 0.01$. This indicates, to a 99% confidence level, that there was a statistically significant difference between the two groups in time spent learning the materials.

Table 6.5 Results of Independent Sample t-test for Differences between the Mean Time Spent in Learning Materials for the two Groups

Variable	Group	N	Mean	Std. Deviation	T	p
Pre-test Answering Time	Adaptive Group	50	22.7800	14.91375	-3.011	0.003**
	Non-Adaptive Group	50	32.4400	17.09298		
Learning Time	Adaptive Group	50	72.3400	34.80184	-3.581	0.001**
	Non-Adaptive Group	50	95.0800	28.36845		
Post-test Answering Time	Adaptive Group	50	21.7600	14.91002	-2.535	0.013*
	Non-Adaptive Group	50	29.4600	15.46320		

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

As shown in Table 6.5, the p-value is 0.013 for post-test answering time, which is less than $\alpha = 0.05$. This indicates, to a 95% confidence level, that there was a statistically significant difference between the two groups in the time spent answering the post-test.

Although the results were consistent with the hypothesis, the outcome of this hypothesis is partially valid, but not countable because the server was sometimes down during the study. Therefore, it is hard to measure the time needed for learning the concepts or answering the post-test questions. In addition, the students were sometimes not learning the concepts all the time, they were distracted, as talking to each other, browsing other pages or going out. Accordingly, hypothesis H4 is rejected.

6.6.3 Hypothesis Test Result

All the hypotheses mentioned in Chapter 4 were examined statistically. The test results indicate that both groups are likely to have benefited significantly from the learning experience with respect to the case study based on the pre-test and the post-test scores.

As shown in Figure 6.1, the adaptive group had an average increase of 65% in the post-test, whereas the average score of the non-adaptive group increased by 35%. The results revealed that the adaptive group had higher average scores in post-test as compared to the non-adaptive group.

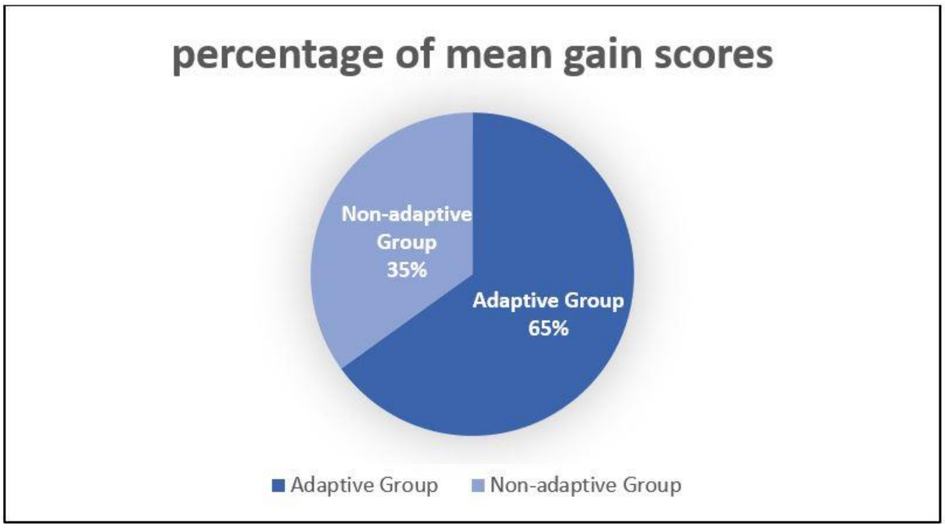


Figure 6.1 Percentage Gain from Pre-test to Post-test Scores for both Groups

The results of a t-test, as explained in Section 6.6.2.3, show the overall change for each group from pre-test to post-test, as depicted in Figure 6.2. The adaptive group post-test had the higher significant difference from the pre-test as compared to the non-adaptive group post-test which showed lower significant difference from the pre-test.

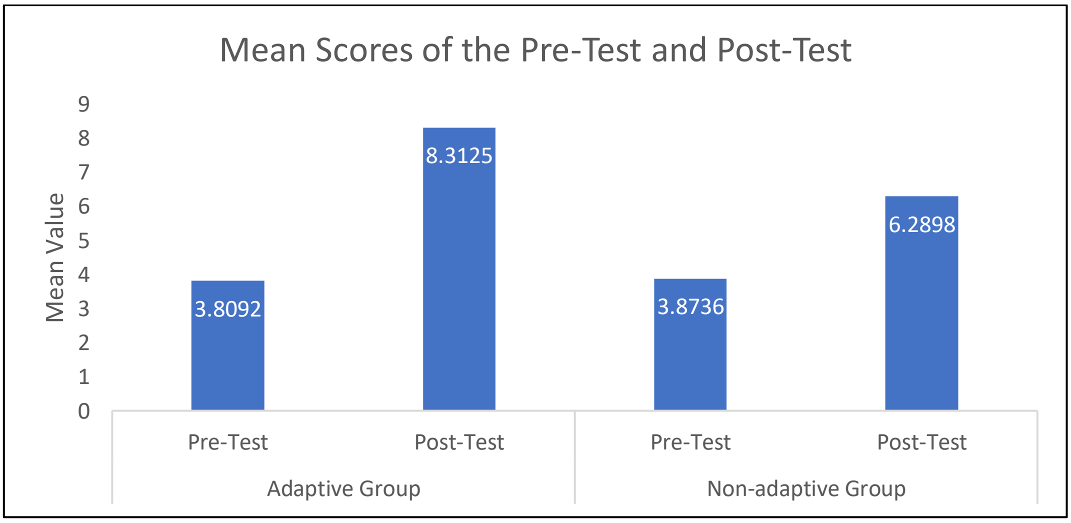


Figure 6.2 Differences between Mean Scores of the Pre-Test and Post-Test

The effect size calculated using Cohen's d term, was 1.74 for the non-adaptive group, which would be considered a large effect size(Valentine and Cooper, 2003), whereas the effect size for the adaptive group was 2.74, which in Cohen's d term (Valentine and Cooper, 2003) would be considered a very large effect size.

Based on the effect size results, Figure 6.3 depicts that the non-adaptive group had the lowest improvement in mean scores from the pre-test to the post-test, 39%, whereas the adaptive group had a mean scores improvement of 61%.

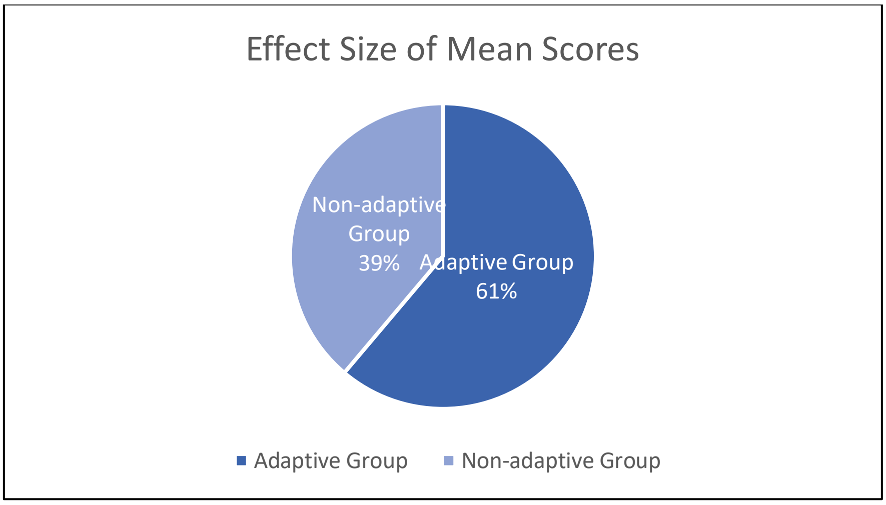


Figure 6.3 Effect Size between the Two Groups in Mean Scores of the Pre-Test and Post-Test

6.6.4 Post-Experiment Questionnaire Findings

The post-experimental questionnaires were designed in regard to group type (adaptive or non-adaptive) for evaluating and comparing user experiences during and subsequent to use of the system. The post-experimental questionnaire consisted of questions in relation to attitude and behaviour. The following sub-sections give more detail of the explanations and analysis of each questionnaire based on each group.

6.6.5 Adaptive Post-Experiment Questionnaire Findings

The questionnaire was utilised to assess system usability and evaluate student experiences of the learning system (Appendix B.2). The questionnaire results are crucial to understand student evaluations of the system and usefully it pertained to their learning experiences. In the adaptive module, the questionnaire consisted of 34 closed-ended questions and 10 open-ended questions.

All participants (50) in the adaptive group answered Part A of the post-experiment questionnaire. However, out of 50 students, only 42 participated in the rest of the post-experiment questionnaire (Parts B and C).

The data recorded from the post-experiment questionnaire and its analysis is given below.

6.6.5.1 Part A: Scalable Measurement Questionnaire Analysis

The captured data was analysed relating to the adaptive group factors. The students were questioned about describing various features, which included their attitudes and behaviours towards using an adaptive e-learning system. Each characteristic was measured by statements which used differing Likert Scales (Clason and Dormody, 1994). Each Likert Scale score (composite score) was computed to interpret the response of each student. The measurement scales used (including Likert scale type) are explained here for each factor.

Every item in each factor was measured using a 5-point Likert scale (‘Strongly agree’, ‘Agree’, ‘Neutral’, ‘Disagree’ and ‘Strongly disagree’).

System Usability (SU)

The *System Usability* factor was measured using four items in the student questionnaire. The collected data was about student perception of system usability. The measuring items are shown in Table 6.6 and the results are shown in a combined graph in Figure 6.4.

Table 6.6 Measured Items for System Usability Factor (Adaptive Group)

Factor	Item code	Statement
System Usability	SU1	The e-learning system was easy to use.
	SU2	The instructions provided to use the tools within the site are clear and precise.
	SU3	Whenever I make a mistake using the system, I recover easily and quickly.
	SU4	I would imagine that most students would learn to use this system very quickly.

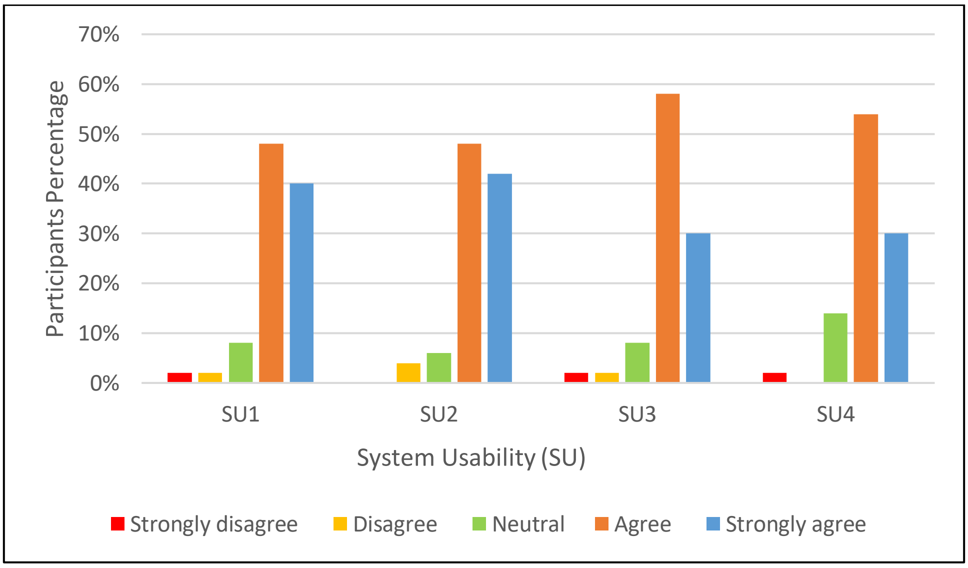


Figure 6.4 Results of Measured Items for System Usability Factor (Adaptive Group)

Item SU1 asked students if they believed that the e-learning system was simple to use. Figure 6.4 shows that 88% of respondents were in agreement with the statement, 8% of them were neutral, and 4% were in disagreement with the statement. The total item score was 4.22, showing student perceptions were highly positive regarding the system’s ease of use.

Item SU2 questioned if students thought that the instructions given on the site were clear and precise. Figure 6.4 shows that 90% of respondents agreed with the statement, whereas 6%

were neutral, and 4% disagreed. This composite item score of 4.28 indicates a very high agreement level that the instructions provided on the site are clear and precise.

The students were questioned in item SU3 on when they made a mistake on the system, they recovered quickly and easily. Some 88% of respondents were in agreement that they would, whereas 4% disagreed, and 8% were neutral. The total item score was 4.12, indicating a high level of agreement that when students made mistakes on the system, they recovered quickly and easily.

Item SU4 questioned participants about whether they learned to use the system very quickly. The SU4 bar chart (Figure 6.4) illustrates that 84% of respondents were in agreement that learning how to use the system happened very quickly, whilst only 2% of them disagreed. Some 14% of the participants stated a ‘neutral’ answer. The total scores of the item were 4.10, thus showing a high agreement level that learning how to use the system happened very quickly.

The calculated composite scores for the *SU* factor were 4.18, showing that the *System Usability* factor very likely to influences use of the adaptive e-learning system. The study guide interprets the descriptive analysis results in Table 4.5 (Chapter 4). It is probable that the *SU* factor is an influential factor regarding student utilisation of the adaptive e-learning system.

Learning Material (LM)

An additional factor was used to measure the *Learning Material* effectiveness. This factor was measured using four items concentrating on various aspects of learning material efficiency. Each measuring item is listed in Table 6.7; the results are shown in the Figure 6.5 combined graph.

Table 6.7 Measured Items for Learning Material Factor (Adaptive Group)

Factor	**Item code**	**Statement**
Learning Material	LM1	The material provided by the e-learning system is easy to understand.
	LM2	The e-learning system made it easy for me to find the material I need.
	LM3	I have no problems accessing and going through the materials.
	LM4	The e-learning system provides sufficient material.

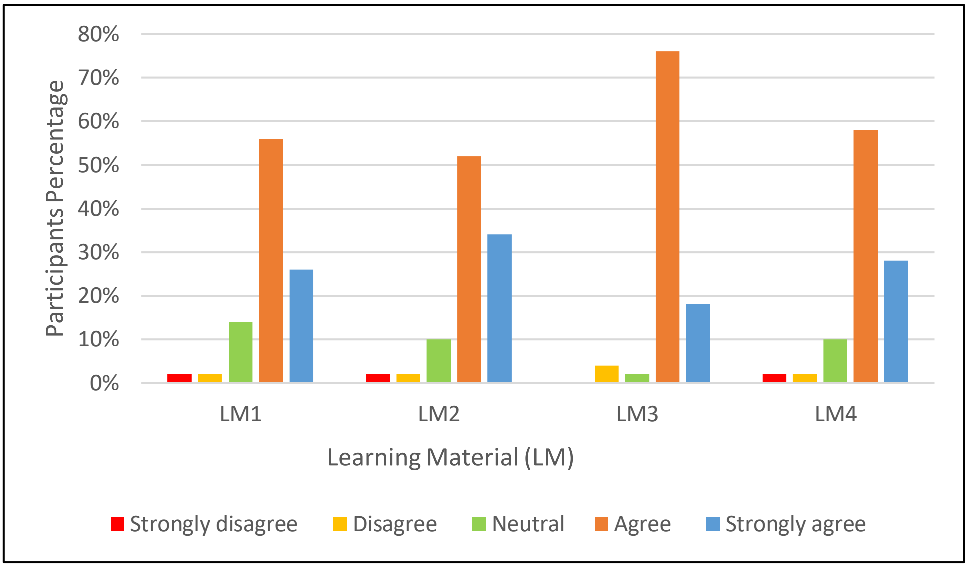


Figure 6.5 Results of Measured Items for Learning Material Factor (Adaptive Group)

In item LM1, the students were questioned whether they agree that the learning material was easy to understand. Figure 6.5 shows that 82% respondents agreed with this statement, while 14% of them were neutral, and 4% respondents disagreed with this statement. The total score of this item was 4.02 indicating that the student perception was positive in terms of the ease of understanding the learning material.

This item LM2 asked the students whether they believe that the e-learning system made it easy to find the material they need. Some 86% of the respondents agreed, 10% were neutral, and 4% of them disagreed. The total Likert score was 4.14 which shows positive feedback regarding the system providing the needed material for the students.

The result of item LM3, presented in Figure 6.5, also shows that the majority of the respondents believed that they had not faced any issues in accessing and going through materials. Some 94% of the participants agreed, whereas 2% were neutral and 4% of them disagreed. The total Likert score was 4.08 which indicates that accessing and going through the materials was not a problem.

Item LM4 asked the participants whether the e-learning system provides sufficient material. It is clear from Figure 6.5 that 86% respondents agreed, while 10% were neutral and only 4% disagreed. The Likert score was 4.08, indicating that the e-learning system provides sufficient material.

The composite score of the *Learning Material* factor is 4.08 showing that *LM* is an influential factor. It is likely that it has a positive influence on the usage of learning materials.

User Satisfaction (US)

User satisfaction (US) is another factor used to measure six items related to different parts of the e-learning system.

Table 6.8 Measured Items for User Satisfaction Factor (Adaptive Group)

Factor	**Item code**	**Statement**
User Satisfaction	US1	I feel I learn more in this system.
	US2	I feel comfortable using this system.
	US3	I believe I became productive using this system.
	US4	This system has all the functions and capabilities I expect it to have.
	US5	The activities/quizzes provided in the course enhanced my learning.
	US6	Overall, I am satisfied with this system

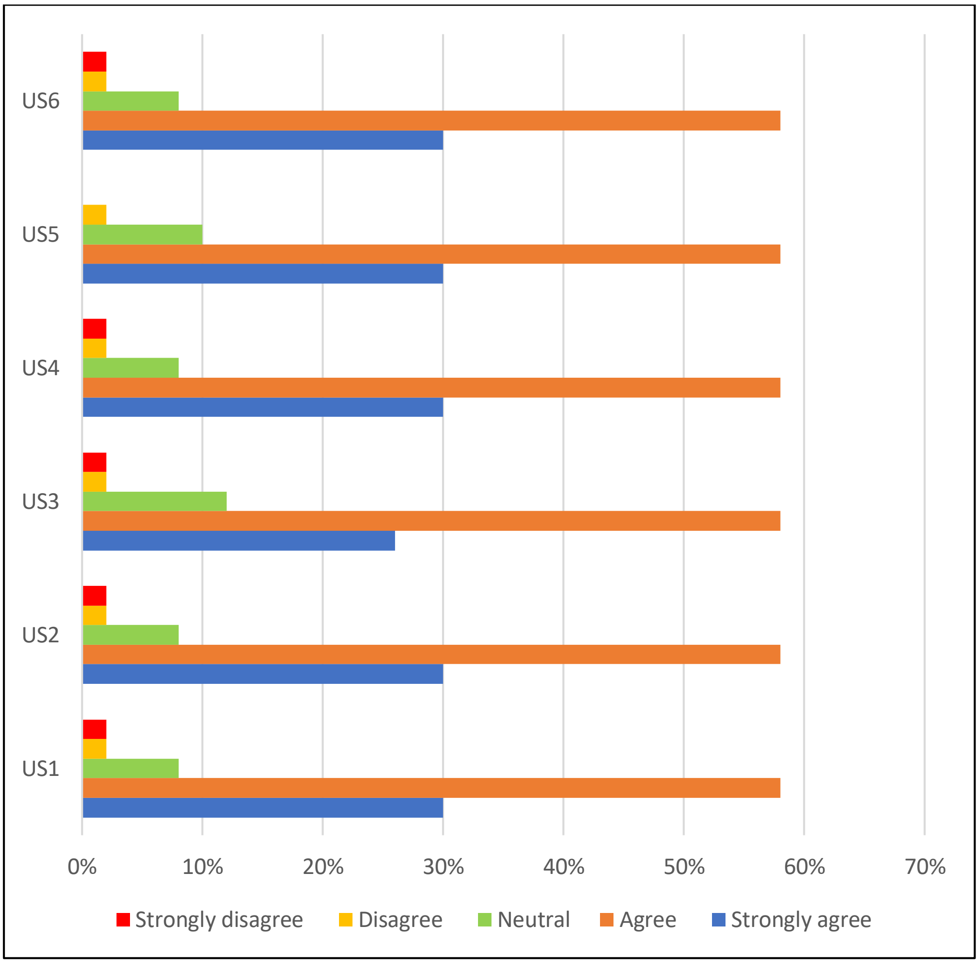


Figure 6.6Results of User Satisfaction Measurement Items (Adaptive Group)

The first item (US1) asked students if they felt that they learn more through using the system. Figure 6.6 illustrates that 88% of respondents felt that they learned more using the system. Some 8% of respondents were neutral, whereas 4% did not feel that they learned more using this system. The composite score was 4.12, indicating an overall satisfaction with learning more using this system.

Item US2 asked the students whether they s feel comfortable using the system. The results show that majority of the surveyed participants (88%) felt comfortable using the system, although 4% disagreed with that. Some 8% of the respondents were neutral (see Figure 6.6). The composite score of this item was 4.12 indicating overall satisfaction.

In item US3 the students were questioned about if they believed they became more productive using this system. Figure 6.6 illustrates that 84% of respondents agreed, whereas 12% were neutral, and 4% were in disagreement with the statement. The combined score of item US3 was 4.04, indicating that most students believed that they became productive using the system.

In item US4, students were questioned about if they thought that the system every function and capability which they expected. Figure 6.6 shows that most participants responded positively and agreed with this statement (88%). Respondents dissatisfied with this statement was 4%, whereas 8% were neutral. This indicates that the system has every function and capability of student expectations. The overall Likert score of this item is 4.12, indicating a high level of student satisfaction with system functions and capabilities.

In US5, the students were asked whether the activities/quizzes provided in the course enhanced their learning. It is evident from Figure 6.6 that 88% respondents agreed that the activities and quizzes enhanced their learning, while 2% disagreed. Around 10% respondents were neutral in their answers. The Likert score of this item was 4.16, indicating that the activities and quizzes provided in the course enhanced learning.

The students were requested in item US6 to state their views in regard to the statement "Overall, I am satisfied with this system". Figure 6.6 shows that around 88% respondents agreed, while 4% disagreed and 8% gave a neutral response. A Likert score of 4.12 indicates an overall satisfaction with this system generally.

The composite score of 4.11 of User Satisfaction (*US*) measuring the *Satisfaction* factor influence means that general agreement exists that user satisfaction has a high impact level.

Adaptation (A)

Adaptation is one of the main factors that was measured with eight items in different parts of adaptation, and it is used to provide more precise and objective results.

Table 6.9 Measured Items for Adaptation Factor

Factor	Item code	Statement
Adaptation	A1	I feel the adaptive e-learning approach can substitute for or enhance the normal online learning approach.
	A2	The e-learning system provided material that exactly fitted my needs.
	A3	The e-learning system enabled me to learn the material I need.

A4	The e-learning system enabled me to control my learning progress.
A5	The e-learning system recorded my learning progress and performance.
A6	The e-learning system was more adaptive than I thought.
A7	The feedback from activities/quizzes helped me to locate where I am having difficulties.
A8	The responses to the pre-test helped me understand where I am having difficulties.

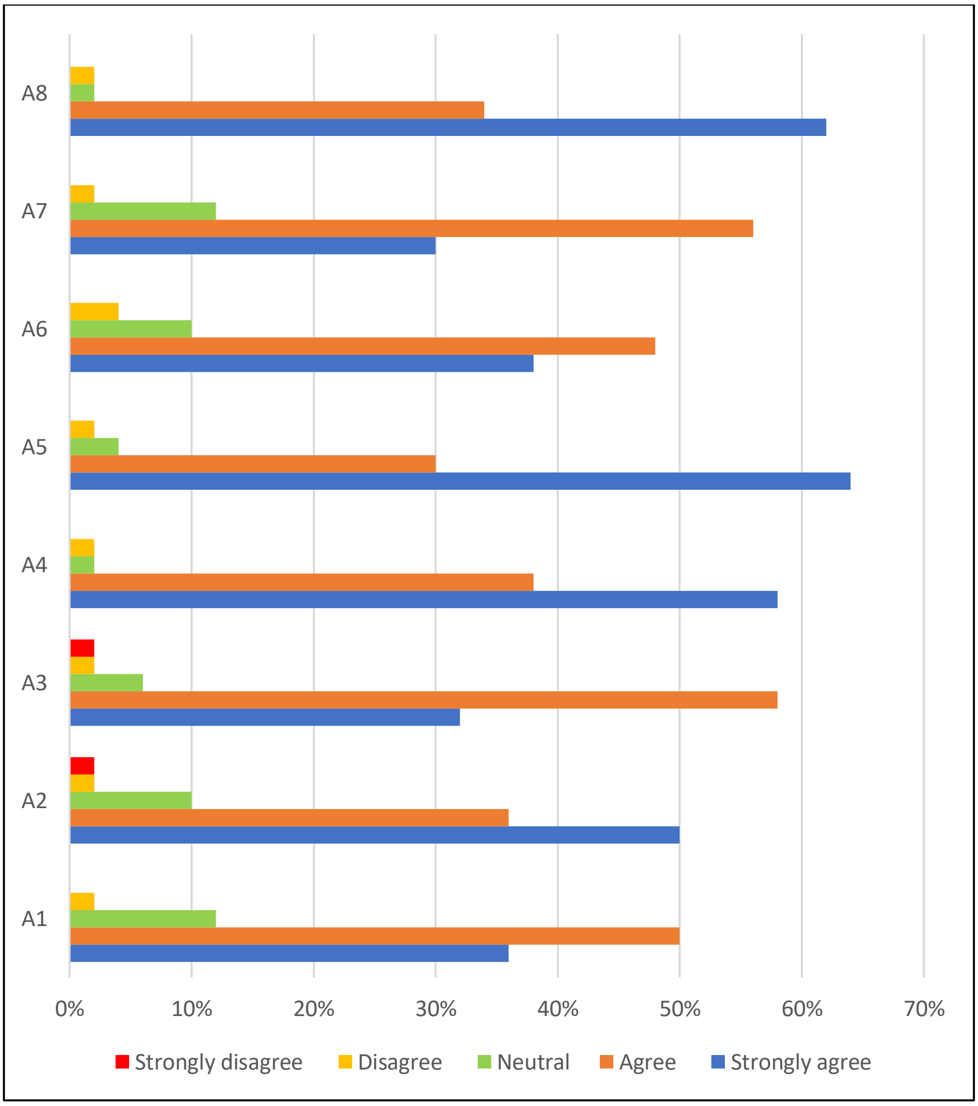


Figure 6.7 Results of Measured Items for Adaptation Factor

As shown in Figure 6.7, 86% students who responded to item A1 felt that the adaptive e-learning approach can substitute for or enhance the normal online learning; around 12% were neutral and only 2% did not agree with this statement. The total Likert score was 4.20 indicating that adaptive learning enhances the normal online learning approach.

In item A2, the participants were asked whether the e-learning system provided material that exactly fitted their needs. Some 86% of the respondents agreed with this, while 10% were neutral and only 4% disagreed. The Likert score of this item was 4.30 which shows that the e-learning system provided appropriate learning materials to the students.

In item A3, the majority of students (90%) agreed with the statement: "the e-learning system enabled me to learn the material I need". 6% of the respondents were neutral, and only 4% didn't agree with this statement. The total score was 4.16 which points that the e-learning system made the students to learn materials they needed.

Students were asked in item A4 to indicate whether the e-learning system enabled them to control their learning process. Most students (96%) agreed with this statement, 2% gave a neutral answer, and 2% disagreed. The total Likert score for this item was very high 4.52 indicating that the e-learning system made the students control their learning process.

In response to item A5, 94% students responded that the e-learning system recorded the learning process and performance. Around 4% were neutral and 2% did not agree with this statement. The total score of this item was 4.56 demonstrating that the e-learning system recorded the learning process and performance for the students.

As can be seen from Figure 6.7, in item A6, 86% respondents agreed that the e-learning system was more adaptive than they thought. Just 4% of them did not agree with that, and 10% were neutral. The total Likert score was 4.20 that shows that the e-learning system was more adaptive than what was expected by the students.

When the participants were questioned in item A7, the majority (86%) agreed that the feedback from activities/quizzes helped them to locate where they were having difficulties, while 12% were neutral and only 2% did not agree with this statement. The total score was 4.14 which indicates a high level of agreement regarding this statement.

Finally, in item A8, the students were asked whether the responses to the pre-test helped them understand where they were having difficulties. A large number of students (96%) felt that the pre-test helped them locate their difficulties, while only 2% disagreed with this statement. The remaining 2% were neutral. The Likert score was very high (4.56) showing that the pre-test helped most students to understand their weaknesses.

The composite score of this factor (A) was 4.33 which highlights a very high influence of adaptation in the e-learning system.

Coloured Concept Map Effectiveness (CCME)

Another factor (*Coloured Concept Map Effectiveness)* was measured with two items to evaluate the effectiveness of coloured concept map.

Table 6.10 Measured Items for Coloured Concept Map Effectiveness Factor

Factor	Item code	Statement
Coloured Concept Map Effectiveness	CCME1	I found the coloured concept map is more helpful and helped me understand my knowledge level.
	CCME2	The coloured concept map showed information that exactly fits my understanding level.

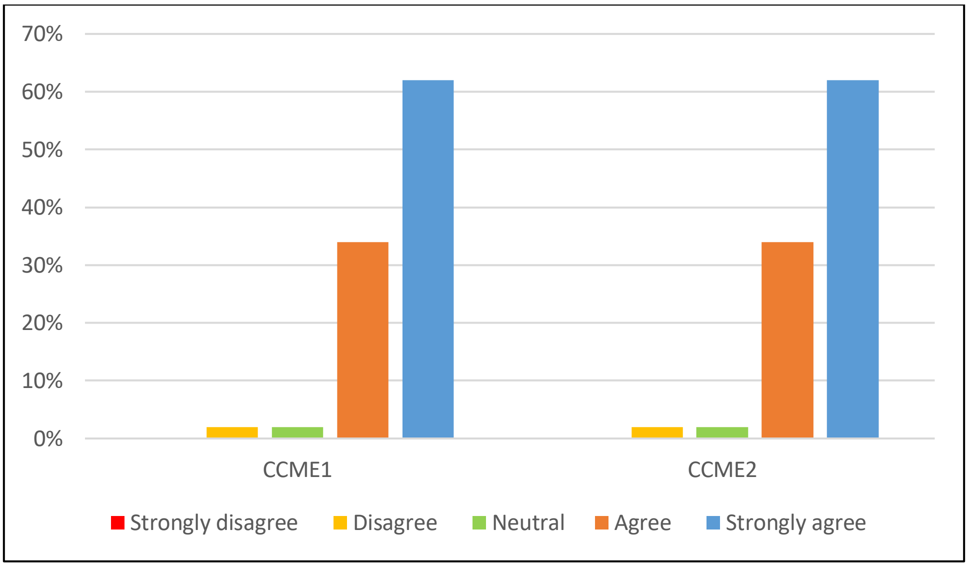


Figure 6.8 Results of Measured Items for Coloured Concept Map Effectiveness Factor

In item CCME1, 96% respondents felt that the coloured concept map is more helpful and helped them understand their knowledge level. A small number of students (2%) did not agree with this statement, while the remaining 2% were neutral. The Likert score was 4.56 that shows that the coloured concept map was helpful and made students understand their knowledge level for each concept in the subject domain.

Looking at Figure 6.8, it is apparent for item CCME2 that most participants (96%) agreed that the coloured concept map showed information that exactly fitted their understanding level, while 2% disagreed with this statement, and the remaining 2% were neutral. The Likert score was very high (4.56) for item CCME2 which indicates that the coloured concept map showed information to the students that exactly fitted their understanding level.

The composite score of this factor (CCME) was 4.56, highlighting a very high impact of the coloured concept map effectiveness.

Ranked Concepts List Effectiveness (RCLE)

For this factor, the students were asked about the effectiveness of ranked concept list and how the ranked concept list helped them understand their difficulties.

Table 6.11 Measured Items for Ranked Concepts List Effectiveness Factor

Factor	**Item code**	**Statement**
Ranked Concept List Effectiveness	RCLE1	The ranked concepts list helped me to locate where I am having difficulties.
	RCLE2	I can follow the ranked concepts list easily.

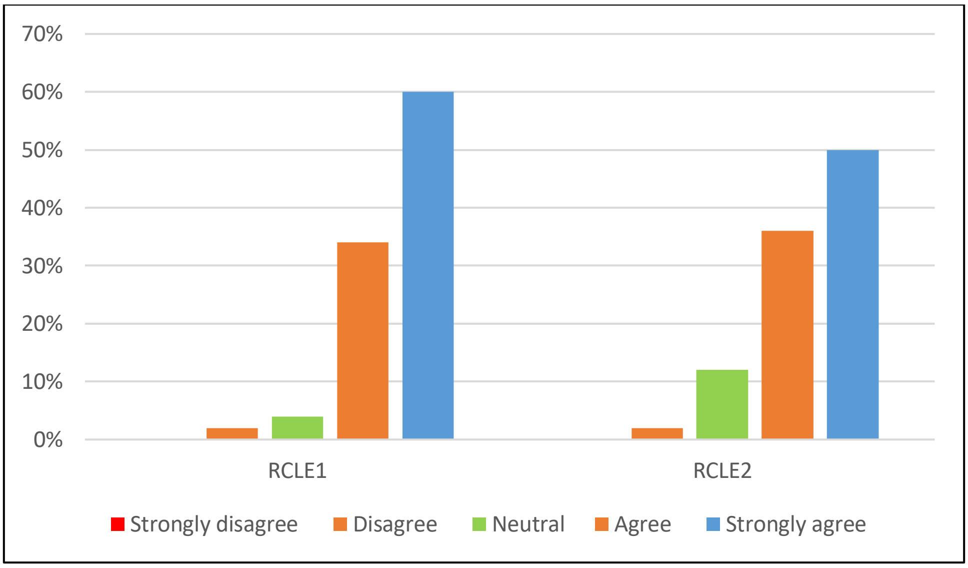


Figure 6.9 Results of Measurement Items for Ranked Concepts List Effectiveness Factor

As shown in Figure 6.9, for item RCLE1, a large number of students (94%) agreed that the ranked concepts list helped them to locate where they were having difficulties. Around 4% were neutral and only 2% disagreed with this statement. The total score (4.52) indicates high level of agreement with this statement.

For item RCLE2, students were asked whether they can follow the ranked concept list easily. Some 86% of the participants felt that they could follow the ranked concept list easily, while only 2% disagreed with this statement, and 12% were neutral. The Likert score of this item was 4.34 which indicates that the ranked concept list was followed easily by most of the students.

The composite score of RCLE factor was 4.43 which shows a very high influence of the ranked concept list effectiveness.

From the factors analysis above, it is likely that the students had a positive perception of the system in different aspects, and a high degree of agreement for all the factors. Despite the general agreement on factors by most students, we need to identify which is the most likable factor for the students. Table 6.12 shows the factors rank based on their mean (composite scores).

Table 6.12 Descriptive Statistics for the Factor Means and Ranking (Adaptive Group)

Factor name	Mean	Std. Deviation	Result	Rank
System Usability	4.18	0.75092	Agree	4
Learning Material	4.08	0.72040	Agree	6
User Satisfaction	4.11	0.74948	Agree	5
Adaptation	4.33	0.58726	Strongly agree	3
Coloured Concept Map Effectiveness	4.56	0.64397	Strongly agree	1
Ranked Concepts List Effectiveness	4.43	0.69260	Strongly agree	2

Based on the results of the factors in Table 6.12, it seems that the Coloured Concept Map Effectiveness, Ranked Concepts List Effectiveness, and Adaptation factors have a very high level of agreement (Strongly agree) among students. Likewise, System Usability, User Satisfaction and Learning Material factors have a high-level agreement (Agree) among students.

As shown in Table 6.12, based on the composite scores for each factor, it appears that the Coloured Concept Map Effectiveness factor has the highest composite score (4.56) among all factors, followed by the Ranked Concepts List Effectiveness (4.43). Adaptation factor is third with a composite score of 4.33. The Learning Material factor has the lowest composite score (4.08) among all factors.

6.6.5.2 Part B: Qualitative Analysis: Ease and Difficulty of Use

In this section of the questionnaire, students were asked about the ease and difficulty in using different parts of the system. Some 82% of the students responded to the question. Table 6.13 summarizes the responses of the students to this question.

Table 6.13 Student Opinions about The Ease and Difficulty of The System Usability (Adaptive Group)

Easy to Use	Percentage	Difficult to Use	Percentage
Navigation flow	30%	Nothing difficult	24%
Tests	11%	Moving between concepts	19%
Course map	4%	Navigation flow	17%
Materials	13%	Coloured concept map	2%
Coloured concept map	13%	Course structure	5%
Course structure	6%	Tests	10%
Ranked concepts list	17%	Ranked concepts list	13%
Other	6%	Other	10%

As can be found in Table 6.13, different parts of the system were stated to know whether they were easy or difficult to use. The results show that the majority of the respondents (30%) believed that the navigation flow was easy to use in moving from one concept to another, or going through the pages, and steps from the beginning to the end. However, 17% of the respondents did not feel that the navigation flow was easy to use especially after taking the pre-test or accessing the materials. Moreover, 13% of the participants considered that the coloured concept map was easy to display their knowledge levels. Some students believed that the coloured concept map was a helpful method which it makes them memorise the weaknesses and strengths abilities, and some others suggested that it increased their motivation and engagement. On the other hand, only one student found that the coloured concept map was difficult to use with no explanation. It is evident that the coloured concept map was found easy to use, with a very high level of agreement among most students. The ranked concepts list was also found easy to use by 17% of the respondents. One of the students stated: "*It is easy for me to follow the ranked list map which showed me my understanding in each topic*". Another student reported: "*Ranked concept list information showed me my knowledge level*". However, 13% of the respondents found that the ranked concepts list was difficult to use as they couldn't follow the list easily, as well as moving between the concepts through the list itself. One student commented that the ranked concepts list did not provide the whole concepts just provided the concepts that he had poor knowledge of. It is likely that the students who found that the ranked concepts list was easy for them is higher than the students who found it difficult to use for them.

As can be seen from Table 6.13, the participants were divided about whether the pre-test or the post-test was easy or difficult to use. Some 11% of the respondents stated that the tests were easy to do, while 10% of them did not find the tests easy to use or do due to their arrangements as they said. Some 13% of the students felt that the materials of the system including the animations were easy to explore and review. Some students stated that using different format of materials, such as short text, images, and animations increased their understanding, motivation and engagement. Some 4% respondents found that the course map helped them to have an overview of the course, while 5% of the students felt that the e-learning system was not clear to them with no explanation for their responses.

From Table 6.13, it is evident that 19% respondents found ticking boxes when going through the concepts, or moving from one concept to the next one, was difficult to use, made the learning slow, and decreased their learning progress. This is one of the system issues that most students had faced in their learning. Furthermore, the majority of the students (30%) found that the system as a whole or some parts were easy to use and there was nothing difficult while using the system. However, only 10% of the students did not agree with this statement without explaining their responses. It seems that the e-learning system was easy to use, with a high level of agreement among students.

6.6.5.3 Part C: Qualitative Analysis:

The third and crucial component of the questionnaire (Part C) was linked to the system's learning support, which was linked directly to the research questions. Such questions were aimed at understanding students' general opinions of the system into how it contributes to their learning, engagement and motivation. In this questionnaire section, 84% students answered every question. Students were requested to give feedback and their impression of the Coloured Concept Map and Ranked Concepts List in greater detail in an open-ended format.

Table 6.14 Results for Closed-Ended Questions in Post-Experiment Questionnaire (Adaptive Group)

Questionnaire Item	Yes	No
Ranked concepts list matched understanding	85.7%	14.3%
Ranked concepts list helped for better understanding	92.9%	7.1%
Coloured concept map determined knowledge level	92.9%	7.1%
Ranked concepts list importance for improved understanding	88.1%	11.9%
The system answered the problems that the students faced in learning	92.9%	7.1%
Ranked concepts list increases learning	90.5%	9.5%
Coloured concept map increases motivation and engagement	90.5%	9.5%
Ranked concepts list and Coloured concept map helped to solve problems	92.9%	7.1%

Table 6.14 shows the findings for the Part C of the questionnaire. As can be seen, that the students were asked whether the ranked concept list matched their understanding of the subject area. Almost 86% of the students felt that the ranked concepts list matched their understanding level, whereas 14% of them did not agree with this. The students who responded positively to this question expressed their views in different ways. More than half of the respondents (56%) believed that the ranked concepts list showed them their abilities and recommended the concepts that they should learn more. Some 23% of the students indicated that the ranked concepts list was clear and easy to follow. One student stated that the ranked concepts list showed him the relationships between the concepts and how they link to each other. 5% of the students responded positively to why they like the system. One student commented: *"Good to see this list after taking the pre-test"*. Another student said: *"I haven't seen list like this before"*.

Here is some of the positive feedback provided by the students:

"It gave me a short review of my understanding level and what I can focus more"
"It covered the material I need in the lecture of the module and filled some gaps that I had"
"The ranked concepts list was clear to me and showed me information about each topic"
"The ranked concepts list shows the relationship between concepts"

14% of the students responded negatively regarding this question. Two students commented that the ranked concepts list provided to some extent the concepts needed to be learned instead of providing all the concepts. One student stated: "*It just shows me the ones that I got wrong"*. Others pointed out that ranked concepts list was not ordered correctly or related to their weaknesses. In these instances, it appears that the students did not understand the structuring method used by the system or the complexity of the information provided.

In general, there was highly positive feedback from students who used the ranked concepts list and felt that it matched their understanding.

Moreover, the students were asked whether the ranked concepts list helped them to have a better understanding of their knowledge towards the subject area. The aim of this question was to measure how the ranked concepts list helped to improve their understanding. As shown in Table 6.14, although 86% of the students felt that the ranked concepts list matched their understanding level, the results display that the majority of the students (93%) agreed that the ranked concepts list helped them to understand their knowledge about the provided concepts. Only 7% did not agree that they had a better understanding of their knowledge level using the ranked concepts list.

Furthermore, to know how helpful the coloured concept map was in determining the knowledge and understanding, participants were asked whether the coloured concept map determined their knowledge and understanding. As evident from Table 6.14, the results indicate that most of the students (93%) agreed that the coloured concept map was a helpful tool in determining their understanding level, whereas only 7% did not agree with this statement. Some 41% of the participants who responded positively considered that the coloured concept map showed them their knowledge level and the concepts that they should learn more. Some 12% of the respondents declared that the coloured concept map was easy to understand and remember the concepts that they had to focus on by colouring category, whereas 27% of the them believed that the coloured concept map was helpful and clear to them. Around 11% of the students stated that the coloured concept map motivated them and made the learning process more interactive. One student stated that the coloured concept map showed him the relationships between the concepts and how they linked to each other.

These are some of the positive responses by the students:

"It showed me where I need to improve and where I'm good"

"I like the coloured concept map because I will remember my understanding level and learn more about these topics"

"This is one of the motivation ways which makes the learning process more interactive"

Only 7% of the students provided negative feedback for this question, such as *"Not organized", "The links between the concepts are not clear"*, and *"I don't think so*" without any explanation. A small number of negative respondents shows that this was not a common outcome and was possibly down to a misunderstanding on part of the student about the system and its functionality.

It appears that most students suggested that the coloured concept map is a helpful way of determining their knowledge and understanding level of the subject area.

As shown in Table 6.14, the participants were asked whether the ranked concepts list was important in improving their understanding. Some 88% of the participants found that the ranked concepts list was significant in increasing understanding, while 12% of them did not agree with this statement. More than half of the participants (51%) who gave positive feedback about the importance of ranked concepts list indicated that it determined their ability and showed them the concepts that they needed to learn more. One student stated: "*It gives short review of the understanding and what needs to be learned more*". Another student commented: "*It makes you focus on the concepts that you should learn first*". Two students pointed out that the ranked concepts list increased their understanding levels and ability. Some 13% of them suggested that the ranked concepts list was clear, helpful and easy to follow. Around 10% of the participants gave different positive responses without any explanation. On the other hand, 18% of the responses were negative, such as related to the arrangement of the ranked concepts list and how it was confusing. Some students commented that ranked concepts list only showed them the concepts for which they got incorrect answers in the quizzes.

As there is high level of agreement among students regarding this question, it seems that the ranked concepts list is important for improving the understanding level.

According to Table 6.14, the majority of the students (93%) found that the system was useful in solving the problems they had faced in their learning. Around 29% of the positive responses indicated that the materials (including different formats, such as short explanations and animations) helped them to understand the concepts. 36% of them stated that the system was organised and helpful in general, and in determining their ability and knowledge level. Two students felt that the coloured concept map was a helpful tool which used to show the ability and memorise the weak parts in the subject area. Around 10% of the respondents considered that the ranked concepts list was a helpful way to be followed by the students based on their abilities. Some 12% of the students provided positive responses regarding ease of use of the system, . Around 7% of the students thought that the system did not help them to find answers to the problems that they had met in their learning. They provided negative feedback about the system, such as how the ranked concepts list showed them the failed ones instead of the whole concepts, as well as the navigation flow when using the system.

On the whole, it is evident from the results that the system helped to solve the problems that the students would meet during learning process.

Through another question, the students were asked if the ranked concepts list was a helpful method for increasing learning, and the coloured concept map increased the motivation and engagement. Large number of students (90.5%) responded that the ranked concepts list increased their learning, and the coloured concept map increased their motivation and engagement. Only 9.5% of the students did not agree with this statement.

The participants were also asked whether they felt that both coloured concept map and ranked concepts list were more understandable and accurate in solving the problems as compared to using the standard online learning system. Table 6.14 shows that the majority of the students (93%) agreed with this statement, while 7% responded negatively. Some 43% of the students who responded positively to this question believed that the coloured concept map and ranked concepts list showed their performance and ability along with the important concepts that needed to be learned. Around 23% of the respondents agreed that both techniques improved their knowledge and understanding level, while 11% of them concurred that both approaches increased their motivation, engagement and interaction. 15% of the participants gave different positive feedback about this question.

Here are some positive comments from participants about the coloured concept map and the ranked concepts list:

"They were good in showing me the areas for which I was good and wrong for others"

"Both are good showing me my ability and recommend the important concepts based on the tests results"

'They built my knowledge level and made me understand the topic in different ways"

"It filled my knowledge gap of the concepts and made the learning more interactive"

"This is a good system; I wish all the courses use the same system"

Only three students provided negative feedback about these two ways, such as "not clear", "Showed me just difficult one in the ranked concepts list", and "Lack of activities".

The overall responses were highly positive indicating that the coloured concepts map and the ranked concepts list are more understandable and more accurate in solving problems as compared to using the standard e-learning system.

Each student was requested to list an advantage and disadvantage of the system regarding the learning process generally. 78% of the students answered the question whilst 22% did not. Almost two-thirds (65%) of responses were positive or an advantage, whereas 35% of them provided negative or a disadvantage of the system. Table 6.15 summarises the main disadvantages and advantages.

Table 6.15 Advantages and Disadvantages of the system (Adaptive Group)

Advantages	Disadvantages

Item	Percentage	Item	Percentage
Coloured concept map	20%	Moving between concepts	48%
System easy to use	10%	Navigation flow	10%
Materials	20%	Tests	10%
Navigation flow	13%	Ranked concepts list	10%
Tests	8%	Others	22%
Ranked concepts list	5%		
System Productivity	10%		
Others	14%		

As evident from Table 6.15, the advantages and disadvantages can be attributed to different aspects of the usability and functionality of the system. These are discussed in more detail in the discussion section.

Table 6.16 The Understanding and Adaptation Levels of the System Rated by the Students (Adaptive Group)

Questionnaire Item	**Measure (1-10)**	**Percentage**
System enhanced learning and understanding	5	7.1%
	6	4.8%
	7	7.1%
	8	19.0%
	9	47.6%
	10	14.4%
Mean	8.38	
System increased adaptation in education	5	7.3%
	6	4.9%
	7	7.3%
	8	17.1%
	9	46.3%
	10	17.1%
Mean	8.40	

Each student was requested to give an overall rating for how the system enhanced student understanding generally. Each respondent rated the system from 1-10, with 1 as the worst and 10 as the best. Table 6.16 shows that the results indicate no rating below 5, and the average rating was 8.38, indicating high agreement by most students who believed that the system enhances understanding and learning.

The students were also asked to rate how the system had increased the adaptation of the system in education in general. As shown in Table 6.16, the results indicate that there was no rating below '5', and the average rating was 8.40 which suggests that the system increased adaptation in learning.

6.6.6 Non-Adaptive Post-Experiment Questionnaire findings:

This questionnaire evaluated system usability and students' experiences with the non-adaptive learning system (Appendix B.3). The results are crucial for understanding student evaluations of the system and how is aided their learning experiences. In the non-adaptive module, the questionnaire contained 23 closed-ended questions and 5 open-ended questions.

All the participants (50) in the adaptive group answered Part A of the post-experiment questionnaire. However, out of the 50 students, only 41 participated in the rest of the post-experiment questionnaire (Parts B and C).

This section presents the data recorded from the post-experiment questionnaire, followed by its analysis and discussion.

6.6.6.1 Part A: Scalable Measurement Questionnaire Analysis

System Usability (SU)

The *System Usability* factor was measured with four items in the questionnaire. The items for measuring the influence of the *SU* factor collected data about the perception of students regarding the system usability.

Table 6.17 Measured Items for System Usability Factor (Non-Adaptive group)

Factor	Item code	Statement
System Usability	SU1	The e-learning system was easy to use.
	SU2	The instructions provided to use the tools within the site are clear and precise.
	SU3	Whenever I make a mistake using the system, I recover easily and quickly.
	SU4	I would imagine that most students would learn to use this system very quickly.

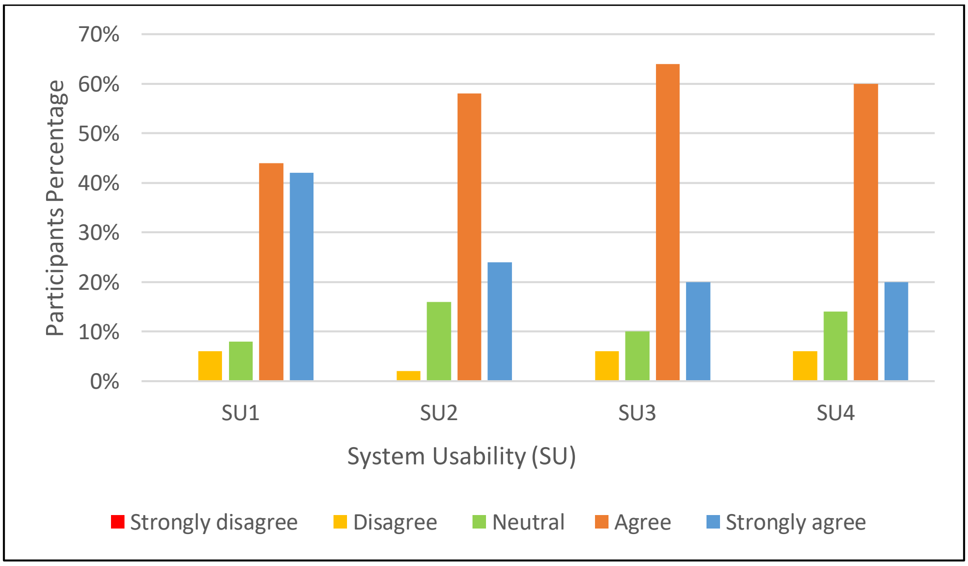


Figure 6.10 Results of Measured Items for System Usability Factor (Non-Adaptive Group)

In item SU1, the students were asked whether they felt that the e-learning system was easy to use. The majority of the respondents (86%) agreed that the system was easy to use, while 8%

were neutral and only 6% disagreed with this statement. The total score of this item is 4.22 which indicates that the system is easy to use.

As shown in Figure 6.10, the participants were asked in item SU2 whether the instructions provided to use the tools within the site were clear and precise. Some 82% of those who participated agreed that the instructions in the system were clear and accurate. Around 16% of the participants were neutral and only 2% disagreed with this. The Likert score was high (4.04) which indicates that the instructions in the system were clear to the students.

In item SU3, the students were asked whether when they made a mistake using the system, they recovered easily and quickly. Most of the students (84%) agreed; only 10% were neutral, and 6% of them did not agree with this statement. The total Likert score was 3.98 indicating that the students could recover easily and quickly whenever they made a mistake while using the system.

The participants were asked in item SU4 whether they would imagine that most students would learn to use this system very quickly. Figure 6.10 shows that 80% participants accepted that the system could be used without difficulties. Some 14% of them were neutral about this statement, while 6% disagreed with this statement. The total score of this item was 3.94 showing that most students could quickly learn to use the system.

The composite score of this factor (SU) was 4.04 indicating that the *System Usability* factor is very likely influencing the utilisation of adaptive e-learning system.

Learning Material (LM)

Another factor was used to measure the *Learning Material* effectiveness. This factor was measured with four items concentrated on different aspects of learning material efficiency.

Table 6.18 Measured Items for Learning Material Factor (Non-Adaptive Group)

Factor	Item code	Statement
Learning Material	LM1	The material provided by the e-learning system is easy to understand.
	LM2	The e-learning system made it easy for me to find the material I need.
	LM3	I have no problems accessing and going through the materials.
	LM4	The e-learning system provides sufficient material.

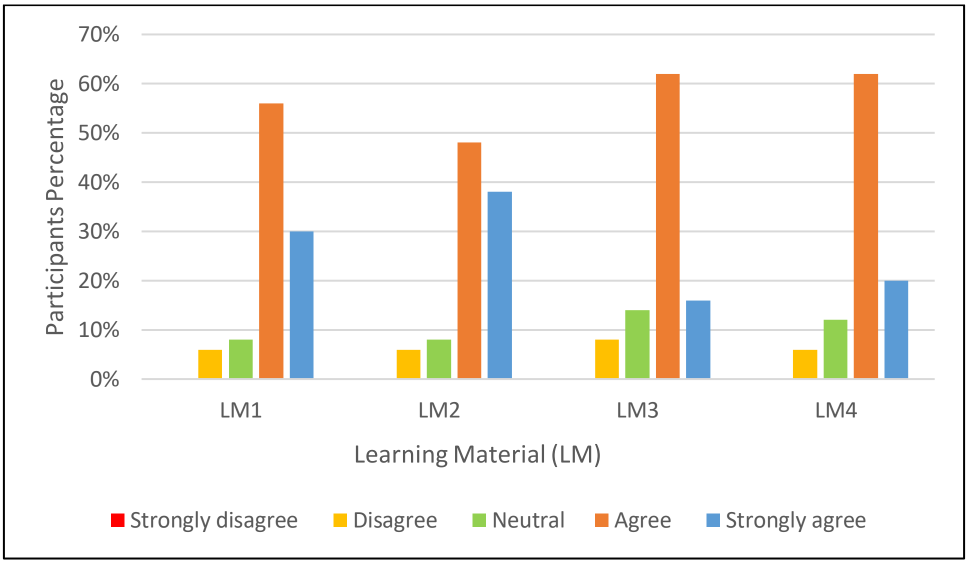


Figure 6.11 Results of Measured Items for Learning Material Factors (Non-Adaptive Group)

As can be seen from Figure 6.11, the majority of the participants (86%) agreed with the statement in item LM1. (i.e., the material provided by the e-learning system is easy to understand. However, 8% of them were neutral about this statement, while 6% did not agree that the material provided by the system was easy to understand. The total Likert score of this item was 4.10 which indicates a very high level of agreement that the material provided by the system was easy to understand for the students.

In item LM2, the students were asked whether the e-learning system made it easy for them to find the material they needed to learn. Around 86% respondents believed that the e-learning system provided them the material they needed in an easy way, while 8% were neutral and only 6% did not agree with this statement. The Likert score was 4.18 indicating that the e-learning system made it easy for the students to find the materials they needed to learn.

Figure 6.11 shows that, in item LM3, 78% of the respondents felt that they did not face any issue while accessing and going through the materials. Around 14% were neutral, and 8% respondents found accessing and going through the materials difficult. The Likert score was 3.86 which indicates a good level of agreement that most students didn't have any problem accessing the materials.

In item LM4, the respondents were asked whether the e-learning system provided sufficient materials. Some 82% agreed with this statement, while 12% were neutral, and 6% respondents did not agree with this. The total score was 3.96 showing that the e-learning system provided sufficient materials to the students.

The composite score of the *Learning Material* factor was 4.02, indicating that *LM* is an influential factor. It is likely that it has a positive influence on the usage of learning materials.

User Satisfaction (US)

User satisfaction (US) is another factor which was investigated by measuring six items related to different parts of the e-learning system.

Table 6.19 Measured Items for User Satisfaction Factor (Non-Adaptive group)

Factor	Item code	Statement
User Satisfaction	US1	I feel I learn more in this system.
	US2	I feel comfortable using this system.
	US3	I believe I became productive using this system.
	US4	This system has all the functions and capabilities I expect it to have.
	US5	The activities/quizzes provided in the course enhanced my learning.
	US6	Overall, I am satisfied with this system

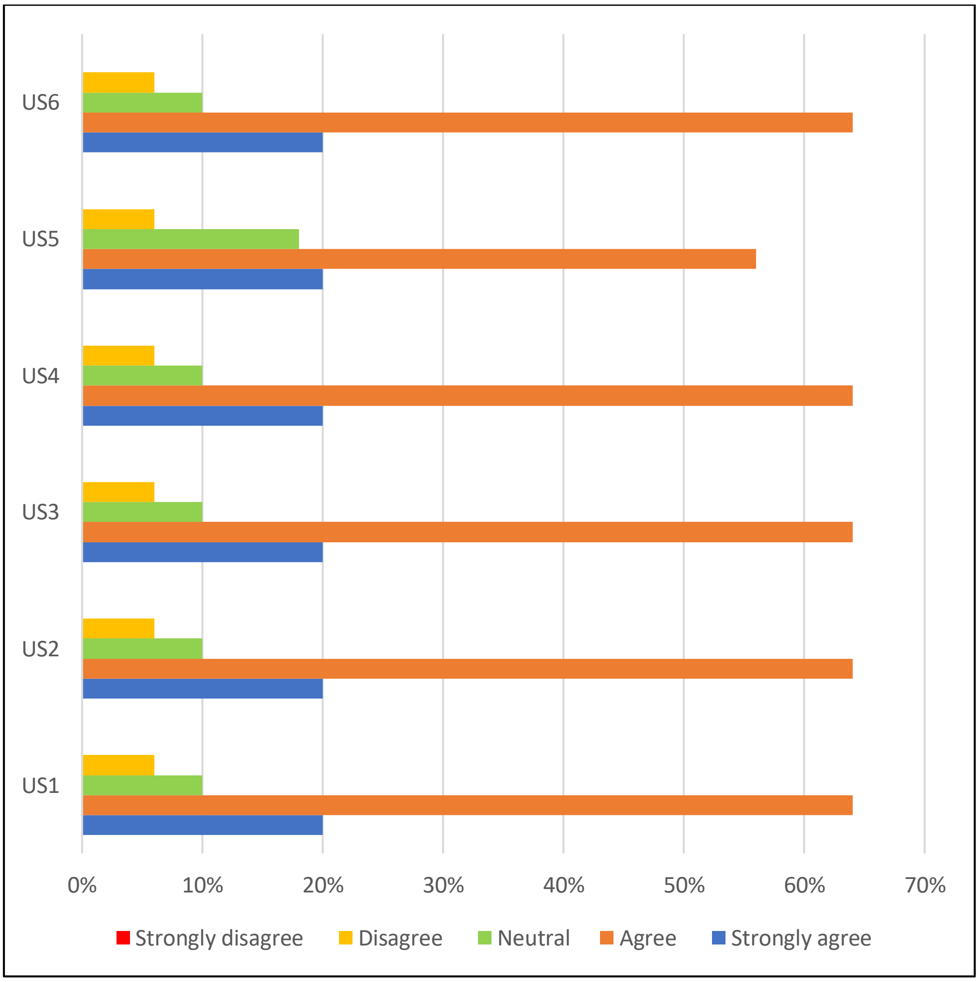


Figure 6.12 Results of Measured Items for User Satisfaction Factor (Non-Adaptive Group)

From Figure 6.12, it can be seen that for item US1, the majority of the participants (84%) felt that they learned more in the e-learning system. Only 10% were neutral about this statement, whereas. 6% respondents did not feel that they learned more using this system. The Likert score of this item was 3.98 which indicates a good level of agreement that the e-learning system made the students learn more.

For item US2, the participants were asked whether they felt comfortable using the e-learning system. Around 84% respondents felt that they used the e-learning system comfortably. Only 10% students were neutral about this statement, while 6% did not agree with this. The total score was 3.98 which shows a high level of agreement that the e-learning system was comfortable to use.

For item US3, 84% of the participants believed that they became productive using the e-learning system. Only 10% of the students were neutral about this statement, while 6% did not agree with this. The Likert score of this item was 3.98 suggesting that the e-learning system made the students productive.

For item US4, it can be seen from Figure 6.12 that the majority of the participants (84%) agreed that the system included all the expected functions and capabilities. Only 6% respondents did not agree with this statement, whereas 10% were neutral. The total score of this item was 3.98 which indicates that the system included all the expected functions and capabilities.

For item US5, the students were asked whether the activities/quizzes provided in the course enhanced their learning. Around 76% respondents agreed with this statement. Only 18% students were neutral, and 6% disagreed. The Likert score of this item was 3.90 indicating that the activities and quizzes provided by the system enhanced student learning.

The participants were also asked whether they were satisfied with the system in general. Most students (84%) agreed that they were satisfied with the system in general, while 10% respondents were neutral. Only 6% did not agree with this statement. The total Likert score was 3.98 which shows that the students were satisfies with the system in general.

The composite score (3.96) of the User Satisfaction (*US*) shows that there is general agreement that user satisfaction is a high impact level.

Ease of Learning (EL)

The *Ease of Learning* was another factor measured with six items in the questionnaire for students. The items for measuring the influence of the *EL* factor collected data about the perception of students regarding ease of learning.

Table 6.20 Measured Items for Ease of Learning Factor

Factor	Item code	Statement
Ease of Learning	EL1	The e-learning system provided material that exactly fitted my needs.
	EL2	The e-learning system enabled me to learn the material I needed.

EL3	The e-learning system enabled me to control my learning progress.
EL4	The e-learning system recorded my learning progress and performance.
EL5	The feedback from activities/quizzes helped me to locate where I was having difficulties.
EL6	The responses to the pre-test helped me understand where I was having difficulties.

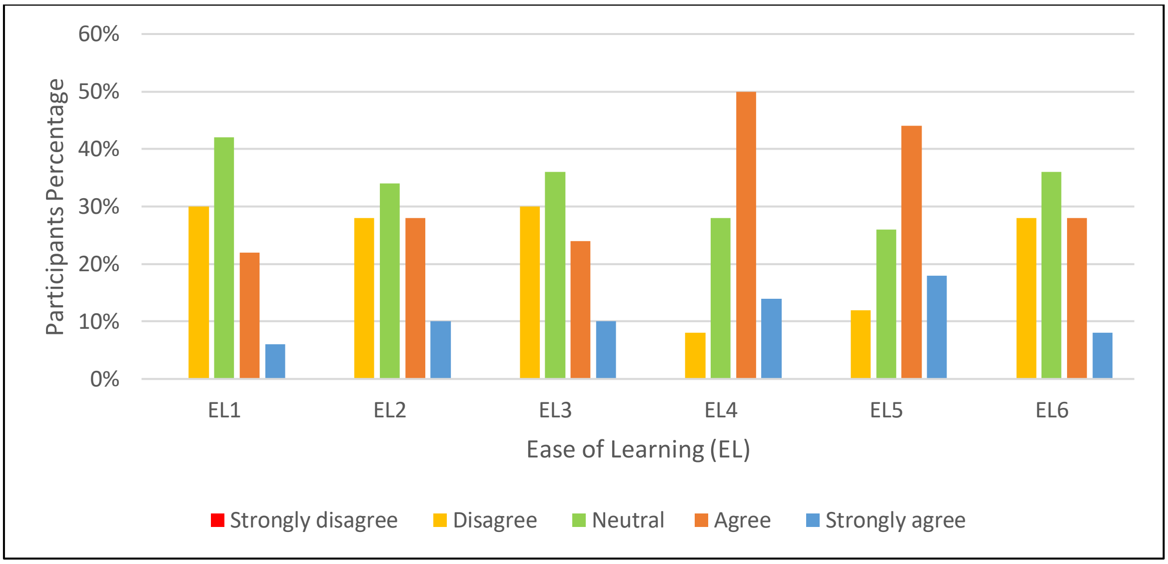


Figure 6.13 Results of Measured Items for Ease of Learning Factor

For item EL1, the participants were asked whether the e-learning system provided them the exact needed materials. Some 28% of the participants agreed that learning material provided by the e-learning system fitted their needs, while 30% did not agree with this statement. Some 42% of the participants were neutral. The Likert score was 3.04 which indicates that the participants didn't feel that the e-learning system provided them the exact needed material.

For item EL2, the participants were asked whether the e-learning system enabled them to learn the material they needed. Figure 6.13 shows that 38% of the participants agreed with this statement. Around 28% students disagreed with this, and 37% respondents were neutral. The total score was 3.20 which shows that the participants were uncertain that the system made them learn the material they needed.

The students were also asked whether the e-learning system enabled them to control their learning progress. Around 36% were neutral about this statement, while 34% respondents believed that they could control their learning progress using this system. Some 30% of the participants did not agree with this statement. The Likert score of this item was 3.14 indicating that the respondents were unclear that the e-learning system enabled them to control their learning progress.

For item EL4, the students were asked whether the e-learning system recorded their learning progress and performance. Around 64% agreed with this statement, while 28% were neutral, and only 8% did not agree with this. The total Likert score was 3.70 which indicates that the students e-learning system recorded the learning progress and performance of students.

Around 62% of the participants agreed with item EL5 which stated that "The feedback from activities/quizzes helped me to locate where I was having difficulties". Only 12% disagreed with this statement, and 26% respondents were neutral. The total score was 3.68 which suggests that the feedback from activities/quizzes helped the students to locate where they were having difficulties.

As can be seen from the Figure 6.13, for item EL6, around 36% participants agreed that the responses to the pre-test helped them understand where they were having difficulties. Some 36% of the respondents were neutral, while 28% of them didn't agree with the statement. The Likert score was 3.16 indicating that the participants were not sure that the responses to the pre-test helped them understand where they were having difficulties.

The composite score of this factor (EL) was 3.32 which indicates that a low influence of agreement of the ease of learning using the e-learning system.

From the factors analysis above, it is likely that the students had a positive perception of the system in different aspects, and it has a high level of agreement of most factors. Although there is general agreement on factors among students, it is great to identify what is the most likable factor among the others by the students. Table 6.21 shows the factors rank based on their mean (composite scores).

Table 6.21 Descriptive Statistics for the Factors means and Ranking (Non-Adaptive group)

Factor name	Mean	Std. Deviation	Result	Rank
System Usability	4.04	0.71730	Agree	1
Learning Material	4.02	0.75297	Agree	2
User Satisfaction	3.96	0.73925	Agree	3
Ease of Learning	3.32	0.84773	Neutral	4

Based on the results of the factors in Table 6.21, it seems that the System Usability, Learning Material and User Satisfaction factors have a high level of agreement (Agree) among students, while the Ease of Learning factor was 'Neutral'.

From Table 6.21, it appears that the System Usability factor has the highest composite score (4.04) among all factors, followed by the Learning Material factor (4.43). User Satisfaction factor is third with a composite score of 3.96. The Ease of Learning has the lowest composite score (3.32) among all factors.

6.6.6.2 Part B: Qualitative Analysis: Ease and Difficulty of Use

In this section of the questionnaire, students were also asked about the ease and difficulty of use of system parts. Around 78% of the students responded to the question, while 22% did not. Some 56% of those answered to the question that related to the difficult of use system's parts, whereas 44% did not answer to this question. The following table summarizes the opinions of the students regarding the ease and difficulty of use of the system parts.

Table 6.22 Opinions of Students about The Ease and Difficulty of Use of the System (Non-Adaptive Group)

Easy to Use	Percentage	Difficult to Use	Percentage
Navigation flow	26%	Nothing difficult	43%
Tests	15%	Navigation flow	21%
Course map	3%	Tests	11%
Materials	15%	Other difficulties	25%
Course structure	23%		
Other	18%		

Table 6.22 presents results for various aspects of the system regarding the ease or difficulty of their use. The results show that 26%of the students believed that the navigation flow was easy to use for going through the parts of a course. However, 21% of the respondents felt that the navigation flow was difficult to use. One of the students stated: "*I have some problems accessing and going through the materials*". Furthermore, 15% of the participants agreed that the tests, including both the pre-test and the post-test, were easy to use, while 11% of the respondents stated that the tests were difficult to do. Around 15% of the students felt that the materials of the system, including the animations, were easy to explore and review. Some students stated that using different formats of materials, such as short text, images, and animations increased their understanding, motivation and engagement. One student commented that the course map helped him to have an overview of the course. Around 23% of the students agreed that the structure of the e-learning system was clear and organised which made the learning process much easier for them. Some 61% of the respondents felt that the system as a whole, or some parts of it, was easy to use and they faced no difficulty while using the system. However, 25% of the students found that the system itself or some parts were difficult to use due to different reasons. Some students experienced difficulty in downloading the slides, or problems with the structure of the system and materials. It seems that there was high level of agreement among students that the e-learning system was easy to use.

6.6.6.3 Part C: Qualitative Analysis:

Table 6.23 Results of Closed-Ended Questions for Post-Experiment Questionnaire (Non-Adaptive Group)

Questionnaire Item	Yes	No
Learning material matched understanding	83.3%	16.7%

Pre-test determined knowledge and understanding	83.3%	16.7%
The system answered the problems that the students faced in learning	83.3%	16.7%

The students were asked whether the system provided suitable learning materials that met their knowledge level in the subject area. Some 83.3% of the students felt that the system provided learning materials that matched their understanding level (as shown in Table 6.23), while 16.7% did not agree with this statement. This indicates that there was high degree of agreement among students that the system provided appropriate learning materials based on the understanding level of students.

The participants were also asked whether the pre-test determined their knowledge and understanding. The majority of the students (83.3%) agreed that pre-test was a helpful method to identify their knowledge level, while 16.7% of them disagreed with this statement. As shown in Table 6.23, there was high level of agreement among students that pre-test was a helpful method for determining knowledge and understanding level of students.

The results in Table 6.23 indicate that most of the students (83.3%) found that the system was helpful in solving the difficulties they had faced in their learning. Only 26% of the positive responses indicated that the materials including different formats, such as visualizations and animations, helped them to understand the concepts. Around 25% of the opinions affirmed that the system was organised and helpful in general, and in determining their ability and knowledge level. Some 13% of the responses indicated that the system was supportive, and it was a good preparation for the exams. Around 25% of the students provided positive responses about why they like the system and how it was easy to use. Some 13% of the participants did not agree that the system helped them to find answers to the problems that they had faced in their learning. They provided negative feedback about the system as listed below:

"There is no feedback after taking the pre-test"

"Sometimes I don't know how to use the system"

"Lack of activities"

Here are some of the positive responses provided by the students:

"Good practice before final exams"

"The system helps with the memorization by using the animations part"

"It showed me where I was good and not good"

"Different types of materials have been used in this system"

It is clear that there was high level of agreement among students that the system helped to solve the problems that the students faced in their learning process.

The students were also asked to provide the advantages and disadvantages of using the system. Some 72% of the students responded to this question, while 28% did not answer. The majority of the responses (80%) were positive, whereas 20% of them provided negative opinions about the system. Table 6.24 summarizes the key advantages and disadvantages.

Table 6.24 Advantages and Disadvantages of the System (Non-Adaptive Group)

Advantages	Percentage	Disadvantages	Percentage
Navigation flow	22%	Materials	33%
Structure of the system	22%	Tests	33%
Materials	16%	Navigation flow	11%
Tests	16%	Other negatives	23%
System easy to use	16%		
Course map	5%		
Other positives	3%		

As presented in Table 6.24, the advantages and disadvantages can be attributed to different features of the system usability and functionality. These are discussed in more detail in Chapter 7.

Table 6.25 Understanding level of the system as Rated by the Students (Non-Adaptive Group)

Questionnaire Item	Measure (1-10)	Percentage
System enhanced learning and understanding	5	9.5%
	6	7.1%
	7	11.9%
	8	35.8%
	9	23.8%
	10	11.9%
Mean	7.92	

The students were also requested to give an overall rating of how the system enhanced student understanding generally. The respondents rated the system from 1-10, with 1 as the worst and 10 as the best. Table 6.25 shows that the results indicate no rating below 5, with the average rating as 7.92, indicating high agreement by most students who believed that the system enhances understanding and learning.

6.7 User Data

The user data was collected from the database between 23rd July 2018 and 28th September 2018. The following information was recorded:

Users: Total registered users in the database was 196, amongst who 193 were a student. Of the 115 students enrolling for the Algorithms and Data Structure course, 100 had volunteered for testing the system.

Pre-Experiment Questionnaire: The questionnaire was uploaded to the system so that the students could respond to the questions using the system. All the students who participated in the experiment answered the questionnaire. Therefore, the total number of records was equal to 100 (from both groups).

Pre-Test: When the students had taken this test, the coloured concept map and the ranked concepts list were generated automatically only in the adaptive group. All the students who had volunteered had taken this test. Therefore, there were 100 records for the pre-test results which were used to analyse the hypotheses.

Post-Test: When the students had taken this test, the coloured concept map and the ranked concepts list were generated automatically only in the adaptive group. All the students who had volunteered had taken this test. Therefore, there were 100 records for the post-test results which were used to analyse the hypotheses.

Coloured Concept Map: There were 100 coloured concept maps generated in the system after taking the pre-test (50 coloured concept maps) and post-test (another 50 coloured concept maps).

Ranked Concepts List: There were 100 ranked concepts lists generated in the system after taking the pre-test (50 ranked concepts lists) and post-test (another 50 ranked concepts lists).

Post-Experiment Questionnaire: This questionnaire was also uploaded to the system. All the responses from both the group were recorded based on how many students answered each question.

6.8 Summary

This chapter has given the study results, which occurred in the summer term in 2018, from July to September in Prince Sattam bin Abdulaziz University (PSAU) in Saudi Arabia. The participants were undergraduate students from the Department of Computer Science who were on the Algorithms and Data Structure course. The students were enrolled onto the course modules based on their groups (adaptive and non-adaptive). The experiment was implemented very smoothly and the students followed the navigation flow that led them to answer the pre-experiment questionnaire, and then take the pre-test to identify their understanding levels by browsing the coloured concept map and the ranked concepts list according to their scores in the test. After learning the materials based on their ranked concepts lists, they took the post-test to assess their performance in the course. Finally, they responded to the post-experiment questionnaire to share their feedback about the system.

Chapter 7: Discussion

7.1 Introduction

The proposed system was designed to enhance the learners' performance and increase their engagement toward the learning process. As explained in Chapter 3 this research has resulted in the creation of two different platforms; the adaptive platform (CaFAE), and the non-adaptive platform. CaFAE consists of two adaptive components (coloured concept map and ranked concepts list), that are not part of the non-adaptive system. Two experiments (pilot study and full study) were conducted using these two platforms (as explained in Chapters 5 and 6). The main aim of these experiments was to test the effectiveness of the proposed adaptive e-learning system, and how it increases learners' understanding and engagement levels. This chapter discusses and analyses the results for both experiments. It provides a general introduction, student's background, hypotheses discussion, system quality factors, aims and findings (understanding, knowledge, motivation and engagement levels) and limitations for each study.

7.2 Discussion of the Pilot Study Results

The pilot study was primarily carried out to test the system functionality and examine the methodology. The system functionality was tested both in terms of usability, and in the acquisition of the results generated from questionnaires and tests at pre-experiment and post-experiment levels. There were no significant problems with the system functionality, although a few minor interface issues were identified and addressed (please see Chapter 3). The structure of the pilot study worked well; the students were able to use the system and the results were gathered. The experiment ran successfully, and it was possible to identify those students in both the groups, adaptive and non-adaptive, who had made progress in their studies based on their test results and their comments/feedback in the post-experiment questionnaire. Forty eight percent of those who completed the pre-experiment level (pre-questionnaire and pre-test) completed the whole study.

7.2.1 Pilot Study Limitations

The pilot study provided results that were indicative of a positive effect of the proposed system. However, these results were not statistically significant due to the small sample size of students in the pilot study. Although the study had a theoretical sample size of 77, many issues influenced the successful implementation of the experiment in terms of sample size. One of the main obstacles was that the pilot study took place towards the end of the term when the students had several course assignments to submit. This was due to a technical delay in the installation of the system. As a result, the experiment was conducted only two months before the students' final year exams in May 2018. Several students mentioned that they did not have enough time to use the entire system. This lack of participation certainly affected the results of the experiment as findings were not statistically significant for some hypotheses. In addition, industrial action at the time of pilot study led to social problems, leading to a smaller number of participants in the study. In general, pilot study showed promise and indicated that the system is working. However, a number of limitations were noticed (as discussed previously) which needed to be considered for the full study.

7.2.2 Background of Students

In the pre-experiment questionnaire, the results showed that the majority of the students (46%) preferred to learn using traditional methods rather than any other learning methods including the online learning systems. Despite more than half of the students (54%) have not used an online learning system before for personal study and also most of them (92%) have not previously used an adaptive e-learning system, the majority of them (92%) of the participants believed that online learning improves understanding. This is quite high and that in fact 100% of the students would have used Moodle at this point, which is arguably e-learning. It is clear that students were defining e-learning as something more than a standard VLE. It may be concluded that although many students had previously used traditional and e-learning methods, a significant majority of them had never used adaptive e-learning methods. This further highlights the lack of adaptive e-learning within institutions (Whittenburg, 2011), as assumed by this research and providing a strong motivation/reason for CaFAE system to be developed.

7.2.3 System Quality Factors

To test the effectiveness of the first three factors (system usability, learning material and user satisfaction), the students were asked to measure these factors using a Likert scale. The purpose of measuring these factors was to ensure the usefulness of them and identify how they assist the students to learn without encountering any problems while using the system. Regarding system usability, a large percentage of students were satisfied, especially over its precision and ease of use. Similarly, most students were satisfied with the learning materials and found these easy to understand and appropriate to their knowledge levels. For the user satisfaction factor, the majority of students were satisfied with the system and were comfortable with its use as well as the manner in which it gave them activities and tests to enhance their education.

In order to measure the extent of the system's adaptation, and its effectiveness in determining the students' understanding levels and providing the appropriate learning materials in different phases in the proposed system, the students were questioned in the post-questionnaire via a Likert scale section and open-ended questions. It is clear from the responses of the students to the questions related to the factors identified in the questionnaire, as well as their responses to the open questions, that there was general satisfaction regarding the adaptation of the system; it helped and motivated them to integrate into the learning process. Therefore, this confirms hypothesis H5 which shows that the system has a good level of usability based on the positive results from the post-questionnaire.

7.2.4 Group Differences

Understanding and Knowledge:

Regarding the increase in understanding and knowledge levels of both groups, adaptive and non-adaptive, the results were evaluated in the pilot study via hypotheses testing (Sections 5.6.2.1, 5.6.2.2 and 5.6.2.3) for both groups, and various questions in the post-experiment questionnaires of the adaptive group. Appropriate statistical tests (e.g. Mann-Whitney U test) were used to test the hypotheses, and the results indicated that the averaged pre-test scores for the two groups showed no statistically significant differences, which suggested that both groups had equivalent/similar experience of the subject area before use of the system, and thus compatible with the first hypothesis.

Although there were no statistically significant differences between the adaptive group and the non-adaptive group in the post-test, the adaptive group had an average rise of 56% in their performance in the post-test as compared to pre-test, whereas the average score of the non-adaptive group increased by 44%. This illustrates that the adaptive group of students improved their learning more than the non-adaptive group of students. As mentioned in Section 5.6.2.3, in each of the groups (adaptive and non-adaptive), separately and combined, the post-test scores were significantly higher than the pre-test scores. This shows that both the groups increased their performance after learning the materials using the proposed e-learning system. This finding is consistent with that of (Alkhuraiji, 2016) who found significant differences between the performances of the three groups (dynamic adaptive group, static group and control group) according to the pre-test and post-test scores.

To ensure that the students in the adaptive group had benefited from the proposed system and increased their understanding levels, their opinions were taken into consideration via the post-questionnaire (please see Section 5.6.3). Despite the small number of the participants collected from the post-questionnaire, the students' responses were positive and agreed that the system helped their learning achievement. The students showed their satisfaction of using the system and how the (CCM) and (RCL) showed them their abilities and increase their learning performance.

Motivation and Engagement:

In terms of motivation and engagement measurements, the general finding from the questionnaire results was that most students were satisfied using the system and how it encouraged them to involve more in the learning materials. For example, 7 out of 9 participants agreed that the system is more fun and engaging than the standard e-learning environment. Thus, a high degree of satisfaction was shown by the students regarding motivation and engagement for the proposed system.

Negative Feedback from Students:

Unlike the positive responses from most students in the post-questionnaire, one student provided negative feedback (relative to his/her peers). This is perhaps due to the student's misunderstanding of the structure of the system and the procedures of the experiment. However, this resulted in improvements to the overall structure of the system to help eliminate this issue in the main study by providing students with more detailed instructions on how to use the system from start to finish.

7.2.5 Summary of the Pilot Study

As mentioned previously, the purpose of this study was to test the functionality and stability of the system, as well as the research methodology and its validity. Although hypotheses were not supported and differences were not significant due to the small number of participants in this study, the results strongly indicated that the proposed system had a positive effect on learning. It was clear from the pilot study that both groups benefited from the CaFAE e-learning system and this was evident from their responses to the post-questionnaire. In general, the system was developed further based on student feedback to eliminate the technical and structural problems that were observed in the pilot study such as a pleasant interface and navigation menu.

7.3 Discussion of the Full Study Results

The main motivation behind this research was to provide adaptation methods to the standard e-learning system in order to increase student performance and engagement. Therefore, the primary purpose of the full study was to find out the effectiveness of the proposed adaptive e-learning system as compared to a standard e-learning system and to ensure that the proposed e-learning system is consistent with the research hypotheses. Besides testing hypotheses, this study intended to investigate the students' experiences and opinions about the use of e-learning through the pre-questionnaire before taking the experiment, as well as to examine the students' experiences, opinions and satisfaction regarding all parts of the system after completing the experiment via the post-questionnaire. Thus, these pre- and post-questionnaires were further supportive of the hypotheses and they could be used to indicate the opinions of students before and after the experiment, independent of whether they were consistent with the results of hypotheses or not.

7.3.1 Overview of Full Study

Similar to the pilot study, the students were assigned to two groups (as explained in Section 6.5): an adaptive group in which the students used the adaptive module of the system as an experimental group, and a non-adaptive group in which the students used the standard module of the system as a control group. In this experiment, both the groups had the same procedures; the students first took a pre-questionnaire to tell about their experience in using online learning methods followed by a pre-test to evaluate their knowledge level of the subject area. The difference between these two groups here was: the adaptive group students obtained two adaptive components, a coloured concept map to show them their understanding levels of how much they understood a specific concept in different categories based on their tests' scores in the pre-test and a recommended ranked concepts list which was arranged based on their pre-test scores; the non-adaptive group students reviewed all the learning materials as a whole without any recommendations based on their abilities in the pre-test. Finally, both groups took a post-test to measure their performance after learning the materials, and then responded to the post-experiment questionnaire to provide their experiences and feedback on how the proposed system helped them to have a better understanding, knowledge, motivation and engagement.

The experiment ran successfully, without any significant problems and with the system functionality improved due to the modifications completed based on the feedback from the pilot study. In contrast to the pilot study, the sample size for the full study was relatively large with 100 students divided into two groups (adaptive and non-adaptive). Most students in both groups completed the whole study with the exception of 18% who did not complete the open-ended questions in the post-experiment questionnaire. A relatively large number of participants provided statistically significant results for this experiment as it was consistent with the suitable tests mentioned in the research methodology. In addition, it gave a comprehensive perception of the extent of the students' experience, and their vision of standard and adaptive e-learning environments through their responses to pre and post-experiment questionnaires.

7.3.2 Background of Students

As discussed in (Section 6.6.1), the pre-experiment questionnaires for both the adaptive and non-adaptive groups were very similar. Consequently, their responses were quite similar as well as they had the same general experience in the use of e-learning, and similar views about its utilization. The results of the pre-experiment questionnaire revealed comprehensive background of the students' preferred learning methods, their use of online learning environment, opinion about online compared to traditional lectures, ways to improve understanding and the use of adaptive e-learning.

In fact, CaFAE system was designed to provide the students with appropriate learning materials because of the lack of use of the adaptive e-learning systems, especially in universities. The findings of the pre-questionnaire showed that more than half of the students (52%) preferred to learn using both methods, traditional and online lecture methods, compared to other learning methods including the online learning systems. Only 15% of the students preferred to learn using online learning method. This low percentage indicated that students were still relying on the traditional method of education rather than on online learning. Although 66% of the students had not used an online learning system before for personal study, and 95% of the students had never used an adaptive e-learning system, more than half of them (54%) believed that online learning improves understanding.

7.3.3 Hypotheses Discussion

Regarding testing of hypotheses to determine the differences in levels of understanding and knowledge of the subject area between both groups, before and after the experiment, the results were analysed in the full study in Section 6.6.2. To examine the hypotheses, the tests scores for both groups were collected. Independent sample t-test and Paired samples t-test were used to test whether there was a statistically significant difference between the pre-test and post-test scores of both groups. The mean of the pre-test scores between the adaptive group and the non-adaptive group showed no statistically significant differences. This result was expected as the first hypothesis says that there are no significant differences in the knowledge level of the subject area between the two groups as they had the same knowledge experience of the subject area before using the proposed system. This result is consistent with those of (Dogan and Dikbıyık, 2016, Alkhuraiji, 2016) who also found that there are no significant differences in the students' knowledge level of the subject area between groups which supports the idea of most students have the same learning experience before learning the actual learning materials.

The mean post-test scores between both groups showed a statistically significant difference. This result was consistent with the second hypothesis which declared that the adaptive group will perform better than the non-adaptive group in the post-test. It was evident that the adaptive group had a higher increase rather than the non-adaptive group in the mean post-test scores. This result is in agreement with the findings of (Alkhuraiji, 2016, Dogan and Dikbıyık, 2016) who showed that the experimental (adaptive) group had a higher increase as compared to the control (non-adaptive) group in the mean post-test scores. More specifically, the adaptive group had an average increase of almost 65% in the post-test, unlike the average score of the non-adaptive group which increased by 35%. This showed that the adaptive group of students enhanced their learning performance more than the non-adaptive group of students. Thus, the third hypothesis was accepted which stated that in each of the groups (adaptive and non-adaptive), separately and combined, the post-test scores would be significantly higher than pre-test scores. This means that both groups improved their learning achievement after learning the materials using the proposed e-learning system.

The fourth hypothesis stated that the adaptive group will take less time in learning the materials, and less time in answering the post-test as compared to the non-adaptive group. Although there were statistically significant differences for the time spent in learning and answering the tests between both groups (as discussed in Section 6.6.2.4), this hypothesis was rejected as the findings were not reliable for several reasons. The first reason was that the server was down occasionally throughout the experiment, hence, it did not provide accurate results in the process of calculating the time, either the time of answering the tests or the time spent in learning materials. The second reason was that regardless of the server issue, it was not guaranteed that the students were learning the materials or answering the questions in the tests during the whole period when they appeared to be using the system. It was observed during the experiment that some students were learning the materials intermittently whilst engaged in other activities, such as talking with their colleagues during the experiment, browsing other sites or other distractions. However, the positive result shown here is indicative of the potential to reduce learning time.

7.3.4 Understanding and Knowledge

As explained in Chapter 1, the main objective of this research was to find an adaptive mechanism to ensure that the appropriate learning material is delivered to the students based on their performance, rather than learning in a random way or a way driven solely by the order in which the content is specified in the module. To investigate students' perception of the increase in their knowledge and understanding, they were asked open-ended questions to examine the influence of the system in increasing the learning performance.

As discussed in detail in Section 6.6.5.3, the students in the adaptive group were asked (more specifically in Q2, Q4, and Q6 of the post-questionnaire) about the contribution of ranked concepts list and its importance in increasing knowledge and better understanding in their achievement. The results indicated that a large percentage of the participating students responded positively to these questions and they agreed that this ranked list helped them directly to increase their learning performance in different ways. However, some negative responses were also identified regarding these questions. Most negative answers were brief with no explanation at all. For example, one of the students commented that this ranking is confusing and the topics in the list are not linked to each other. This may be attributed to the fact that this small set of dissatisfied students did not understand the complexity of the information provided and how the ranked concepts list was arranged. One student also claimed that not all subjects, but only difficult topics are presented. T Clearly, this student did not understand the nature of the ranked concepts list, which is only a list suggested in an order that is based on a specific student’s understanding of the topics.

Question 11 asked for an overall evaluation of the effectiveness of the system as a whole in increasing students' understanding and knowledge. The mean rating was 8.38, which shows high positive response. In the non-adaptive group, however, the same question only asked the students regarding the increase of knowledge and understanding, and the mean rating was 7.92.

7.3.5 Motivation and Engagement

Regarding motivation and engagement measurements, the students in the adaptive group were asked directly in the form of an open-ended question whether the coloured concept map increased their motivation and engagement. The result showed that most of the students were satisfied using the system and how it helps them to engage more and interact with the learning materials, and how this method motivated them to understand their weaknesses and concentrate on the difficult concepts. Thus, there was high degree of agreement among the students regarding motivation and engagement of the proposed system.

7.3.6 Adaptation Factors

As explained in detail in Section 6.6.5.1, it was clear through the positive responses of the students regarding the adaptation factor, the coloured concept map factor, and the ranked concepts list factor, that there was a high degree of agreement on the effectiveness of these factors and the extent to which they contributed to increasing the student performance. In the open-ended questions section, the students in the adaptive group were asked whether the ranked concepts list matched their understanding level after taking the tests (pre and post). As explained in Section 6.6.5.3, the majority of the students believed that the ranked concepts list met their understanding level by showing them their abilities and suggesting the proper concepts they should learn in an orderly way based on their performance in the test taken. Other students believed that the ranked concepts list was clear and easy to follow, while one student said that the list showed him the relationship between the concepts and how they linked together.

Only14% of the students provided negative responses regarding the ranked concepts list. One student was wondering why the list just showed the topics that they had difficulty with instead of showing all the topics including the ones that were understood. The whole idea behind the ranked concepts list is to provide the students with the recommended topics, especially the important ones, and to eliminate the redundant topics in the list and save time for the students. Some students believed that the ranked concepts list was not ordered correctly or confused them without explanation. Perhaps, these students did not completely understand the nature of this ranked concepts list and how the concepts were arranged; they, therefore, deemed that this list contained topics that were not interrelated. This is in contradiction to most other students who believed the positive impact of the list as discussed earlier.

Regarding the coloured concept map effectiveness, the students were asked whether this map determined their knowledge level. As explained earlier in Chapter 6, most of the students had a positive attitude towards using the coloured concept map and how it helped them to identify their strengths and weaknesses as well as motivated them by remembering the concepts in different knowledge category by colouring. Some students commented that it was easy to understand and clear. However, three students responded negatively saying that this map was not organized and the links between the concepts were not clear. It is clear that these students did not understand the instructions at the top of the map which were crucial in order to understand the relationship between the subjects and also the levels of knowledge by colouring.

The students in the adaptive group were also asked an explicit question to rate how the system increased the adaptation in education. The mean value of the rating was 8.40 which reflected the satisfaction of the students with the level of adaptation in this system compared to other systems and gives a perception of positive attitudes in the use of this adaptive system by students. In general, it appears that the adaptation factor and its components (CCM and RCL) made a difference in the students' understanding levels.

7.3.7 System Quality Factors

To compare the adaptive group with the non-adaptive group in terms of proposed system quality, same factors were used in the post-questionnaires for the two groups. These factors were system usability, learning material and user satisfaction. As reported in Chapter 6, although there was no statistically significant difference between the two groups, the mean of all factors in the adaptive group was higher than the mean in the non-adaptive group. It is clear that both groups had a high degree of agreement regarding the factors influences (according to the Likert scale measurement). This confirms that these factors increased motivation and engagement to use this proposed e-learning system for both groups, and this is also confirming H5 which shows a good level of usability for the system.

7.3.8 Conclusion of the Full Study

Overall, the results of the full study reflected a high level of satisfaction from both groups regarding the proposed system; this certainly gives a good impression of how effective the system was and how it contributed to increasing the students' knowledge, understanding, and motivation and engagement levels.

7.4 Summary

In this chapter, the results of the pilot and full studies were analysed and discussed. Both experiments went well without any significant technical problems and provided positive results through pre- and post-tests, and via responses by the students to the pre- and post-questionnaires.

In the pilot study, although the results were not statistically significant, it still demonstrated the system usability and validity of the methodology used while providing indicative positive results. This was evident by the difference in the performance of participating students in the pre-test and the post-test.

The proposed system was further enhanced based on the observations and feedback from the pilot study which significantly contributed to the success of the full study. All hypotheses were accepted statistically except for the hypothesis that related to the estimation of the time spent in learning and in answering the post-test due to technical problems and behavioural issues of the students. These hypotheses were tested using the Independent Sample t-test and Paired Sample t-test. The results of these tests show increasing in the knowledge level of the subject area in the adaptive group over the non-adaptive group. It was clear through the post-test results and responses to the post-questionnaires that the adaptive group of students benefitted more as compared to the non-adaptive group of students. The system provided a coloured concept map to the students to explore their abilities in the subject area; it also provided them with the ranked concepts list commensurate with their knowledge and understanding abilities. The overall finding of the two studies support the proposed adaptive e-learning system CaFAE and consider it as an effective system with significant teaching advantages over standard e-learning.

Chapter 8: Conclusions and Future Work

This chapter presents the overall conclusions of this research and discusses the significant benefits of the proposed novel adaptive e-learning system CaFAE (as proven by the two studies). It then evaluates the answers to the research questions, and the research contributions, before discussing limitations of the research and future directions.

8.1 Conclusions

The aim of this research was to show that the proposed novel adaptive e-learning system CaFAE improved a learner's knowledge, understanding, motivation and engagement as well as participants' overall learning level and effectiveness. To evaluate the effectiveness of the proposed system, two experiments were performed in two different universities on two different subjects in the field of Computer Science. Both experiments were successful and provided positive results that were consistent with the main research hypotheses. In each experiment, students were divided into two groups, adaptive and non-adaptive, to examine if the adaptive group students benefited more from the e-learning system than the non-adaptive group. The results confirmed that the performance of adaptive group students increased significantly as compared to the non-adaptive group students.

8.1.1 Research Contributions

This section presents the main contributions that this research makes in the area of adaptive e-learning systems. These contributions can be divided into three key areas:

Academic Contributions:

This thesis critically reviews a set of previous studies in the field of adaptive e-learning systems. It discusses how the previously presented systems adapt to provide suitable learning materials based on the learner's ability. The previous studies focused on measurements to determine the student's knowledge levels, algorithms to adapt the learning process based on the understanding levels of students, and recommendations of appropriate learning materials to increase student performance. This review of previous studies provides a better understanding of how the adaptive e-learning systems work and how these systems are useful and needed for the educational sector. In addition, theories and techniques used in the literature are reviewed that underpin the novel work presented in this thesis. Therefore, this contribution helps both researchers and practitioners in the area of e-learning systems. This work also delivers a contribution to understanding comparisons between adaptive e-learning system and standard e-learning system by undertaking studies and analysis of students using two different systems.

Additionally, this research gives numerous contributions to the methodology, reflecting on the research in a positive manner, its discoveries, and how reliable and valid it is. First, the research collects primary data from various approaches and various courses in two different universities in the UK and Saudi Arabia. This reinforces the research findings generalisability. Second, and unlike much literature research, this is a rare example of a research (in particular research on fuzzy logic and concept map techniques in adaptive e-learning systems) which are collected from different data collections e-learning system users. Previous research only used qualitative or quantitative methods for data collection and testing system effectiveness. However, this research used a combination of these two methods (mixed method) to test the efficacy, validity, and reliability of the CaFAE system. This approach used various measurements, such as a pre-questionnaire, to understand e-learning in different aspects prior to the use of the CaFAE system and a post-questionnaire to understand user satisfaction and how they feel in regard to system effectiveness and usability. Additionally, the mixed method approach tested the validity of the CaFAE system by testing the hypotheses, particularly for those related to knowledge increases and student engagement levels. Third, the research instrument design used for data collection is one of the researches' methodological contributions. This includes how questions are asked, the variations in options to the answers, and the design and appearance of the questionnaire in the pre and post experiments.

Technical Contributions:

This research provides a way of enhancing student learning and understanding while removing some of the common drawbacks of traditional e-learning. The thesis presents a novel adaptive e-learning system using a combination of fuzzy logic and concept map techniques. These two key adaptive techniques have been used to produce two bespoke learning objects for each student, the coloured concept map and the ranked concepts list, which help the students to identify their knowledge levels, and follow the instructions to increase their understanding levels.

The CaFAE system makes three main contributions:

1. Implementation of a bespoke test system based on multiple-choice answers were answers have a variable value of correctness. Unlike other standard systems which provide multiple-choice answers were answers have only one correct answer for each question, this system provides range of correctness values, and each range of these values represents a knowledge level.

2. A concept map-based model of student understanding created from the test results using a fuzzy logic system. This concept is a coloured map which show the students their knowledge level for each concept of the subject area.

3. A bespoke ordered list of learning materials based on student understanding and course concept map. This ordered list contributes to increase the students' understanding and engagement levels.

Practical Contributions:

Many universities use standard e-learning systems, such as Blackboard, and other learning environments that do not provide students with adaptive learning. Providing adaptive e-learning systems makes the learning process easier for the students by obtaining appropriate learning materials or learning styles. This specific research applied the proposed adaptive e-learning system CaFAE in two experiments (pilot study and full study) in two different universities. It was found that most students (92%) in the pilot study (Chapter 5), as well as 95% students in the full study (Chapter 6), never used an adaptive e-learning system before. This indicates that the majority of students in both studies used an adaptive e-learning system for the first time (CaFAE in this case). The positive results from these studies highlight the importance of adaptive e-learning in future systems.

8.1.2 Research Questions

The main question of the research was: Is an adaptive e-learning system capable of enhancing learners' understanding and making learning more effective as compared to the standard e-learning system? To answer the research question, five hypotheses were evaluated and discussed in Chapter 6 as outlined below. Hypotheses 1 to 3 were proven, whereas Hypothesis 4 was partially proven. Hypothesis 5 was proven from qualitative analysis.

H1. The adaptive group is predicted to have a more significant positive performance result of the post-test as compared to the non-adaptive group.

H2. Both groups (adaptive and non-adaptive) are predicted to have no significant difference in knowledge level between them in the pre-test.

H3. Both groups are predicted to have a significant positive performance result from pre-tests to post-tests.

H4. Both groups are predicted to have a positive significant difference between them in the time spent in learning the concepts, and the time spent in answering the post-test.

H5. Students are predicted to find the system engaging with good usability.

As the first 3 hypotheses have been statistically proven through the main experiment, therefore, the main question of the research has been answered. However, although the results support it, H4 was rejected due to technical issues, such as server down times and lack of guarantee that the students were learning during that time or answering questions.

The main research question asked whether the students' understanding, knowledge, engagement and motivation is improved by the proposed adaptive e-learning system. This question can be considered to consist of two parts: improving understanding and knowledge level and increasing engagement and motivation. From the research presented in this thesis, this question can be answered as follows:

Understanding and knowledge level:

The increase in students' understanding and knowledge level using the proposed adaptive e-learning system CaFAE was discussed in Chapter 7. The research results showed that the adaptive group (that used the adaptive e-learning system) significantly increased their performance as compared to the non-adaptive group after using CaFAE. In addition, in the pre-experiment questionnaire, nearly half the students (45%) in both groups together did not agree that online learning increases understanding. On the other hand, most students in the adaptive group (90.5%) and the non-adaptive group (83%) answered in the post-questionnaire that online learning improves the understanding level.

Engagement and motivation:

As discussed in Chapter 7, the students were asked whether the coloured concept map as part of the adaptation process of the system increased their engagement and motivation. The results showed that the majority of the students (90%) of the adaptive group agreed that the coloured concept map improved their engagement and motivation.

The second question of the research was: Are students satisfied with the engagement provided by an adaptive learning system? This question is discussed in Chapter 6 (sections 6.6.5.1 and 6.6.6.1). In the post-questionnaires for both groups, the students were asked about their satisfaction of using the system in different items. Generally, the majority of the students in the adaptive group (88%) and the non-adaptive group (84%) were satisfied, felt comfortable and believed that they became more productive using the system.

The third question of the research was: Are students' needs met using the proposed system without additional tools? This question was used in the post-questionnaire for both groups and was asked in this format:

"Was this system useful in finding answers to the problems you have faced in your learning?"

This question is addressed in Chapter 6 (sections 6.6.5.3 and 6.6.6.3). In the adaptive group, the majority of the students (93%) believed that the system helped them to solve all the problems they had faced during their learning without help from different sources. Similarly, in the non-adaptive group, most students (83%) agreed that the system met their needs and solved the problems they found in the learning process.

8.2 Research Limitations

This research concluded the addressed hypotheses and answered the research questions. Nevertheless, there are some limitations of this research as follows:

Technical issues:

One of the technical barriers encountered in this research was that the server was sometimes down. Therefore, some students could not complete the whole experiment in the expected time duration and the fourth hypothesis (H4) that related to the time consumption is rejected.

Gender issue:

The educational system in Saudi Arabia divides male and female students into different sections in different buildings due to the cultural and religious reasons. Therefore, it was hard to run the experiment in a female section. The sample in the full study applied to a male section only in Prince Sattam bin Abdulaziz University in Saud Arabia; Although similar results are expected for a mixed gender group (as in the pilot study), the results here are only truly representative of a male-only group.

Sample size:

Unlike the sample size in the full study where a large number of students participated in the experiment, the sample size of the pilot study was limited due to reasons discussed in Section 7.2.1. More specifically, the lack of participation in the pilot study was due to the timing of the experiment during the term time, and industrial action occurring at the same time as the pilot study running.

8.3 Future Work

Directions for future work in the area of adaptive e-learning systems are given below.

8.3.1 Recommendation for practitioners

Running the CaFAE system with different types of courses (subject matter), and with different gender mixes will help to obtain more results from participating universities and the educational sector in general. This system can be provided to the teachers with a tutorial to take advantage of its services. Therefore, it is a good opportunity for practitioners to explore CaFAE and apply it to their universities/schools.

8.3.2 Recommendation for researchers

Adaptive e-learning is still a new trend in the field of e-learning systems. Therefore, many areas still require to be investigated and future work should develop the knowledge and understanding of adaptive e-learning.

First, this research can be improved by adding one or more adaptive techniques, such as neural-fuzzy logic system, big data, or another algorithm to the current adaptive mechanism used in this research. Applying a new adaptive technique may contribute to develop the current system further and provide better results. Secondly, new learning styles can be embedded into the system that may also contribute to identify students' learning preferences and provide appropriate learning materials based on their preferred learning methods.

Although hypothesis 4 appears reasonable, other factors were observed during the study which may need further investigation (in addition to server problems), e.g. the students did not always engage with the learning materials for all of the time. Students read/review/learn at different rates, indicating that this work has highlighted the complexities of the concept of 'time' and, from a practical perspective, system functionality impact. In future, it is possible to investigate and measure the depth of understanding which students might have in using learning materials quickly to gather enough information to pass the questions.

8.4 Summary

This chapter has summarised the research done in this thesis, explained the main contributions, suggested recommendations for both practitioners and researchers, reviewed the research limitations and explored areas for future work.

More specifically, this research has reviewed relevant literature to find a knowledge gap and proposed a novel system by integrating two adaptive techniques, fuzzy logic and concept map, to produce two main components (coloured concept map and ranked concepts list). This system provides students with appropriate learning materials based on their knowledge levels by using a bespoke pre-test with fuzzy outputs. Two experiments (pilot study and full study) were conducted to test the effectiveness of the proposed system. Both studies were successful and provided positive results, whether evaluating the hypotheses, or the positive responses and feedback given by the students.

To sum up, it is clear that the novel adaptive e-learning system CaFAE proposed in this thesis can motivate students and improve their learning performance. It is hoped that this research will help other researchers to further enhance the current adaptive e-learning systems and develop new ones.

References

AB HAMID, S. H., CHUAN, T. H. & KASIRUN, Z. M. L3OP: Learning styles application using learning objects approach. The Sixth IEEE International Conference on Computer and Information Technology (CIT'06), 2006. IEEE, 255-255.

AL DUHAYYIM, M. & NEWBURY, P. Concept-based and fuzzy adaptive e-learning: Case Study. 2019 International Conference on Computer and Information Sciences (2019 ICCIS), 2019. Institute of Electrical and Electronics Engineers.

ALBANO, G. Knowledge, skills, competencies: A model for mathematics e-learning. International Conference on ICT in Teaching and Learning, 2011. Springer, 214-225.

ALEVIZOU, P. 2002. To wire or not to wire? Encyclopaedia Britannica versus Microsoft Encarta. *Journal of Educational Technology & Society,* 5**,** 163-167.

ALKHURAIJI, S. M. 2016. *DYNAMIC ADAPTIVE E-LEARNING MECHANISM BASED ON LEARNING STYLES.* UNIVERSITY OF MANCHESTER.

ALMOHAMMADI, K., HAGRAS, H., YAO, B., ALZAHRANI, A., ALGHAZZAWI, D. & ALDABBAGH, G. 2017. A type-2 fuzzy logic recommendation system for adaptive teaching. *Soft Computing,* 21**,** 965-979.

ALSHAMMARI, M. 2016. *Adaptation based on learning style and knowledge level in e-learning systems.* University of Birmingham.

ALSHAMMARI, M., ANANE, R. & HENDLEY, R. J. Adaptivity in e-learning systems. Complex, Intelligent and Software Intensive Systems (CISIS), 2014 Eighth International Conference on, 2014. IEEE, 79-86.

ALZAHRANI, J. 2015. *Investigating role of interactivity in effectiveness of e-learning.* Brunel University London.

ARIS, T. N. M. & BADAWI, B. 2017. An agent-based adaptive E-content and elearning architecture design and implementation. *Journal of Theoretical and Applied Information Technology,* 95**,** 87-104.

ASLAM, F. 2014. *A Conceptual Evaluative Framework for the Management of Virtual Learning Environments in UK Universities.* Coventry University.

AWATI, M. A. S. & DIXIT, A. 2017. Automated Evaluation Framework for Student Learning using Concept Maps.

BAKER, T. 1994. Doing Social Research. New York: McGraw-Hill Inc.

BELDAGLI, B. & ADIGUZEL, T. Illustrating an ideal adaptive e-learning: A conceptual framework. Procedia - Social and Behavioral Sciences, 2010. 5755-5761.

BEN-GAL, I. 2007. Bayesian networks. *Encyclopedia of statistics in quality and reliability*.

BETITO, M. 2004. *Diagnosis of OSA syndrome from PAT and oximetry recordings using fuzzy decision trees*, Tel Aviv University.

BEZOVSKI, Z. & POORANI, S. The evolution of e-learning and new trends. Information and Knowledge Management, 2016. IISTE, 50-57.

BLACKBOARD. 2019. *Blackboard | Education Technology & Services* [Online]. Available: https://www.blackboard.com/index.html [Accessed 10/05/2019].

BLANCHARD, E., RAZAKI, R. & FRASSON, C. Cross-cultural adaptation of e-learning contents: A methodology. E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, 2005. Association for the Advancement of Computing in Education (AACE), 1895-1902.

BRAUN, V. & CLARKE, V. 2006. Using thematic analysis in psychology. *Qualitative research in psychology,* 3**,** 77-101.

BRUSILOVSKY, P. 1996. Methods and techniques of adaptive hypermedia. *User modeling and user-adapted interaction,* 6**,** 87-129.

BRUSILOVSKY, P. 1999. Adaptive and intelligent technologies for web-based eduction. *Ki,* 13**,** 19-25.

BRUSILOVSKY, P. Adaptive educational hypermedia. International PEG Conference, 2001. 8-12.

BRUSILOVSKY, P., KARAGIANNIDIS, C. & SAMPSON, D. 2004. Layered evaluation of adaptive learning systems. *International Journal of Continuing Engineering Education and Life Long Learning,* 14**,** 402-421.

BRUSILOVSKY, P. & NIJHAVAN, H. 2002. A Framework for Adaptive E-Learning based on Distributed Reusable.

BRUSILOVSKY, P. & PEYLO, C. 2003. Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education (IJAIED),* 13**,** 159-172.

BRYMAN, A. 2016. *Social research methods,* Oxford university press.

BURGOS, D., TATTERSALL, C. & KOPER, R. 2006. Representing adaptive eLearning strategies in IMS Learning Design.

CAÑAS, A. J., COFFEY, J. W., CARNOT, M.-J., FELTOVICH, P., HOFFMAN, R. R., FELTOVICH, J. & NOVAK, J. D. 2003. A summary of literature pertaining to the use of concept mapping techniques and technologies for education and performance support. *Report to the Chief of Naval Education and Training*.

CAÑAS, A. J., HILL, G., CARFF, R., SURI, N., LOTT, J., GÓMEZ, G., ESKRIDGE, T. C., ARROYO, M. & CARVAJAL, R. 2004. CmapTools: A knowledge modeling and sharing environment.

CHAKRABORTY, B. & SINHA, M. 2016. STUDENT EVALUATION MODEL USING BAYESIAN NETWORK IN AN INTELLIGENT E-LEARNING SYSTEM. *Journal of Institute of Integrative Omics and Applied Biotechnology (IIOAB),* 7**,** 2.

CHEN, C.-M., LEE, H.-M. & CHEN, Y.-H. 2005. Personalized e-learning system using item response theory. *Computers & Education,* 44**,** 237-255.

CHRYSAFIADI, K. & VIRVOU, M. 2012. Evaluating the integration of fuzzy logic into the student model of a web-based learning environment. *Expert Systems with Applications,* 39**,** 13127-13134.

CHRYSAFIADI, K. & VIRVOU, M. 2013a. A knowledge representation approach using fuzzy cognitive maps for better navigation support in an adaptive learning system. *SpringerPlus,* 2**,** 81.

CHRYSAFIADI, K. & VIRVOU, M. 2013b. PeRSIVA: An empirical evaluation method of a student model of an intelligent e-learning environment for computer programming. *Computers & Education,* 68**,** 322-333.

CHRYSAFIADI, K. & VIRVOU, M. 2013c. Student modeling approaches: A literature review for the last decade. *Expert Systems with Applications,* 40**,** 4715-4729.

CHRYSAFIADI, K. & VIRVOU, M. 2015. Fuzzy logic for adaptive instruction in an e-learning environment for computer programming. *IEEE transactions on Fuzzy Systems,* 23**,** 164-177.

CLASON, D. L. & DORMODY, T. J. 1994. Analyzing data measured by individual Likert-type items. *Journal of agricultural education,* 35**,** 4.

CODE. 2019. *What will you create? | Code.org* [Online]. Available: https://code.org/ [Accessed 10/05/2019].

COHEN, L., MANION, L. & MORRISON, K. 2011. Surveys, longitudinal, cross-sectional and trend studies. *Research Methods in Education, 7th edition. Abingdon: Routledge***,** 261-4.

COOK, T. D., CAMPBELL, D. T. & SHADISH, W. 2002. *Experimental and quasi-experimental designs for generalized causal inference,* Houghton Mifflin Boston, MA.

CORBETT, A. T. & ANDERSON, J. R. 1994. Knowledge tracing: Modeling the acquisition of procedural knowledge. *User modeling and user-adapted interaction,* 4**,** 253-278.

COURSEARS. 2019. *Start Learning at Coursers* [Online]. Available: http://coursears.com/ [Accessed 10/05/2019].

COWELL, R. 1998. Introduction to inference for Bayesian networks. *Learning in graphical models.* Springer.

CRESWELL, J. W. & CRESWELL, J. D. 2017. *Research design: Qualitative, quantitative, and mixed methods approaches,* Sage publications.

CRISTEA, A. & STASH, N. AWELS: adaptive Web-based education and learning styles. Sixth IEEE International Conference on Advanced Learning Technologies (ICALT'06), 2006. IEEE, 1135-1136.

CRONBACH, L. J. & SNOW, R. E. 1977. *Aptitudes and instructional methods: A handbook for research on interactions*, Irvington.

CROSS, J. 2004. An informal history of eLearning. *On the Horizon*, 12**,** 103-110.

DARE, F. T. 2011. A Novel Methodology for E-Learning Space Design in HEI Campuses.

DE VAUS, D. A. & DE VAUS, D. 2001. *Research design in social research*, Sage.

DOGAN, B. & DIKBıYıK, E. 2016. OPCOMITS: Developing an adaptive and intelligent web based educational system based on concept map model. *Computer Applications in Engineering Education*, 24**,** 676-691.

DOLENC, K. & ABERŠEK, B. 2015. TECH8 intelligent and adaptive e-learning system: Integration into Technology and Science classrooms in lower secondary schools. *Computers & Education*, 82**,** 354-365.

DOROOB. 2019. *National Training Platform* [Online]. Available: https://www.doroob.sa/ar/ [Accessed 10/05/2019].

DOS SANTOS GUIMARÃES, R., STRAFACCI, V. & TASINAFFO, P. M. 2016. Implementing fuzzy logic to simulate a process of inference on sensory stimuli of deaf people in an e-learning environment. *Computer Applications in Engineering Education*, 24**,** 320-330.

DRIGAS, A. S., ARGYRI, K. & VRETTAROS, J. Decade review (1999-2009): Artificial intelligence techniques in student modeling. World Summit on Knowledge Society, 2009. Springer, 552-564.

DUHAYYIM, M. A. & NEWBURY, P. 2018. Concept-based and Fuzzy Adaptive E-learning. *Proceedings of the 2018 The 3rd International Conference on Information and Education Innovations.* London, United Kingdom: ACM.

DUOLINGO. 2019. *Duolingo* [Online]. Available: https://www.duolingo.com/ [Accessed 10/05/2019].

EDX. 2019. *edX | Free Online Courses by Harvard, MIT, & more* [Online]. Available: https://www.edx.org/ [Accessed 12/05/2019].

ESICHAIKUL, V., LAMNOI, S. & BECHTER, C. 2011. Student modelling in adaptive e-learning systems. *Knowledge Management and E-Learning*, 3**,** 342-355.

ESPOSITO, F., LICCHELLI, O. & SEMERARO, G. 2004. Discovering student models in e-learning systems. *Journal of Universal Computer Science*, 10**,** 47-57.

FIELD, A. 2005. Discovering statistics through SPSS. London, Sage.

FIELD, A. 2013. *Discovering statistics using IBM SPSS statistics*, sage.

FOUNDATION, M. 2019. *MiSK Foundation* [Online]. Available: https://misk.org.sa/en/ [Accessed 10/05/2019].

GARDNER, H. 2000. Intelligence reframed.

GAUDIOSO, E., MONTERO, M. & HERNANDEZ-DEL-OLMO, F. 2012. Supporting teachers in adaptive educational systems through predictive models: A proof of concept. *Expert Systems with Applications*, 39**,** 621-625.

GEORGOULI, K. Virtual learning environments-An overview. 2011 15th Panhellenic Conference on Informatics, 2011. IEEE, 63-67.

GLUSHKOVA, T. Adaptive model for user knowledge in the e-learning system. Proceedings of the 9th International Conference on Computer Systems and Technologies and Workshop for PhD Students in Computing, 2008. ACM, 78.

GODWIN-JONES, R. 2006. Emerging technologies: blogs and wikis: environments for on-line collaboration.: An article from: Language, Learning & Technology.

GRAF, S. 2005. Fostering adaptivity in e-learning platforms: A meta-model supporting adaptive courses. *CELDA*, 1**,** 440-443.

GRAF, S. & LIST, B. An evaluation of open source e-learning platforms stressing adaptation issues. Fifth IEEE International Conference on Advanced Learning Technologies (ICALT'05), 2005. IEEE, 163-165.

GROVES, R. & FOWLER, F. 2004. J., Couper, MP, Lepkowski, JM, Singer, E., and Tourangeau, R. *Survey Methodology*.

GUTIÉRREZ, I., ÁLVAREZ, V., PAULE, M., PÉREZ-PÉREZ, J. R. & DE FREITAS, S. 2016. Adaptation in E-Learning Content Specifications with Dynamic Sharable Objects. *Systems,* 4**,** 24.

HAFIDI, M. & BENSEBAA, T. 2013. Development of an adaptive and intelligent tutoring system by expert system. *International Journal of Computer Applications in Technology,* 48**,** 353-365.

HÁJEK, P. 2006. What is mathematical fuzzy logic. *Fuzzy sets and systems,* 157**,** 597-603.

HAMMERSLEY, M. & TRAIANOU, A. 2012. Ethics and educational research, British Educational Research Association on-line resource. *British Educational Research Association.*

HOOSHYAR, D., AHMAD, R. B., YOUSEFI, M., FATHI, M., HORNG, S.-J. & LIM, H. 2016. SITS: a solution-based intelligent tutoring system for students' acquisition of problem-solving skills in computer programming. *Innovations in Education and Teaching International***,** 1-11.

HSIEH, T.-C., LEE, M.-C. & SU, C.-Y. 2013. Designing and implementing a personalized remedial learning system for enhancing the programming learning. *Educational Technology & Society,* 16**,** 32-46.

HSIEH, T.-C., WANG, T.-I., SU, C.-Y. & LEE, M.-C. 2012. A Fuzzy Logic-based Personalized Learning System for Supporting Adaptive English Learning. *Educational Technology & Society,* 15**,** 273-288.

JADHAV, M., RIZWAN, S. & NEHETE, A. User profiling based Adaptive Test Generation and Assessment in E-Learning System. Advance Computing Conference (IACC), 2013 IEEE 3rd International, 2013. IEEE, 1425-1430.

JAMESON, A. 2009. Adaptive interfaces and agents. *Human-Computer Interaction: Design Issues, Solutions, and Applications,* 105**,** 105-130.

JEREMIĆ, Z., JOVANOVIĆ, J. & GAŠEVIĆ, D. 2009. Evaluating an intelligent tutoring system for design patterns: The DEPTHS experience. *Educational Technology & Society,* 12**,** 111-130.

JEREMIĆ, Z., JOVANOVIĆ, J. & GAŠEVIĆ, D. 2012. Student modeling and assessment in intelligent tutoring of software patterns. *Expert Systems with Applications,* 39**,** 210-222.

KAKOTY, S. & SARMA, S. 2011. Expert System Applications in E-learning Environment: Analysis on Current Trends and Future Prospects. *International Journal of Internet Computing,* 1**,** 90-93.

KASS, R. 1991. Building a user model implicitly from a cooperative advisory dialog. *User Modeling and User-Adapted Interaction,* 1**,** 203-258.

KHANACADEMY. 2019. *Khan Academy | Free Online Courses, Lessons & Practice* [Online]. Available: https://www.khanacademy.org/ [Accessed 12/05/2019].

KHEMAJA, M. & TAAMALLAH, A. 2016. Towards Situation Driven Mobile Tutoring System for Learning Languages and Communication Skills: Application to Users with Specific Needs. *Educational Technology & Society,* 19**,** 113-128.

KIRKPATRICK, D. L. 1979. Techniques for evaluating training programs. *Training and development journal*.

KLAŠNJA-MILIĆEVIĆ, A., VESIN, B., IVANOVIĆ, M., BUDIMAC, Z. & JAIN, L. C. 2017. Personalization and Adaptation in E-Learning Systems. *E-Learning Systems.* Springer.

KOLB, D. A. 2014. *Experiential learning: Experience as the source of learning and development,* FT press.

KOZIERKIEWICZ-HETMAŃSKA, A. & NGUYEN, N. 2011. A method for learning scenario determination and modification in intelligent tutoring systems. *International Journal of Applied Mathematics and Computer Science,* 21**,** 69-82.

KUMAR, A. A scalable solution for adaptive problem sequencing and its evaluation. International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems, 2006a. Springer, 161-171.

KUMAR, A. N. Using Enhanced Concept Map for Student Modeling in Programming Tutors. FLAIRS Conference, 2006b. 527-532.

LEKA, L., KIKA, A. & GRECA, S. Adaptivity In E-learning Systems. RTA-CSIT, 2016. 135-139.

LIAW, S.-S. 2008. Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: A case study of the Blackboard system. *Computers & Education,* 51**,** 864-873.

LIEBOWITZ, J. 1995. Expert systems: A short introduction. *Engineering Fracture Mechanics,* 50**,** 601-607.

LIEBOWITZ, J. & ADYA, M. 2000. An Analysis of Using Expert Systems and Intelligent Agents for the Virtual Library Project at the Naval Surface Warfare Center-Carderock Division.

LIMONGELLI, C., SCIARRONE, F., TEMPERINI, M. & VASTE, G. 2009. Adaptive learning with the LS-plan system: a field evaluation. *IEEE Transactions on Learning Technologies,* 2**,** 203-215.

MAHNANE, L., LASKRI, M. T. & TRIGANO, P. 2012. An adaptive hypermedia system integrating thinking style (AHS-TS): model and experiment. *International Journal of Hybrid Information Technology,* 5**,** 11-28.

MAMDANI, E. H. & ASSILIAN, S. 1975. An experiment in linguistic synthesis with a fuzzy logic controller. *International journal of man-machine studies,* 7**,** 1-13.

MARKOV, A. 1971. Extension of the limit theorems of probability theory to a sum of variables connected in a chain.

MARTIN, A. 2010. *Building classroom success: Eliminating academic fear and failure*, A&C Black.

MARTINS, C., FARIA, L., DE CARVALHO, C. V. & CARRAPATOSO, E. 2008. User modeling in adaptive hypermedia educational systems. *Educational Technology & Society,* 11**,** 194-207.

MATVEEV, A. V. 2002. The advantages of employing quantitative and qualitative methods in intercultural research: Practical implications from the study of the perceptions of intercultural communication competence by American and Russian managers. *Theory of communication and applied communication,* 1**,** 59-67.

MOODLE. 2019a. *Concept-based and Fuzzy Adaptive E-learning* [Online]. Available: http://cafae.co.uk/ [Accessed 10/05/2019].

MOODLE. 2019b. *Moodle - Open-source learning platform* [Online]. Available: https://moodle.org/ [Accessed 10/05/2019].

NEGNEVITSKY, M. 2005. *Artificial intelligence: a guide to intelligent systems*, Pearson Education.

OLMUS, H. & ERBAS, S. O. 2004. Determining the conditional probabilities in Bayesian networks. *Hacettepe Journal of Mathematics and Statistics,* 33**,** 69-76.

ÖZYURT, Ö., ÖZYURT, H. & BAKI, A. 2013a. Design and development of an innovative individualized adaptive and intelligent e-learning system for teaching–learning of probability unit: Details of UZWEBMAT. *Expert Systems with Applications,* 40**,** 2914-2940.

ÖZYURT, Ö., ÖZYURT, H., BAKI, A. & GÜVEN, B. 2013b. Integration into mathematics classrooms of an adaptive and intelligent individualized e-learning environment: Implementation and evaluation of UZWEBMAT. *Computers in Human Behavior,* 29**,** 726-738.

PECHENIZKIY, M., CALDERS, T., VASILYEVA, E. & DE BRA, P. Mining the student assessment data: Lessons drawn from a small scale case study. Educational Data Mining 2008, 2008.

PHOBUN, P. & VICHEANPANYA, J. 2010. Adaptive intelligent tutoring systems for e-learning systems. *Procedia-Social and Behavioral Sciences,* 2**,** 4064-4069.

PLOTNICK, E. 1997. Concept Mapping: A Graphical System for Understanding the Relationship between Concepts. ERIC Digest.

POLIT, D. F. & BECK, C. T. 2006. *Essentials of nursing research: Methods, appraisal, and utilization*, Lippincott Williams & Wilkins.

POPESCU, E., TRIGANO, P. & BADICA, C. Evaluation of a learning management system for adaptivity purposes. 2007 International Multi-Conference on Computing in the Global Information Technology (ICCGI'07), 2007. IEEE, 9-9.

QIYAS. 2019. *National Center for Assessment* [Online]. Available: https://www.qiyas.sa/en/Pages/default.aspx [Accessed 12/05/2019].

R-MORENO, M. D., CAMACHO, D. & OBIETA, U. 2008. A plan-based tool for automatic eLearning courses redesign. *International Journal of Computer Science Applications*.

RICH, E. 1979. User modeling via stereotypes. *Cognitive science,* 3**,** 329-354.

RIVERS, R. 1989. Embedded user models—where next? *Interacting with Computers,* 1**,** 13-30.

RWAQ. 2019. *Arabic platform for open education to spread knowledge* [Online]. Available: https://www.rwaq.org/ [Accessed 10/05/2019].

SHUTE, V. & TOWLE, B. 2003. Adaptive e-learning. *Educational psychologist,* 38**,** 105-114.

STANSFIELD, J. L. 1976. Wumpus Advisor I. A First Implementation of a Program That Tutors Logical and Probabilistic Reasoning Skills. AI Memo 381.

STOCKLEY, D. 2003. E-learning definition and explanation (Elearning, online training, online learning). *Retrieved March,* 15**,** 2010.

STOYANOV, S. & KIRCHNER, P. 2004. Expert concept mapping method for defining the characteristics of adaptive e-learning: ALFANET project case. *Educational technology research and development,* 52**,** 41-54.

TAKAGI, T. & SUGENO, M. 1985. Fuzzy identification of systems and its applications to modeling and control. *IEEE transactions on systems, man, and cybernetics***,** 116-132.

TROCHIM, W. 2000. The research methods knowledge base (2nd edn)(Cincinnati, OH, Atomic Dog).

TSIRIGA, V. & VIRVOU, M. Initializing the student model using stereotypes and machine learning. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, 2002. Citeseer.

UDEMY. 2019. *Online Courses - Learn Anything, On Your Schedule | Udemy* [Online]. Available: https://www.udemy.com/ [Accessed 10/05/2019].

VAN TEIJLINGEN, E. & HUNDLEY, V. 2002. The importance of pilot studies. *Nursing Standard (through 2013),* 16**,** 33.

VANIDES, J., YIN, Y., TOMITA, M. & RUIZ-PRIMO, M. A. 2005. Concept maps. *Science Scope,* 28**,** 27-31.

VARGAS, R. E. 2010. *Fuzzy logic: theory, programming and applications*, Nova Science Publ.

VASILYEVA, E., PECHENIZKIY, M. & DE BRA, P. Adaptation of elaborated feedback in e-learning. International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems, 2008. Springer, 235-244.

VIOLANTE, M. G. & VEZZETTI, E. 2015. Design of web-based interactive 3D concept maps: A preliminary study for an engineering drawing course. *Computer Applications in Engineering Education,* 23**,** 403-411.

WANG, F., LI, J. & HOMAYOUNFAR, H. 2007. A space efficient XML DOM parser. *Data & Knowledge Engineering,* 60**,** 185-207.

WHITTENBURG, J. B. 2011. *Adapting to adaptive e-learning: Utilizing adaptive e-learning programs within educational institutions*, University of Southern California.

YEN, J., WANG, L. & GILLESPIE, C. W. 1998. Improving the interpretability of TSK fuzzy models by combining global learning and local learning. *IEEE Transactions on fuzzy Systems,* 6**,** 530-537.

ZADEH, L. A. 1965. Fuzzy sets. *Information and control,* 8**,** 338-353.

ZADEH, L. A. 1984. Making computers think like people [fuzzy set theory]. *IEEE spectrum,* 21**,** 26-32.

ZADEH, L. A. 1996. Fuzzy logic= computing with words. *IEEE transactions on fuzzy systems,* 4**,** 103-111.

ZAFAR, A. & ALBIDEWI, I. 2015. Evaluation study of eLGuide: A framework for adaptive e-learning. *Computer Applications in Engineering Education,* 23**,** 542-555.

ZHANG, X. & HAN, H. 2005. An empirical testing of user stereotypes of information retrieval systems. *Information processing & management,* 41**,** 651-664.

ZIMMERMANN, H.-J. 2011. *Fuzzy set theory—and its applications*, Springer Science & Business Media.

Appendices

Appendix A Ethical Approval

Appendix A.1 Information Sheet

INFORMATION SHEET

INVITATION TO TAKE PART

You are being invited to take part in a research study to further our understanding of Concept-based and Fuzzy Adaptive E-learning (CaFAE). Thank you for carefully reading this information sheet, a copy of which you can keep for your records.This study is being conducted by Mr Mesfer Al Duhayyim and Dr Paul Newbury from the School of Engineering and Informatics, University of Sussex, who are happy to be contacted (M.Al-Duhayyim@sussex.ac.uk, p.newbury@sussex.ac.uk) if you have any questions. The research is additionally being organised by Mr Mesfer Al Duhayyim, Dr Paul Newbury, Dr Phil Watten.

Before you decide whether or not to take part, it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully.

WHAT IS THE PURPOSE OF STUDY?

The purpose of this study is to evaluate your learning experience using a novel adaptive e-learning system (CaFAE)., and satisfaction level during your participation in the use of the system

WHY HAVE I BEEN INVITED FOR TESTING AND WHAT WILL I DO?

We are testing students taking the Algorithms and Data Structure module, and the study will take approximately 8 weeks. We will be measuring your understanding level of a selection of topics and recommending to you a suitable set of learning materials to improve your understanding. Thus, we hope this will have a noticeable positive effect on your understanding of the subject area.

DO I HAVE TO TAKE PART?

It is up to you to decide whether or not to take part to this research. If you do decide to take part, you will be given this information sheet to keep and be asked to sign a consent form. If you decide to take part, you are still free to withdraw at any time and without giving a reason. Choosing to either take part or not take part in the study will have no impact on your marks, assessments or future studies.

WHAT WILL HAPPEN TO ME IF I TAKE PART?

If you decide to take part in this study, you will complete a pre-test and a post-test questionnaire, and will participate in using the system. During the study you will take a pre-test as part of the module, and a post-test at the end of this study, but please note these tests will have no bearing on your assessment for the module as a whole. You may review the questionnaires before deciding whether take part.

WHAT ARE THE POSSIBLE DISADVANTAGES AND RISKS OF TAKING PART? (WHERE APPROPRIATE)

The project is a term-long experiment and some participation will be needed for the 8 weeks of the study. You will be expected to take part in the study as part of your normal studies for Algorithms and Data Structure, and there is no expected overhead above your normal studies required for this module. You will only be required to complete a questionnaire twice during the study, once at the beginning and once at the end.

WHAT ARE THE POSSIBLE BENEFITS OF TAKING PART?

Taking part of this study will help the lecturers improving the delivery method of information and module materials by providing a different tool for learning and helping them understand what can be improved to make learning more enjoyable and effective. This will result in more effective teaching and it is expected to improve your understanding of the subject area.

WILL MY INFORMATION IN THIS STUDY BE KEPT CONFIDENTIAL?

The data you produce during this study will be kept confidential and your name will not be used nor associated with data in papers, dissertation, thesis, reports, or any printed or unprinted volumes associated with this study.

WHAT SHOULD I DO IF I WANT TO TAKE PART?

If you wish to take part in this research please contact Mesfer Al Duhayyim either telling him in person or emailing him at M.Al-Duhayyim@sussex.ac.uk

WHAT WILL HAPPEN TO THE RESULTS AND MY PERSONAL INFORMATION?

The results of this research may be written into a thesis for PhD degree and also for publication purposes. They can be accessed through the university archived theses and/or published sources. The data generated from this experiment can be re-used with other research publications in the same area. We anticipate being able to provide a summary of our findings on request from M.Al Duhayyim@sussex.ac.uk. Your anonymity will be ensured in the way described in the consent information below. Please read this information carefully and then, if you wish to take part, please sign to show *y*ou have fully understood this sheet, and that you consent to take part in the study as it is described here.

WHO WILL APPROVE THIS STUDY?

This study has been approved by the Science & Technology Cross-Schools Research Ethics Committee (crecscitec@sussex.ac.uk). The project reference number is ER/MA857/2. The University of Sussex has insurance in place to cover its legal liabilities in respect of this study.

Thank you for carefully reading this information sheet, a copy of which you can keep for your records. Date: 25/06/2018

Appendix A.2 Consent Form

CONSENT SHEET

PROJECT TITLE: Concept-based and Fuzzy Adaptive E-learning (CaFAE).

Project Approval Reference: --

- I understand that by signing below I am agreeing to take part in the University of Sussex research described here, and that I have read and understood this information sheet. I understand that agreeing to take part means that I am willing to:

  - Participate in the use of the system and complete all the required tasks.
  - Complete pre-test and post-test questionnaires based on my own previous knowledge and experience with the system.

- I understand that my participation is entirely voluntary, that I can choose not to participate in part or all of the study, and that I can withdraw at any stage of testing without having to give a reason and without being penalised in any way.

- I understand I can request without penalty that my data be withdrawn and deleted even after testing is complete, any time up until the results are analysed. I understand that to withdraw from the study, I should request to do so via email to (M.Al-Duhayyim@sussex.ac.uk), at which point my consent form will be securely destroyed. I understand that I can request withdrawal from the study and removal of my data up to three weeks after the end of the study.

- I consent to the processing of my personal information for the purposes of this research study. I understand that such information will be treated as strictly confidential (subject to legal limitations) and handled in accordance with the Data Protection Act 1998 and General Data Protection Regulation (GDPR) (EU) 2016/679.

- I understand that my data including my personal information (e.g. name) will be stored safely. Electronic data will be stored on a password-protected computer, and hard-copies will be stored behind a locked door.

- I understand that my identity will remain confidential in any written reports of this research, and that no information I disclose will lead to the identification in those reports of any individual either by the researchers or by any other party, without first obtaining my written permission.

- I understand that my name and data will not be shared with any third party outside the research group, unless I later provide written permission.

☐ I consent to the reuse of the data collected in this research in future research projects.

______________________	______________	___________________
Name of Participant	Date	Signature

Appendix A.3 Recruitment Email

I am a PhD student in the School of Engineering and Informatics at the University of Sussex, and I am conducting a research study on a novel e-learning system – Concept-based and Fuzzy Adaptive E-learning.

The aim of this study is to design an effective adaptive e-learning system that uses a coloured concept map to show student knowledge level for each concept in the topic, and provides a ranked concept list of learning materials based on understanding levels. This study also aims to improve consistency and performance of learning by using adaptive tools.

This study will be completed as part of the Algorithms and Data Structure module, and you are receiving this email as you are a student who is taking this module. I am looking for participants and would be very thankful if you would be willing to take part in my study. If you do so, you will have the chance to find out more about the study before coming to any decision. You would be under no obligation to take part and this will have no impact on your marks, assessments or future studies. It is completely up to you whether to participate in this research study.

The project is a term-long experiment and your participation will be needed during the whole term, however you will have the chance to be familiar with new educational tools. You will be expected to take part in the study as part of your normal studies Algorithms and Data Structure, and there is no expected overhead above your normal studies required for this module. You will only be required to complete a questionnaire twice during the study, once at the beginning and once at the end. The data produced from your participation will be kept confidential and your name will not be used nor associated with the data in papers, dissertations, or any printed or non-printed volumes associated with this study. The result of this study will be used in my thesis for PhD degree and also for publication purposes and can be accessed through the University archived theses library and/or published sources.

My research is supervised by Dr Paul Newbury and Dr Phil Watten and they can be contacted on: P.Newbury@sussex.ac.uk and P.L.Watten@sussex.ac.uk respectively. The use of email to recruit participants for this study will be approved by the Sciences and Technology Cross-Schools Research Ethics Committee (CREC:crecscitec@sussex.ac.uk)

Thank you and Best Regards,
Mr Mesfer Al Duhayyim
School of Engineering and Informatics Department of Informatics
University of Sussex

M.Al-Duhayyim@sussex.ac.uk

Appendix B Experiments Questionnaires

Appendix B.1 Pre- Experiment Questionnaire

Concept and Fuzzy Adaptive E-learning (CaFAE)

Pre-Experiment Questionnaire

Adaptive e-learning system is a system which gives you different learning materials depending on how well it thinks you know the subject while the standard e-learning system gives you the same learning materials whether you know the subject, or you don't.

Thank you for your time to complete this survey. Your feedback is very important to my research. This survey should only take about 5 minutes of your time. Your answers will be completely anonymous and survey results may be published for educational purposes.

1. What is your favourite way to learn?

   - ○ Online lecture
   - ○ Traditional (attending Lecture)
   - ○ Both
   - ○ Other [Specify]

   ……………………………………………………………………

2. Have you used an online learning environment for personal learning before? If No you will be directed to question 4

   - ○ Yes
   - ○ No

   If yes

3. Which learning management system have you used?

4. How many hours a week do you spend on online learning?

   - ○ Less than 2 hours
   - ○ Between 2 and 4 hours
   - ○ Between 6 and 8 hours
   - ○ More than 8 hours

5. How did you find using online learning lectures compared to traditional learning?

- ○ Superior
- ○ Inferior
- ○ Similar

Please write more details based on your selection:

6. Do you think that using an online learning environment is a useful way to improve your understanding?
   - ○ Yes
   - ○ No

Explain

7. Have you ever used an adaptive e-learning system before? If you select “No” you completed the questionnaire, and if you select “Yes” you will be directed to answer the next question.
   - ○ Yes
   - ○ No

If yes

8. Which an adaptive e-learning system have you used?

9. Did the adaptive learning system improve your understanding?
   - ○ Yes
   - ○ No

How

Appendix B.2 Adaptive Post-Experiment Questionnaire

Concept and Fuzzy Adaptive E-learning (CaFAE)

Adaptive Post-Experiment Questionnaire

Adaptive e-learning system is a system which gives you different learning materials depending on how well it thinks you know the subject while the standard e-learning system gives you the same learning materials whether you know the subject, or you don't.

Thank you for your time to complete this survey. Your feedback is very critical to my research. This survey should only take about 15 minutes of your time. Your answers will be completely anonymous and survey results may be published for educational purposes. This survey has three sections. The first two sections are related to the usability of the system while the third part is related to system learning support.

A. On a scale of 1 to 5 please answer the following questions:

Questions	Strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly agree (5)
1. The e-learning system was easy to use.	**O**	**O**	**O**	**O**	**O**
2. The material provided by the e-learning system is easy to understand.	**O**	**O**	**O**	**O**	**O**
3. The e-learning system made it easy for me to find the material I need.	**O**	**O**	**O**	**O**	**O**
4. The e-learning system provided material that exactly fitted my needs.	**O**	**O**	**O**	**O**	**O**
5. The e-learning system provides sufficient material.	**O**	**O**	**O**	**O**	**O**
6. The e-learning system enabled me to learn the material I need.	**O**	**O**	**O**	**O**	**O**
7. I have no problems accessing and going through the materials.	**O**	**O**	**O**	**O**	**O**

8. The e-learning system enabled me to control my learning progress.	**O**	**O**	**O**	**O**	**O**
9. The e-learning system recorded my learning progress and performance.	**O**	**O**	**O**	**O**	**O**
10. The e-learning system was more adaptive than I thought.	**O**	**O**	**O**	**O**	**O**
11. I would imagine that most students would learn to use this system very quickly.	**O**	**O**	**O**	**O**	**O**
12. I feel the adaptive e-learning approach can substitute for or enhance the normal online learning approach.	**O**	**O**	**O**	**O**	**O**
13. The feedback from activities/quizzes helped me to locate where I am having difficulties.	**O**	**O**	**O**	**O**	**O**
14. The activities/quizzes provided in the course enhanced my learning.	**O**	**O**	**O**	**O**	**O**
15. The responses to the pre-test helped me understand where I am having difficulties.	**O**	**O**	**O**	**O**	**O**
16. I found the coloured concept map is more helpful and helped me understand my knowledge level.	**O**	**O**	**O**	**O**	**O**
17. The coloured concept map showed information that exactly fits my understanding level.	**O**	**O**	**O**	**O**	**O**
18. The ranked concepts list helped me to	**O**	**O**	**O**	**O**	**O**

locate where I am having difficulties.					
19. I can follow the ranked concepts list easily.	**O**	**O**	**O**	**O**	**O**
20. The instructions provided to use the tools within the site are clear and precise.	**O**	**O**	**O**	**O**	**O**
21. I feel I learn more in this system.	**O**	**O**	**O**	**O**	**O**
22. I feel comfortable using this system.	**O**	**O**	**O**	**O**	**O**
23. I believe I became productive using this system.	**O**	**O**	**O**	**O**	**O**
24. Whenever I make a mistake using the system, I recover easily and quickly.	**O**	**O**	**O**	**O**	**O**
25. This system has all the functions and capabilities I expect it to have.	**O**	**O**	**O**	**O**	**O**
26. Overall, I am satisfied with this system.	**O**	**O**	**O**	**O**	**O**

B. Please briefly answer the following questions

1- Which parts of the system were easy to use?

2- Which parts of the system were difficult to use?

C. Please briefly answer the following questions

1- Did the system provide you with an appropriate ranked concepts list that you felt matched your understanding of the subject area?

- Yes
- No

Explain how

2- Did the ranked concepts list help you to have a better understanding of your knowledge of the subject area?

- Yes
- No

3- Did you find the coloured concept map helpful in determining your knowledge and understanding?

- Yes
- No

Explain how

4- Was the ranked concepts list important in improving understanding?

- Yes
- No

Explain

5- Was this system useful in finding answers to the problems you have faced in your learning?

- ○ Yes
- ○ No

Explain how

6- Do you think the ranked concepts list was a helpful method in increasing learning?

- ○ Yes
- ○ No

7- Do you think the coloured concept map was a helpful method in increasing motivation and engagement?

- ○ Yes
- ○ No

8- Did you find the coloured concept map and the ranked concepts list more understandable and more accurate to solve problems than using the standard online learning system?

- ○ Yes
- ○ No

Explain.

9- Briefly list the main advantages or disadvantages of this system on learning process.

10- Overall, how do you rate this system in enhancing learning and understanding (From 1=very poor to 10=excellent)?

11- Overall, how do you rate this system in increasing adaptation in education (From1 to 10)?

Appendix B.3 Non-adaptive Post-Experiment Questionnaire

Concept and Fuzzy Adaptive E-learning (CaFAE)

Non-adaptive Post-Experiment Questionnaire

Thank you for your time to complete this survey. Your feedback is very critical to my research. This survey should only take about 15 minutes of your time. Your answers will be completely anonymous and survey results may be published for educational purposes. This survey has three sections. The first two sections are related to the usability of the system while the third part is related to system learning support.

A. On a scale of 1 to 5 please answer the following questions:

Questions	Strongly agree (1)	Agree (2)	Satisfied (3)	Disagree (4)	Strongly disagree (5)
27. The e-learning system was easy to use.	**O**	**O**	**O**	**O**	**O**
28. The material provided by the e-learning system is easy to understand.	**O**	**O**	**O**	**O**	**O**
29. The e-learning system made it easy for me to find the material I need.	**O**	**O**	**O**	**O**	**O**
30. The e-learning system provided material that exactly fitted my needs.	**O**	**O**	**O**	**O**	**O**
31. The e-learning system provides sufficient material.	**O**	**O**	**O**	**O**	**O**
32. The e-learning system enabled me to learn the material I need.	**O**	**O**	**O**	**O**	**O**
33. I have no problems accessing and going through the materials.	**O**	**O**	**O**	**O**	**O**
34. The e-learning system enabled me to control my learning progress.	**O**	**O**	**O**	**O**	**O**
35. The e-learning system recorded my learning progress and performance.	**O**	**O**	**O**	**O**	**O**
36. I would imagine that most students would learn to use this system very quickly.	**O**	**O**	**O**	**O**	**O**
37. The feedback from activities/quizzes helped me to	**O**	**O**	**O**	**O**	**O**

locate where I am having difficulties.					
38. The activities/quizzes provided in the course enhanced my learning.	O	O	O	O	O
39. The responses to the pre-test helped me understand where I am having difficulties.	O	O	O	O	O
40. The instructions provided to use the tools within the site are clear and precise.	O	O	O	O	O
41. I feel I learn more in this system.	O	O	O	O	O
42. I feel comfortable using this system.	O	O	O	O	O
43. I believe I became productive using this system.	O	O	O	O	O
44. Whenever I make a mistake using the system, I recover easily and quickly.	O	O	O	O	O
45. This system has all the functions and capabilities I expect it to have.	O	O	O	O	O
46. Overall, I am satisfied with this system.	O	O	O	O	O

B. Please briefly answer the following questions

1- Which parts of the system were easy to use?

2- Which parts of the system were difficult to use?

C. Please briefly answer the following questions

1- Did the system provide you with an appropriate learning material that you felt matched your understanding of the subject area?

- ○ Yes
- ○ No

2- Did you find the pre-test helpful in determining your knowledge and understanding?

- ○ Yes
- ○ No

3- Was this system useful in finding answers to the problems you have faced in your learning?

- ○ Yes
- ○ No

Explain how

4- Briefly list the main advantages or disadvantages of this system on learning process.

5- Overall, how do you rate this system in enhancing learning and understanding (From 1 to 10)?