Learning Experience in Dynamic and Non-Dynamic Curriculum Sequencing Systems

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Abstract

This PhD thesis presents a series of interrelated studies about computer-based learning experience with a focus on a dynamic curriculum sequencing system (DCSS). A DCSS is an adaptive computer-based system that organises learning material dynamically, based on the learners' learning parameters such as prior knowledge, learning styles and preferences. The learning experience refers to the learners' cognitive engagement during their interactions with computer-based systems. It is important to note that the learning experience discussed here is reviewed in the context of the flow theory. Many previous studies have claimed that learners' psychological well-being and future use of computer-based learning are correlated with their learning experiences. Hence, this thesis provides some empirical evidence about the DCSS learning experience to complement the existing literature in the area of computer-based learning.

The thesis intends to achieve two main objectives. First, it aims to identify whether or not the DCSS learning experience is significantly different in comparison to the non-DCSS (i.e., a recommendation system). Additionally, it intends to examine whether the DCSS and the non-DCSS learning experiences change over time. It also develops and validates a new technique that can improve the DCSS learning experience, known as a skill-challenge balancing (SCB) technique. In order to achieve the first objective, two experimental studies were conducted using two types of computer-based systems (i.e., the DCSS and the non-DCSS) for teaching 'Computer Networks'. The self-reporting technique was employed to measure the learning experiences in both studies. For the second objective, the software analysis and design tasks were performed to visualize the SCB technique conceptually and technically. It was followed by an experimental study that validates the new technique using the same methodological approach as in the first two studies.

The first two experimental studies suggested that the DCSS and the non-DCSS gave the learners different learning experiences. These studies further identified the learners' cognitive states showing some of them suffered from boredom and anxiety in particular learning conditions. The findings of these studies emphasized that there

is a need for a novel approach to maintain learning experience in computer-based learning. For this reason, this thesis also proposes a new learning experience monitoring technique (i.e., the SCB) considering some underlying principles from the flow theory. This technique was empirically validated to be effective in improving the DCSS learning experience.

As computer-based learning is an essential tool in current higher educational settings, the outcomes of this thesis are discussed in relation to adaptive design of computer-based learning and human-computer interaction.

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List of Abbreviations

Acronyms	Full Names
AI	Assessment Items
CLT	Cognitive Load Theory
CS	Computer Science
CSS	Curriculum Sequencing Systems
DCSS	Dynamic Curriculum Sequencing Systems
DM	Domain Model
DSA	Dynamic Sequencing Approach
EM	Engagement Model
IC	Instructional Contents
IIMS	Institute of Information and Mathematical Sciences
IT	Information Technology
ITS	Intelligent Tutoring Systems
K-S	Kolmogorov-Smirnov
LO	Learning Object
LOR	Learning Object Repository
LTM	Long Term Memory
NASA-TLX	NASA Task Load Index
QoE	Quality of Experience
RQ	Research Questions
SCB	Skill-Challenge Balancing
SCSS	Static Curriculum Sequencing Systems
SE	Sequencing Engine
SM	Student Model

Preface

This thesis presents interrelated studies about learning experiences in the dynamic curriculum sequencing system (DCSS). It primarily aims to uncover knowledge about the importance of maintaining an optimal level of computer-based learning experience. The thesis intends to offer a technique that improves the learning experience following a psychological concept known as the flow theory.

The implementation of the thesis is divided into four sections. Section I introduces the readers to the theoretical framework that guides the overall execution of the thesis. It also emphasises the importance of the optimal learning experience and techniques to achieve it through an extensive review of secondary evidence from literature.

Section II aims to explain basic DCSS concepts including the common components of the systems and existing examples of DCSS. This section also describes the design and development tasks of a DCSS named IT-Tutor. At the end of this section, a study that evaluates the usability of IT-Tutor is presented. The system has been used as the main learning tool for the empirical studies in this thesis.

Section III describes two empirical studies to investigate the DCSS learning experience which are evaluated from multiple perspectives. Firstly, it comprises of a study which intends to measure the learning experience in a DCSS with a non-DCSS. Secondly, it predicts the learners' cognitive states while engaging with computer-based learning tasks. Thirdly, this section attempts to understand how the learning experience progresses from the beginning of an interaction with the computer-based learning towards the end. Finally, it describes the cognitive loads that the computer-based systems may impose on the learners and its relationship with the learners' learning experiences.

Section IV proposes a technique to improve the DCSS learning experience which is fundamentally based on the flow theory, known as the skill-challenge balancing (SCB) technique. This section also presents an empirical study that evaluates the effectiveness of the proposed method in enhancing the DCSS learning experience.

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I am heartily thankful to my best friend and my husband, Azwan Azmi whose patience, encouragement, and support; enabled me to complete the thesis. I pray to God to bestow him with a doctoral degree as well for the effort and faith he puts in his study. He deserves it too. To our son, Adam, you are the sunshine that always makes mom and dad happy. May you grow up to be a good person and successful in your life.

I would also like to thank my fellow friends: Azlina, Tingting, Lornie and Ramesh for their time in listening to my problems, difficulties and joy during the period of the study. I strongly believe that all of you will also complete your doctoral study successfully soon and will be doing well in your future career.

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Last but not least, I would like to thank everyone who had contributed to this thesis in any way either directly or indirectly. Your support and assistance are really appreciated.

Declaration

I declare that the works written in this thesis have been fully prepared and executed myself with supervision given by Dr. Hokyoung Ryu and Dr. Ruili Wang. The doctoral study was started in October 2008 and completed in December 2011. The first two years of the study were carried out in the Institute of Information and Mathematical Science (IIMS), where Dr. Hokyoung Ryu was the primary supervisor, and later in the School of Engineering and Advanced Technology (SEAT), where Dr. Ruili Wang was the primary supervisor. The following publications were published from the studies reported in this thesis. The information about the publications and its corresponding chapters are presented in the following table:

Information about the publications	**Corresponding Chapters**
Katuk, N. & Ryu, H. (2010). Finding an optimal learning path in dynamic curriculum sequencing with flow experience, The 2010 International Conference on Computer Applications and Industrial Electronics (ICCAIE) 5-8 Dec. 2010, pp.227-232	Chapter 5
Katuk, N. & Ryu, H. (2011). Does a Longer Usage Mean Flow Experience? An Evaluation of Learning Experience with Curriculum Sequencing Systems (CSS), 2011 Sixth IEEE International Symposium on Electronic Design, Test and Application (DELTA) 17-19 Jan. 2011, pp.13-18	Chapter 5
Katuk, N., Wang, R., Ryu, H., & Parsons, D. (2011). The Dynamics of Computer-based Learning Experience. The Proceedings of the IIMS Postgraduate Conference, 26 October 2011, Massey University, New Zealand	Chapter 6
Katuk, N., Wang, R., & Ryu, H. (2011). Enhancement of Learning Experience Using Skill-Challenge Balancing Approach. In D. Wang & M. Reynolds (Eds.), *Lecture Notes in Computer Science*, (Vol. 7106, pp. 707-716): Springer Berlin / Heidelberg	Chapter 7

I also declare that the following papers were published during the early period of the doctoral study as preliminary works towards a more specialised research study; however, these papers were not very closely relevant with the theme of the thesis.

Information about the publications
Katuk, N., Sarrafzadeh, A., & Dadgostar, F. (2009) "Effective ways of encouraging teachers to design and use ITS: feature analysis of intelligent tutoring systems authoring tools," *International Conference on Innovations in Information Technology, 2009 (IIT '09)* 15-17 Dec. 2009, pp.100-104
Katuk, N. & Ryu, H. (2010). Seeing is believing? Rehearsing Mayer's multimedia effects in intelligent tutoring systems. In the *Proceedings of the 11th International Conference of the NZ Chapter of the ACM Special Interest Group on Human-Computer Interaction* (CHINZ '10). ACM, New York, NY, USA, pp. 25-28

CHAPTER 1: INTRODUCTION TO THE THESIS

This chapter introduces the reader to the structure of the thesis. It gives an overview of the thesis and a concise summary of each chapter, to overarch the whole theme of the thesis.

Overview of the Thesis

The main objective of this thesis is to examine learning experience in the context of dynamic curriculum sequencing systems (DCSS). In doing so, there are two approaches that the thesis seeks for: (i) to understand how the DCSS learning experience would evolve, and (ii) to study a practical method to improve the DCSS learning experience through substantiating the flow theory concepts (Csikszentmihalyi, 1975, 1990, 1997). In brief, learning experience refers to learners' cognitive states while interacting with computer-based learning systems[1].

The primary motivation for this study was inspired by the author's personal experience of delivering a few courses in a blended mode[2], when working as a junior lecturer in a public Malaysian university. During that time, it was noted that many students did not greatly benefit from the computer-based learning systems that the university had provided as a major component of the blended course structure. An informal interview with the students revealed that their e-learning experiences were poor and affected their intentions to use the computer-based learning system. This thesis addresses this issue, and some empirical investigations have been carried out to understand the nature of this problem. Therefore, a novel solution is proposed to foster the computer-based learning experience.

[1] The computer-based learning experience is defined in Chapter 2.

[2] Blended learning refers to a course that is accomplished through combination of classroom lecture and independent e-learning study.

The thesis has been organised into seven chapters, consisting of four sections of the interrelated chapters. Section I (Chapter 2 and Chapter 3) accounts for the development of the theoretical foundation of the thesis. In Section II, the design and development of a DCSS (i.e., IT-Tutor) are described. Evaluation of the DCSS learning experience is the main theme of Section III (Chapter 5 and Chapter 6). The last section (i.e., Section IV) designs a method to improve the adaptive computer-based learning experience and assesses the effectiveness of the method. Figure 1.1 depicts the structure of the whole thesis.

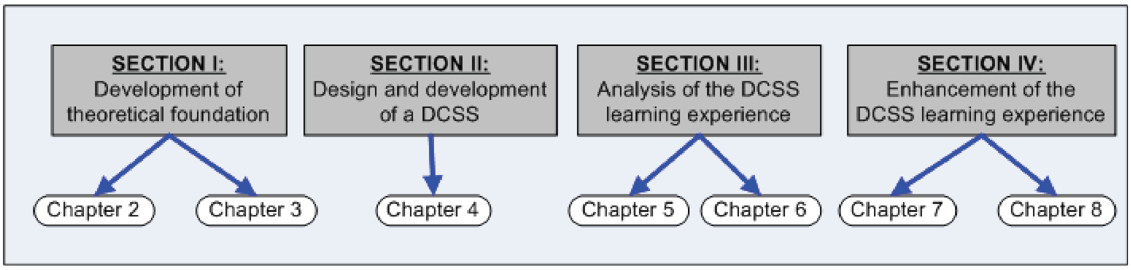

Figure 1.1: The overall structure of the thesis

The following paragraphs briefly describe the objectives of each chapter and the main research activities in that chapter.

<u>SECTION I: Development of Theoretical Foundation</u>

Section I presents the overall research framework and the literature review about learning experiences in Chapters 2 and 3, respectively.

Chapter 2: Research Framework

This chapter begins with the motivation for conducting this research and the definition of the technical terms used in this thesis. It also formulates some research questions to guide the implementation of the whole thesis. Based on the research questions, the overall research framework of the thesis is proposed.

Chapter 3: Related Literature

Chapter 3 mainly discusses relevant literature about computer-based learning experience in distance learning (or online learning), to establish a main research question of the thesis. This chapter attempts to portray the importance of an optimal learning experience in the context of computer-based learning through an extensive literature survey. The chapter also examines techniques to achieve the optimal learning experiences that were used in the previous studies.

SECTION II: Design and Development of a DCSS

Section II explains the design, development, and usability evaluation of IT-Tutor, a dynamic curriculum sequencing system (DCSS) that serves as the main apparatus for the thesis experimental studies.

Chapter 4: Development and Evaluation of IT-Tutor: A Dynamic Curriculum Sequencing System

The chapter discusses a general overview about curriculum sequencing systems (CSS). In particular, the discussion is narrowed down within the purview of this thesis, i.e., dynamic CSS (DCSS). We review the existing DCSS and analyse the design parameters used to achieve adaptive features in these systems. Next, in this chapter, the component and architecture of a DCSS named IT-Tutor are described, and a usability study of the DCSS is carried out.

SECTION III: Analysis of the DCSS Learning Experience Evolution

This section comprises two empirical studies that aim to understand how the learning experience evolves in the DCSS.

Chapter 5: A Study of DCSS Learning Experience

Chapter 5 presents an empirical study to understand learning experience with the DCSS. The DCSS (i.e., IT-Tutor) is used as a learning tool in this chapter. Learning experience with the DCSS is compared against a freely-browsing computer-based learning system, i.e., non-adaptive curriculum sequencing system. In addition to the learning experience itself, another parameter; i.e., learning outcomes is also being studied. Two additional variables (i.e., prior knowledge and types of learners) are analysed to see whether these variables affect the participants' learning experiences. With regard to the *flow theory*, this chapter also attempts to predict the learners' cognitive states while engaging with the given computer-based learning tasks.

Chapter 6: Cognitive Load and Progressive Evaluation of Learning in the DCSS

The chapter aims to understand how the learning experience evolves whilst a learner works with the computer-based learning system. It also analyses the dynamics of computer-based learning experience, and investigates how it changes. Additionally, Chapter 6 intends to understand the computer-based learning cognitive loads.

SECTION IV: Improvement of the DCSS Learning Experience

This section describes a technique to improve the DCSS learning experience known as the skill-challenge balancing (SCB) technique. Then, it explains the empirical study to validate the effectiveness of the new technique. It also describes the practical contributions of the thesis in the context of computer-based learning and human-computer interaction.

Chapter 7: Integration of the *Flow Theory* in the Design of DCSS

Chapter 7 proposes a technique with an aim to improve the DCSS learning experience that is mainly based on the flow theory. The fundamental idea of this technique is to achieve a state of balance between skills and challenges in performing a computer-based learning task. Hence, this SCB technique is incorporated in the new design of the DCSS (i.e., IT-Tutor). This will be assessed by how much the DCSS learning experience will be improved.

Chapter 8: Conclusions and Discussion

This chapter summarises the main contributions of the thesis to the body of knowledge especially, in the area of computer-based learning and human-computer interaction. Chapter 8 also describes the limitations of the thesis and potential future studies.

SECTION I: DEVELOPMENT OF THEORETICAL FOUNDATION

Section I comprises two chapters that describe the background and basis of the research. Chapter 2 presents the overall research framework and Chapter 3 describes a literature review about learning experiences.

CHAPTER 2: RESEARCH FRAMEWORK

This chapter discusses the overall structure of the research framework that is employed in this thesis. An issue here is how an optimal learning experience can be achieved in curriculum sequencing systems (CSS), and how the optimal learning experience can be interpreted in the design of new CSS. Hence, the purpose of this chapter is to draw on the research questions and the theoretical framework, which will be used to complete the thesis.

Overview of the Chapter

This chapter is divided into three sections. Section 2.1 provides an overview of the research, including motivation in conducting the study. In Section 2.2, the research questions for the study are explained. Next, the research framework and methodology are presented in Section 2.3.

2.1. Motivation for this Study

The emergence of computer technology in contemporary learning environments has led to a lot of research in the learning technology discipline. Although many advances in the area of computer-based learning have been made over the past decades, there is still an issue that has not been fully addressed and needs further examination. This concerns how to create interesting and engaging computer-based instruction for the learners (Georgouli, 2002).

Through six years of experience in teaching Information Technology (IT) courses, I found that many of the students had some difficulties in using the computer-based learning systems that I created for them to complement the classroom lectures. This situation was making me quite curious, so I had conducted some informal conversations with the students in order to understand the nature of this difficulty. From the conversations, it was revealed that the common computer-based learning systems were unable to motivate them intrinsically. This personal experience had inspired me to study further on how to design a computer-based learning system that can motivate the students intrinsically, so that they could enjoy and benefit from the unsupervised computer-based learning.

The ideal of computer-based learning is *to make it interesting and enjoyable to students*. It is generally known that learning in the classroom is not as pleasurable as playing games especially among young adults at the university level. Thus, finding an approach that could make computer-based learning environment pleasurable is a great challenge and more research is needed (Shin, 2006).

This thesis aims to fill the gaps through a combination of technical and psychological approaches. It studies learner experiences in using computer-based learning, and designs a new technique so that an enjoyable learning experience could be obtained. Learners' experiences in using computer-based learning are an important parameter which indicates how learners feel about the learning activity itself (Chou & Liu, 2005).

In this thesis, an optimal learning experience represents a cognitive state in which a learner enjoys the computer-based learning and at the same time obtains the learning objectives given in the computer-based lesson. The concept of the optimal experience is adapted from Csikszentmihalyi's (1975, 1990, 1997) theory on '*flow*'. The flow theory suggests an optimal experience as a mental state where a person is totally absorbed with what he or she is doing. The optimal learning experience is achieved when the optimal experience and learning objectives are juxtaposed in computer-based systems. In other words, an optimal learning experience is achieved if and only if a learner enjoys the learning session and at the same time achieves some academic objectives defined in the computer-based lesson. The literature has shown that learners who had enjoyable computer-based learning experiences were more likely to have a better understanding of the learning contents; and achieved higher performance on subsequent assessments (Engeser & Rheinberg, 2008).

Although the fact that an optimal learning experience is important in computer-based learning, only a few studies have specifically addressed the inclusion of learners' experiences in the design of CSS. Further, none of them has focused on the use of computer techniques to integrate learning experiences in relation to users' internal cognitive states when they are learning. Hence, this thesis fills this gap by proposing a novel approach to incorporate the optimal learning experience in the design of CSS.

2.2. Research Questions

The previous section briefly described the key motivation to drive this research. Specifically, the thesis investigates adult learners' experiences in using computer-based systems with curriculum sequencing particularly at university. Dynamic curriculum sequencing systems (DCSS) are a type of computer-based learning that provides learners with an optimal sequence of learning units or learning tasks (Brusilovsky, 1999). The main purpose of DCSS is to provide learners with an adaptive computer-based learning environment.

In this thesis, we focus on learning experience of adult learners at university. This is important because children and adults are different in terms of their cognitive and psychological aspects. In the literature, it has been well established that adults and children learn differently and require different approaches in learning (Kerka, 2002). Hence, the discussion and findings of the thesis are primarily relevant to the context of adult learners only.

It can be seen that adults experience different learning states when using computer-based learning systems, such as confusion, frustration, anxiety, boredom, delight, flow, surprise, and many others (D'Mello *et al.*, 2008). For example, an advanced learner in a particular domain of knowledge might be in the boredom state if he or she is presented with some simple learning materials, because it is too easy to hold the learner's attention. On the other hand, a novice learner could be in the state of anxiety if he or she is presented with some hard materials against the learner's skill set. In this case, if the learner does not have sufficient skills to address the domain of knowledge, anxiety could be the result. Hence, it is likely that if the learner is presented with some contents that parallel his or her levels of skill or knowledge, the learner might have a better learning experience.

From a psychological perspective, a good quality and enjoyable experience is usually driven by individual intrinsic motivation. The motivation to perform a particular activity is obtained intrinsically without external pressure (e.g., money, social recognition, or punishment). In other words, an individual performs a particular activity for his or her own sake (Graef *et al.*, 1983). In learning, intrinsic motivation stimulates the learner's inner-will to perform a particular learning activity and it generates satisfaction and enjoyable experiences (Konetes, 2010). For many studies, intrinsic motivation has been linked to engagement in performing a particular learning task (Sharek, 2010). It can thus be seen that intrinsic motivation drives learners to engage in a particular learning activity, and in turn, assists them to achieve an optimal learning experience.

The engagement with learning may have a broad definition, such as engagement with a particular problem, engagement with a domain of knowledge, engagement with communities, and engagement with a small group (Stahl, 2005). In the context of this thesis, engagement with a particular problem and engagement with a domain of knowledge are very important and relevant in describing learning experiences. A learner will engage in a particular problem when the problem challenges the learner's understanding. However, the levels of challenge must be within the reach of the learner's understanding. In addition, a learner could engage in a particular problem when the domain of knowledge is within his or her interest. This definition is quite broad and does not describe exactly how engagement happens.

A more specific definition by Clark (2002) suggested that cognitive or mental engagement is the best state to describe engagement in learning. In the traditional teaching and learning environment, cognitive engagement can be well administered through some interactions between the teacher and the students (Beal *et al.*, 2010). However, in the computer-based environment, cognitive engagement is highly dependent on the learner's self-management (Chauncey & Azevedo, 2010), which is not an easy task. The key question raised in this thesis is; *how can DCSS be designed to help learners intrinsically engage in learning activities*? Hence, the thesis is concerned with the issue of how to design a DCSS that can intrinsically motivate learners to engage in computer-based learning.

A more engaging computer-based learning experience would increase the quality of time spent in learning, and the amount of time a learner spends on the system beyond the minimum required time (Sharek, 2010). Besides, when a learner is engaged in a learning activity, his or her mind concentrates on that activity which gives no room to other thoughts. This mental state can be best described by a psychological theory known as flow (Csikszentmihalyi, 1975, 1990, 1997). Through a series of studies by Csikszentmihalyi on various groups of people such as athletes, chess players, rock climbers, composers and dancers (Whitson & Consoli, 2009), any person would experience the state of flow in doing some activities, as long as the characteristics which lead to engagement are present (these characteristics are described further in Chapter 3).

Take an example of how flow can be associated with learning, and how flow can foster learning engagement. A fifteen-year old school student shows a great interest in playing computer-games. He spends hours in a day playing computer games and sometimes he skips his meals while he keeps playing. Why would he spend hours in playing computer games without any interruption? His engagement in computer games occurs because the games give the student with the feeling of enjoyment (McGinnis *et al.*, 2008; Sweetser & Wyeth, 2005). The feeling of enjoyment and fun was actually derived when the student successfully overcame the challenges in the computer games using his current skills. As his skills were constantly increased (at least not decreased), his mind would have totally absorbed with the challenges given by computer games. This is well in line with the flow theory, where most computer games tend to provide a player with constant learning (skills improvement) and increase challenges while they are playing (Eagle & Barnes, 2010). In this thesis, the state of flow and the manipulation of challenges and skills in dynamic curriculum sequencing systems (DCSS) are the central strategy to perform the empirical study.

As described earlier in this section, the goal of DCSS is to provide learners with customised learning paths (Brusilovsky, 1999). In identifying the optimal learning path for an individual learner, the sequencing techniques take into account a few learner's parameters such as background of knowledge, learning objectives and preferences (Chen, 2008). The optimal learning path in DCSS is dynamically generated based on the learner's individual learning requirements. In other words, DCSS handles learners individually by providing them with individualised learning sequences. In this research, the sequence of learning contents of a particular domain of knowledge is dynamically generated based on individual learners' prior knowledge. It will be specifically referred to as a dynamic curriculum sequencing system (DCSS) in this thesis. In order to differentiate between DCSS and the traditional computer-based learning system[3], the term non-dynamic curriculum sequencing system (non-DCSS) is used. The discussion about DCSS is described in Chapter 4.

There are four major aspects pertaining to this study. Firstly, the study aims to investigate whether or not the two types of CBL systems (i.e., DCSS and non-DCSS) would give different learning experiences to learners. If this is the case, how they are different would be consequently examined. In order to examine learners' experiences better, the research adopted three states of learning experiences based on the flow theory (Csikszentmihalyi, 1975, 1990, 1997). The three states are (i) flow (i.e., learners who had equal skill and challenge), (ii) anxiety (i.e., learners with lower skills and higher challenge), and (iii) boredom (i.e., learners with higher skills and lower challenge). Figure 2.1 depicts how these three states can be represented in relation to challenges and skills. In this research, the optimal learning experience would be represented by learners who were in flow while using CSS for learning. In addition, the research aims to investigate if there is any difference in terms of the learning outcomes of learners who had used DCSS and non-DCSS. This study is described in Chapter 5.

[3] The traditional computer-based learning system provides learners with a static and permanent sequence of learning contents where all learners will have a single sequence of learning path.

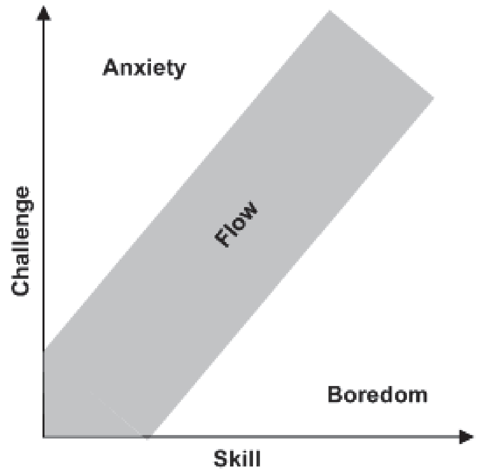

Figure 2.1: Learning states based on the *flow theory*

Secondly, the thesis aims to understand how learning experiences in DCSS and non-DCSS evolve. Specifically, the author anticipates understanding whether or not the learning experiences are dynamic by studying the learning experiences in a progressive manner. If it is the case, the author would be interested to know what are the characteristics of the dynamic learning experiences and what factors influence the conditions. This is further described in Chapter 6.

Thirdly, a learning process involves cognitive loads. In particular, working memory or long-term memory would be the primary resources in any learning activities. It is also true that the three learning states especially boredom and anxiety would be associated with learner's cognitive capability which has not been much studied yet. Thus, the following question is to examine the potential relationship between cognitive capability and learning experiences. The cognitive load is measured using a tool proposed by NASA known as NASA TLX. Chapter 6 describes the tool in detail.

Finally, the research aims to study a technique or an approach where the flow theory can be incorporated into the design of the DCSS so that it could help learners to achieve an optimal learning experience. As an optimal experience is assumed to be achieved only when one is in a condition where the skill and challenge is equivalent, the manipulation of learners' skills and challenges appears to be one of the solutions. Subsequently, we would like to know whether an inclusion of the balance of skill-challenge manipulation into the design of the DCSS could assist learners in achieving an optimal learning experience. This objective is further explained in Chapter 7.

In summary, five research questions for the thesis are:

- ***RQ1:*** Is there any difference in learning outcomes and learning experiences between learners who had used the dynamic curriculum sequencing system (DCSS) and the non-DCSS?
- ***RQ2:*** Do learning experiences change throughout a DCSS learning task?
- ***RQ3:*** Is there any difference in cognitive loads between learners who had used the DCSS and the non-DCSS?
- ***RQ4:*** How can the flow theory be incorporated in the design of the DCSS to improve the learning experience?
- ***RQ5:*** Is there any difference in learning experience between learners who had used the DCSS with the skill-challenge balancing (SCB) technique and the DCSS without the technique?

2.3. Research Framework

Section 2.2 explained the research questions of this thesis that attempt to explore the learning experiences in CBL, particularly the DCSS and the non-DCSS. To do so, this section discusses the methodology for the research.

Figure 2.2 depicts the research theoretical framework in the form of a process diagram. The research comprises seven tasks (derived from the five research questions) as represented by a sequence of numbers in brackets. From the figure, tasks (1), (2), and (3) are related to research question 1 (RQ1). Next, tasks (4) and (5) are associated with research question 2 (RQ2) and research question 3 (RQ3) respectively, while tasks (6) and (7) are linked to research question 4 (RQ4) and research question 5 (RQ5) respectively.

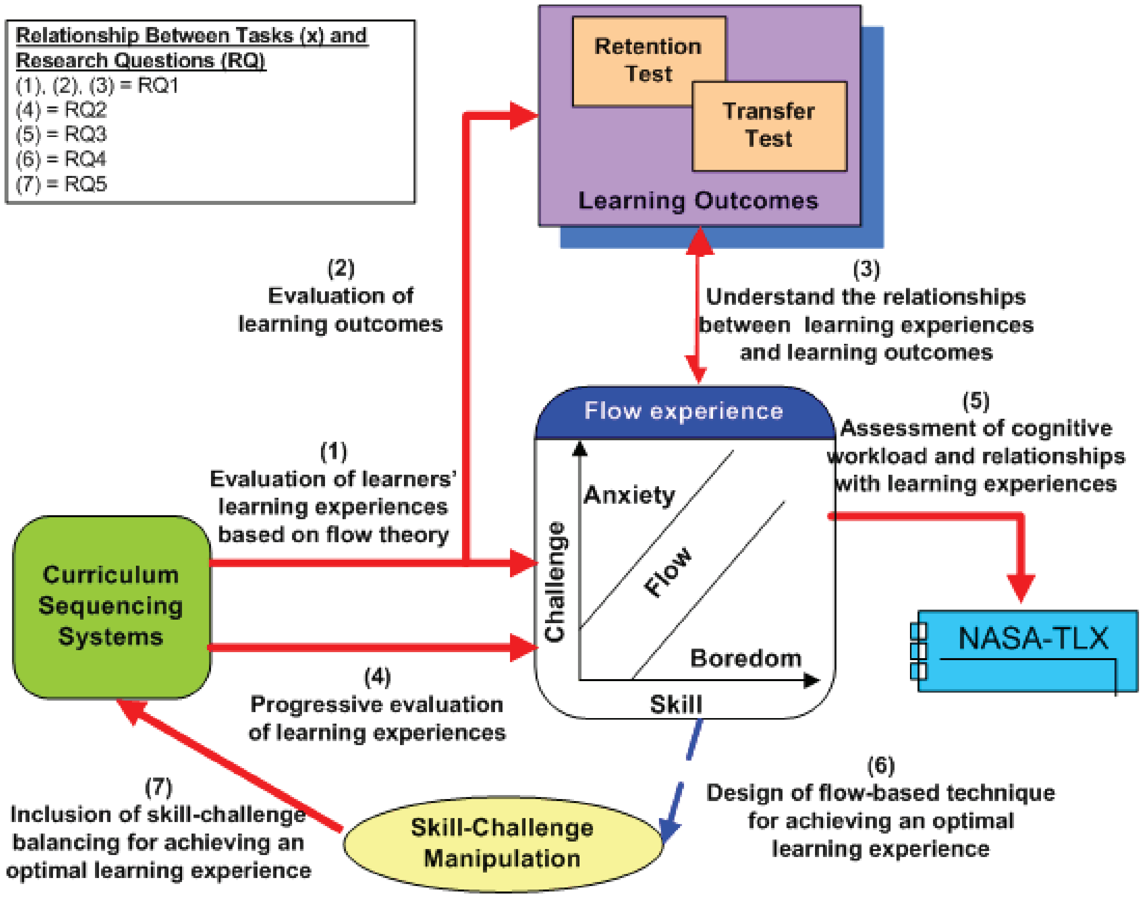

Figure 2.2: Research framework

Firstly, the research aims to study learners' experiences in using the DCSS and non-DCSS based on the flow theory. The overall learning experience is studied, and a prediction of cognitive states (i.e., flow, boredom, and anxiety) is made. At the same time, the research intends to understand the learning outcomes[4] derived from the DCSS and non-DCSS. Further, the relationships between learning experiences and learning outcomes are investigated.

Then, a progressive evaluation of the learning experiences is conducted in order to understand learners' chronological experiences while using the DCSS and non-DCSS. Next, the learners' cognitive load while using the DCSS and non-DCSS is analysed

[4] Assessment of the learning outcomes is conducted through two types of tests: (i) a retention test and (ii) a transfer test. Chapter 5 of the thesis further describes the two types of tests.

using NASA-TLX[5] (Hart & Staveland, 1988). The relationships between the learners' learning states and cognitive workloads are also examined.

Finally, the research aims to study a technique or an approach that could manipulate the difficulty levels of learning activities so that they match with learners' levels of skill. The approach takes into consideration two parameters: skills and challenges. These two parameters are based on the flow theory, which may help learners to achieve an optimal learning experience. The ultimate objective of the research is to measure the effectiveness of the approach through an experimental study.

The research activities for finding the answers to the five research questions have been divided into five phases. Table 2.1 shows each of the five phases of research with milestones and corresponding methods. The summary of each phase is explained in the following subsections. This research has been peer-reviewed and classified as low-risk. Please refer to Appendix I for the approval letter from the Research Ethics Department of Massey University.

Table 2.1: Milestone of the research in this thesis

	Phase I	Phase II	Phase III	Phase IV	Phase V
Purposes/ Aims	Understand the role of an optimal learning experience in computer-based learning	Understand the role of DCSS with regard to learning experience	Understand learning experience and learning outcomes in DCSS	Understand progressive learning experience and cognitive load in DCSS	Inclusion of learning experience in the design of DCSS
Method/s	Literature analysis	Prototype development	Experimental study	Experimental study	• Prototype development • Experimental study
Results and Deliverables	[Chapter 3]	[Chapter 4]	[Chapter 5]	[Chapter 6]	[Chapter 7]

[5] NASA-TLX is a workload assessment tool which is used for evaluating workload of various human-machine systems. Detail explanation of NASA workload can be found in Chapter 6.

2.3.1. Phase I: Understand the role of an optimal learning experience in computer-based learning

The first phase of the research involves understanding learning experiences in computer-based learning systems. This phase analyses three aspects of literature. The first issue is "*what are the possible learning experiences that learners might come across when using a computer-based system?*". The second issue is "*how important is an optimal learning experience in a computer-based learning environment?*". The third issue is *"what are the approaches that have been used for achieving an optimal learning experience?"*. The analyses of the issues are presented in Chapter 3 of this thesis.

2.3.2. Phase II: Understand the role of a Dynamic Curriculum Sequencing System (DCSS) with regard to learning experiences

As mentioned earlier in this section, the research focuses on the DCSS. The main task in this phase is to understand the role of DCSS. The major issue in this phase is to understand some questions concerning the DCSS such as "*how a DCSS works*", "*what are the components and the architecture of a DCSS*", and "*how a DCSS differs from other computer-based learning systems*". The detail descriptions about these concerns are explained in Chapter 4.

2.3.3. Phase III: Understand learning experiences and learning outcomes in the DCSS

In Phase III of the research, an empirical study is conducted to understand the role of learners' experiences in using the DCSS. The phase includes studies of the learners' learning states while using the system. The detail of the studies is presented in Chapter 5. In this phase, studies of the learning outcomes obtained from the DCSS usage are also conducted.

2.3.4. Phase IV: Understand progressive learning experiences and cognitive load in the DCSS

Phase IV of this research involves understanding learning experiences progressively. The main purpose of this phase is to study how individual learning experiences develop from the beginning to the end of a DCSS learning session. In this phase, learners' cognitive load is measured while interacting with computer-based learning tasks. Chapter 6 of the thesis describes this phase in detail.

2.3.5. Phase V: Inclusion of learning experience in the design of a DCSS

Phase V of the research involves a study on how the flow theory could be incorporated in the design of a DCSS, so that an optimal learning experience could be achieved. The phase aims to investigate a technique that manipulates[6] learning challenges with learners' skills. An effectiveness evaluation of the proposed technique is also conducted in this phase. The explanation of the research tasks in this phase can be found in Chapter 7.

2.4. Summary

This chapter explained the research path of the thesis. It justified the motivations of conducting the research, the research questions, the theoretical framework of the study and the research milestones. In the next chapter, a literature review in the area of computer-based learning and learning experiences are critically discussed.

[6] The flow theory suggests that an optimal experience could be achieved when a person's skill is equivalent to the level of challenge of a particular activity.

CHAPTER 3: RELATED LITERATURE

This chapter reviews the literature concerning learner experiences in using computer-based learning systems. It addresses the fundamental aspects of the research such as, "*what are the possible learning experiences that learners might come across when using a computer-based system?*", "*how important is an optimal learning experience in computer-based learning environments?*", and *"what are the approaches that have been used for achieving an optimal learning experience?"*. The purpose of this chapter is to examine the gaps in research concerning computer-based learning, which will be addressed by this thesis.

Overview of the Chapter

This chapter is divided into three sections. Section 3.1 discusses some related literature about learners' experiences in computer-based learning systems. In Section 3.2, the importance of the optimal experience in learning is described. Finally, Section 3.3 reveals some existing techniques used for achieving the optimal experience in learning.

3.1. Learners' Experiences in Computer-based Learning

Many research studies in the area of computer-based learning focus on the development of subject courses and tend to highlight what would be done online (Alexander, 2001). Hence, few studies have reported on the investigation of students' learning experiences in using computer systems for learning. As the students are the target audience of computer-based learning systems, their experiences are important to improve the quality of computer-based learning (Alexander & Golja, 2007).

In many studies, learners' experiences with computer-based learning are examined in various contexts. For example, Deepwell and Malik (2008) investigated the learners' experiences in the context of their expectations of the technology, the lecturers’ engagement with technology and how the technology might support processes of transition in the higher education sector. In a study by Paechter *et al.* (2010), course design, interaction with the instructors, interaction with students, individual learning processes and course outcomes are the main concern. Gilbert *et al.* (2007) claimed that learners’ experiences are equivalent to learners’ satisfaction towards learning in the computer-based environment. In aggregation, it seems that learners’ experiences are involved with learners’ perceptions on a particular issue concerning computer-based learning. It includes how a learner perceives about the design of a course, the design of user interface, interaction with tutors, interaction with peer students, learning processes, and learning outcomes.

As the previous literature gives a rather broad definition on *learners’ experiences,* we may need to have a specific definition to render the scope of this thesis. The learner experiences in this thesis refer to some states or conditions, which a learner might undergo during his or her individual computer-based learning processes and interactions. It measures the learner’s learning conditions and internal cognitive states while engaging in a particular computer-based learning activity. In other words, learner experiences can be described by *how much an individual learner engages in a particular computer-based learning activity*.

Indeed, it is not able to measure precisely how much a student engages in a particular computer-based learning activity. In the traditional classroom setting, learners’ engagement can be mostly observed by a teacher. Hence, an experienced teacher could easily know whether or not a student is fully engaged in a learning activity. For instance, a teacher might see the situation through the student’s gestures or face reading in responding to a learning activity. Usually, a teacher will then take some actions so that the student could engage again in the activity and achieve an optimal engagement in the activity.

Unlike traditional classroom learning, learner engagement with a computer-based learning activity is difficult to observe. Hence, it is hard to regulate individual learner engagement to an optimal level (Clark, 2002). In the current computer-based environment, an individual learner’s engagement in a particular learning activity is entirely dependent on the learner's intrinsic motivation. In other words, most current computer-based learning systems do not have the capabilities to control and manipulate learner engagement at an optimal level. The absence of this mechanism is a challenge to ensure the sustainability of future computer-based learning. Thus, arguably, this thesis aims to address the issue by highlighting the techniques that could be used to observe and regulate learner engagement in computer-based learning activities.

As mentioned above, learner experiences can be described by "*how much an individual learner engages in a particular computer-based learning activity"*. It is very true that this question could lead to some subjective answers. One may say that he or she is fully engaged, a little bit engaged, or not engaged at all. The states of engagement (or disengagement) are very elusive and difficult to quantify. Hence, some studies described engagement through combinations of a few characteristics such as attention, concentration, control, and enjoyment, to name but a few. Others have tried to examine engagement or disengagement through the use of some possible cognitive or behavioural states.

As an example, Sharafi *et al*. (2006) suggested the engagement mode (EM) model in describing engagement in information technology (IT) acceptance. The model describes five engagement modes in which a user may experience using an IT product: (i) enjoying/ acceptance, (ii) ambition/curiosity, (iii) avoidance/hesitation, (iv) frustration/anxiety, and (v) efficiency/productivity. The EM model assumes that when a subject (e.g., an IT user) is engaged in an object (e.g., IT systems), he or she may experience different modes of engagement, depending on three factors: (i) the positive or negative effects of the object, (ii) locus of control between subject and object, and (iii) dimensions of motivation. Figure 3.1 shows the engagement modes in relation to the three factors.

From Figure 3.1, a subject who has high extrinsic motivation and is capable of controlling an IT product, may gain efficiency/productivity from the technology. On the other hand, an extrinsically motivated user might experience frustration or anxiety when he or she is unable to have control of the IT product. Generally, frustration/anxiety and avoidance/hesitation fall under negative experiences while pleasure/acceptance, efficiency/productivity and ambition/curiosity are considered as positive experiences.

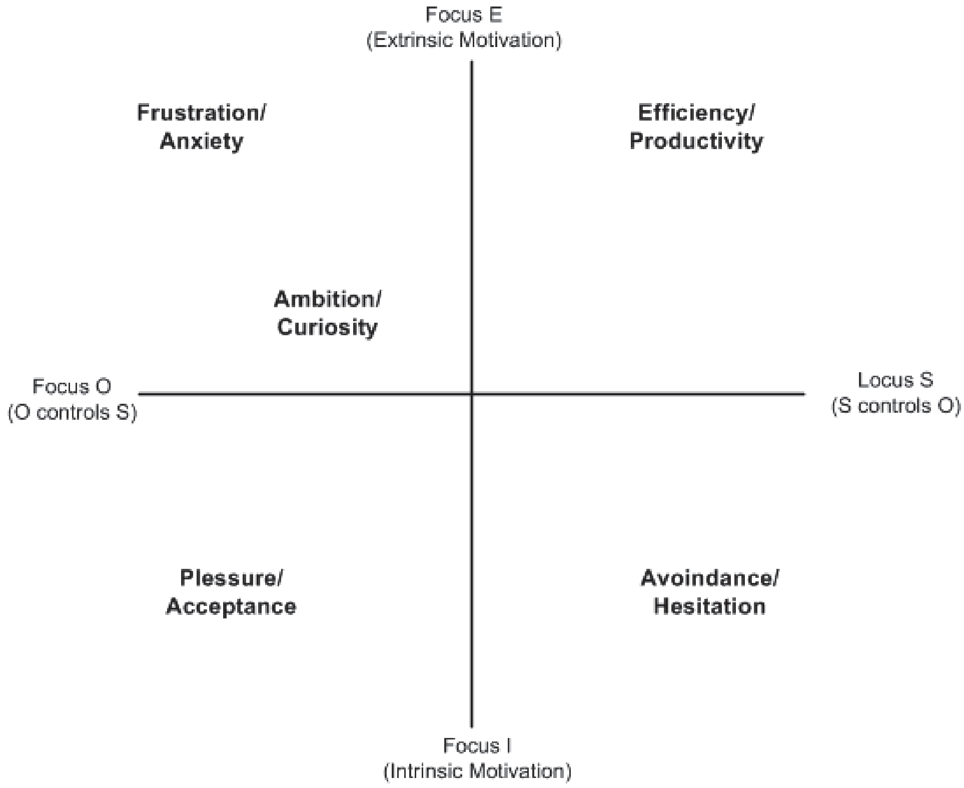

Figure 3.1: Engagement Mode (EM) model by Sharafi *et al*. (2006)

A more systematic definition of engagement is found in a study by O'Brien & Toms (2008). The study described engagement as a quality of user experiences characterised by ten attributes: challenge, positive affects, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control. Through an exploratory study, the research suggested that engagement in computer-based systems is a process comprised of four stages: (i) point of engagement, (ii) period of sustained engagement, (iii) disengagement, and (iv) reengagement. Each stage of engagement can be described by some attributes as illustrated in Figure 3.2. A person will remain in the engagement stage as long as he or she can maintain his or her attention and interest in the computer-based system. On the other hand, if a person could not sustain his or her attention towards the system, the stage changes from engagement to disengagement. Disengagement from a particular computer-based system results in either positive (e.g., feeling of success and accomplishment) or negative (e.g., uncertainty, frustration, boredom) experiences.

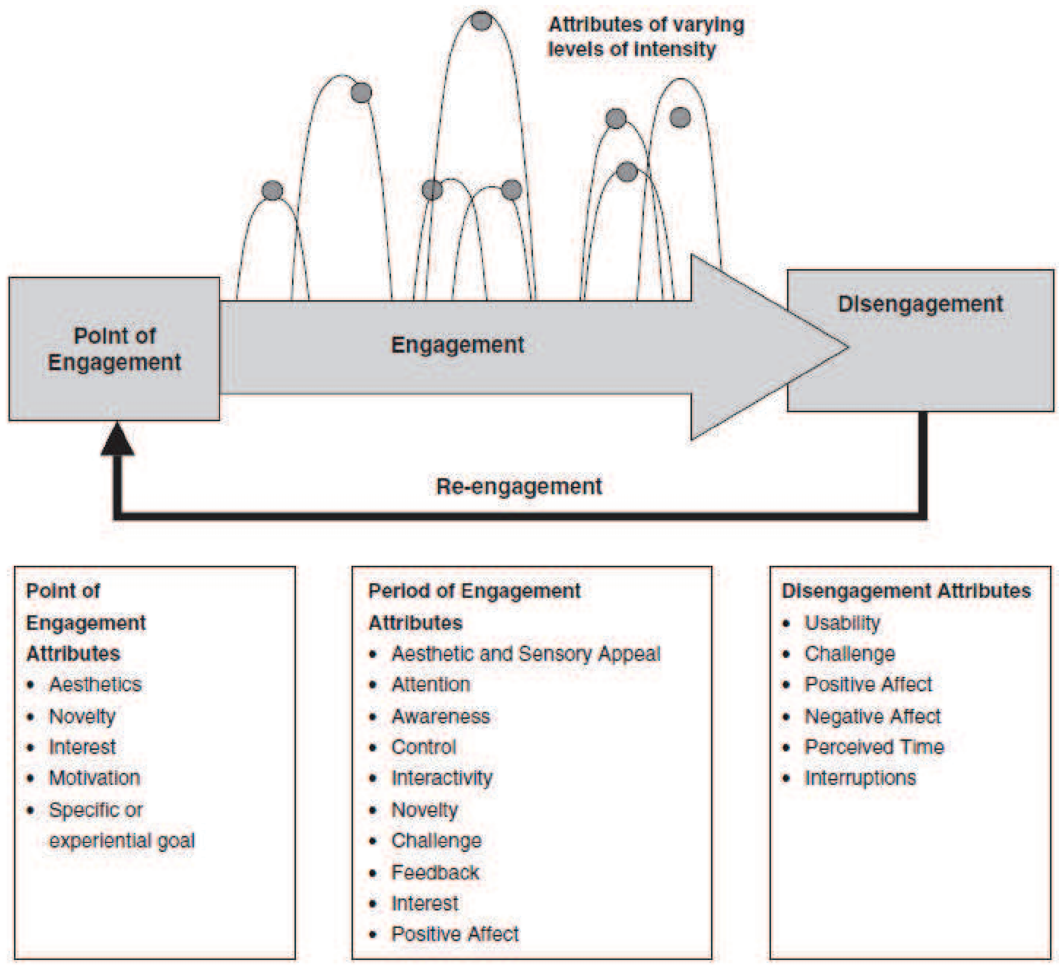

Figure 3.2: Process Model of Engagement (O'Brien & Toms, 2008)

It is important to bear in mind that individual engagement in a particular activity is forced by either intrinsic or extrinsic factors[7] (O'Brien & Toms, 2008). Intrinsic factors motivate a person to perform a particular activity for no apparent reinforcement, rather for the sake of the activity itself (Teo *et al.*, 1999). The person chooses to perform a particular activity (or task) because of the sense of accomplishment or satisfaction derived when the activity is completed. Engagement forced by the intrinsic factors would give a feeling of enjoyment to a person.

[7] Extrinsic factors are not discussed in this thesis.

Engagement and the feeling of enjoyment have systematically been studied by Csikszentmihalyi (1975, 1990, 1997). He found that engagement in a particular activity could produce a few mental states to an individual. First, an optimal engagement gives a person an intrinsic reward and enjoyment, which lead to an optimal experience known as "flow". On the other hand, non-optimal engagement could lead to either one of two cognitive experiences: (i) anxiety, or (ii) boredom. Anxiety and boredom are two negative feelings that limit a person's potential from reaching its maximum level. Hence, the two feelings restrain a person from achieving the optimal experience in doing a particular activity.

The three cognitive states of the flow theory are very relevant in describing learners' experiences in the context of this thesis. As illustrated earlier in Figure 2.1, flow state is achieved when there is a balance between a person's skills and the challenges given by a particular activity. On the contrary, if a person's skills are not sufficient to satisfy the challenges, he or she might experience anxiety. If a person has a high level of skill, a low level of challenge given to him or her might cause boredom. Figure 3.3 shows the four points of cognitive states (A_1, A_2, A_3, and A_4) that a learner may experience.

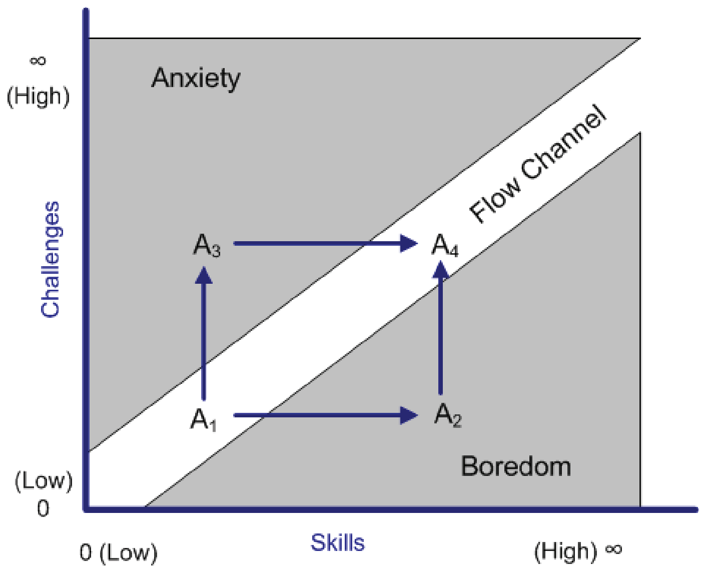

Figure 3.3: Changes of cognitive states based on flow theory

In Figure 3.3, at A_1, a learner could be at the initial flow state as the challenge (e.g., difficulty level of knowledge or assessment items) is very low and the learner might have limited prior knowledge, which could be associated with the current challenge given. Hence, it keeps the learner's attention and focus to the learning activity. However, if the learner's prior knowledge is advanced while the levels of challenge do not increase much, the learner's cognitive state might move to A_2, which will cause boredom. The same situation happens at A_3, where the level of challenge is very high against the learner's level of skill. At this point i.e., A_3, the learner would experience anxiety, which prevent the optimal engagement. In order to evolve the learner's new flow state into A_4, a balance between the level of challenge and the learners' skills is required as represented in Figure 3.3.

Based on the four points of the learning states, it can be said that learning experiences are changing from one state to another during learning. At the beginning, a learner might be in the flow state; however, it is not necessarily the same at other points of learning. This is due to the fact that learning experiences are influenced by the learner's levels of skill and the levels of challenge given during learning. A dynamic approach is required to ensure that the learner's learning state is always in the flow channel[8] so that the optimal learning experience can be achieved.

In this thesis, the optimal learning experience is achieved when a learner's cognitive state is located within the flow channel (refer to Figure 3.3). It is anticipated that a manipulation of the two attributes (i.e., skills and challenges) in the design of computer-based learning systems would help learners to achieve a certain flow state, which gives an optimal learning experience. Engagement with regard to flow state, in the context of computer-based learning could increase learning quality and retention, and improve the whole learning experiences (Lim, 2004). Thus, the thesis intends to look at the optimal learning experience, and identifies the way to achieve it. Therefore, the balance between challenges and skills could improve computer-based learning experiences.

[8] The flow channel is represented by unshaded (white) area in Figure 3.3

Learning outcomes of a lesson at university level have always been measured through learners' performance. Learners' experiences and their cognitive states during learning are often ignored. It is also important to ensure that learners are not stressful and could achieve the targeted objective of the lesson, hence obtaining an optimal experience in learning. Section 3.2 explains further about the importance of the optimal experience.

This thesis considers the three original cognitive states (i.e., flow, boredom, and anxiety) by Csikszentmihalyi as these are the most common states that happen in learning. Some other states were proposed following the original such as found in Massimini & Massimo (1988); however, these are impractical to be used in the context of this thesis due to their complexity and lack of applicability to computer-based learning.

3.2. The Importance of an Optimal Learning Experience

The concept of optimal learning experience is rarely mentioned in the previous learning literature. Through an extensive academic database search, we found four publications that described the optimal learning experience. A summary of the studies is presented in Table 3.1.

Table 3.1: Definition of optimal learning experience

Author/s	Type of study	Definition of optimal learning experience	Evaluation of optimal learning experience
Ceraulo (2003)	Review of literature	An optimal learning experience is the state termed as flow as proposed by Csikszentmihalyi (1990)	Optimal learning experience was not evaluated
Davis & Wong (2007)	Questionnaire survey	An optimal e-learning experience can be described by learners' technology acceptance and flow experience	Learners' past experiences and perceptions
LaPointe & Reisetter (2008)	Experimental study	An optimal learning experience is achieved when learners' psychological needs of autonomy, competence, and relatedness are fulfilled	Learners' past experiences and perceptions
Fontijn & Hoonhout (2007)	Experimental study	An enjoyable learning experience which obtained through an assessment of learners' skills and manipulation of the challenges with regard to each level of skills	During learning process

As shown in Table 3.1, the definitions of optimal learning experience vary from one to another. For example, Ceraulo (2003) defined the optimal learning experience based on a literature analysis, without an evaluation study to support the definition. Davis & Wong (2007) and LaPointe & Reisetter (2008) measured the optimal learning experience based on the learners' past experiences and perceptions. These can be considered as learners' general experiences rather than an "optimal learning experience" due to the fact that the optimal experience must be measured during or immediately after an interaction (Pearce, 2005; Webster *et al.*, 1993). In a study by Fontijn & Hoonhout (2007), the optimal learning experience was measured at some certain points during the learning process. This study gives an accurate definition and measure about the optimal learning experience as it used a real time assessment tool to help learners to achieve the condition. This definition is quite similar to the approach of this thesis.

We considered that, the optimal learning experience in the context of this thesis refers to the condition where the optimal experience[9] (Csikszentmihalyi, 1975, 1990, 1997) and learning objectives are achieved. This study focuses on evaluating the optimal learning experience during and immediately after the learners' interactions with computer-based learning systems. Hence, the thesis suggests a very specific definition of the optimal learning experience, to help us better understand this concept.

Research about learners' experiences in using computer-based systems for learning is very important in improving the effectiveness of the learning environment. Information obtained from the approach described here could be used to improve the design of such systems, to better meet the learning needs. In this thesis, learning experiences are examined with the flow theory.

The findings of past studies had shown the benefits of an optimal learning experience in maintaining the quality of learning and shaping the future of education. Indeed, the effects of the optimal learning experience could be divided into three perspectives: (i) learners, (ii) educational institutions, and (iii) technology. In order to

[9] Optimal experience has been described in Section 3.1.

have a clear understanding of learning experience benefits, the author integrates information from the literature as illustrated in Figure 3.4.

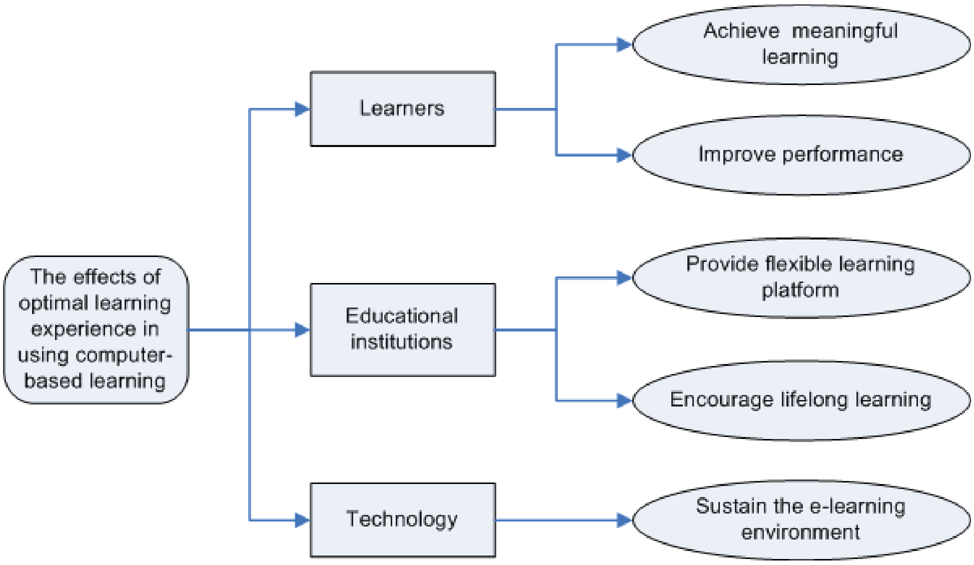

Figure 3.4: The importance of optimal learning experience

As shown in Figure 3.4, an optimal learning experience could assist a learner to achieve a meaningful learning. This is only achieved when individual prior knowledge is combined with the new knowledge that the learner has gained through the current learning process (Mayer, 2005). Then, the combined knowledge is stored in the learner's long-term memory (LTM) and will be used for future learning; hence, this creates a cycle of learning processes. A meaningful learning can be measured through evaluation of the learner's capability to recall the new knowledge and apply the knowledge in a new situation.

The implementation of computer-based learning systems serves two purposes: (i) as a complement to classroom teaching and learning, and (ii) as a learning platform for off-campus programmes. Over the last decades, computer-based learning has revolutionised tertiary education (Selwyn, 2007). The learning technology gives an opportunity to educational institutions to setup a flexible and independent learning platform, thereby allowing more people to enrol in higher education programs. Through this way, learning is made available to everyone and some constraints such as time and place are eliminated. Consequently, it helps in improving individual well-being and creating a knowledgeable society.

Computer-based systems that give learners the optimal learning experience, in the long run, would develop learners' interest and encourage them to educate themselves continuously for their own benefits. In other words, it could help learners to develop intrinsic motivation to learn, thus promoting lifelong learning. This is supported by prior research that suggested that learners who experienced enjoyable learning through computer-based systems are highly likely to use computer systems for learning in the future (Sharek, 2010). This approach helps in developing a culture that recognises learning as an enjoyable and continuous activity.

From the technology development context, computer-based learning systems that promise the optimal learning experience could be the way forward to the future technology for learning. In order to sustain the future of computer-based systems, it is important to study the optimal learning experience so that it can be exploited during the instructional design process. An important aspect to understand at this stage is "*how to model and integrate learning experiences in computer-based learning*?". Some of the existing techniques and approaches are described in Section 3.3. Also, Chapter 7 in this thesis suggests a novel approach that could be used to achieve an optimal learning experience in computer-based learning systems.

3.3. Techniques to Achieve an Optimal Learning Experience

It has been explained above that the optimal learning experience gives certain benefits to learners and could help in creating a knowledgeable society. However, how to make this happen is the key question. In the previous literature, the optimal learning experience is rarely mentioned, so how to achieve it has not been widely discussed. A brief description of the techniques or approaches is presented in Table 3.2. Some of the techniques are used to motivate users to use the computer systems, and others are used to provide users with enjoyable experiences.

In Table 3.2, the second and third columns represent a simple categorisation of the approaches and techniques. The columns identify whether the techniques involve the use of specific equipment (hardware) or pre-programmed models (software). The categorisation is very important because it involves some other issues during deployment of computer systems especially in the context of cost and feasibility. This issue will be discussed later in this section. To motivate users to use the computer systems, half of the techniques presented in the table have used special devices for identifying users' affective states. The users' affective states are identified through automatic recognition of facial expressions, voice modulation, gestures, posture and motor behaviours (e.g., hand muscles, head movement)(Kaklauskas *et al.*, 2008). On the other hand, some of the software-based approaches generally suggested a set of design criteria in order to motivate users and to offer experiences that are more enjoyable to the users. The complete description of studies in Table 3.2 can be found in Appendix A.

Table 3.2: Related methods/approaches towards achieving flow

Author/s	Dimension(s) of experience	Hardware approach	Software approach
Chou (2010)	Flow experience	√	√
Woolf *et al.* (2010)	Emotion, Motivation	√	
Muldner *et al.* (2010)	Excitement, Motivation	√	
Kaklauskas *et al.* (2009)	Emotions	√	
Leontidis *et al.* (2009)	Emotions, Cognition		√
Sabine (2008)	Flow experience, Quality of experience		√
van den Hoogen *et al.* (2008)	Game experience, Emotions	√	
Ryoo *et al.* (2008)	Engagement, Flow experience		√
D'Mello *et al.* (2007)	Emotions, Flow experience, cognition	√	
D'Mello *et al.* (2006)	Affective states,		√
Sweetser & Wyeth (2005)	Flow experience, Playfulness, Enjoyment		√
Georgouli (2002)	Motivation		√

Unlike other approaches that highlight motivation through a set of design criteria; an approach by Georgouli (2002) suggested a computational model in order to increase users' motivation and engagement during the use of computer-based systems. The computational model[10] can be pre-programmed and can be incorporated into the

[10] Computational model can be in the form of algorithms, rules, or mathematical equations that can be pre-programmed and embedded into the design and development of computer-based applications.

computer-based system design and development. This approach can be classified as a simple and cost effective one. Not only is a computational model much easier to design and develop, it is scalable to be implemented in a wider perspective than a computer laboratory. For example, a computer-based system with built-in computational model can be easily installed in users' (or learners') existing computer infrastructure, or it can be accessed online through the web. This technique allows the systems to be used without the need of additional hardware, thus, making it feasible for everyone to use the systems.

In contrast, the use of special devices or sensors for automatic affective state recognition will make computer-based learning available to be accessed only within computer laboratories. Many of the devices are very specific to be used with particular computer-based learning systems and are not yet a part of standard computer system in the market. Hence, users' decision to invest in buying additional devices for the computer-based learning system might be unlikely. Although it is the fact that the devices can accurately recognise learners' affective states, their usage in other systems is limited.

In effect, a simple and cost effective method is necessary. A computational model would be the ideal solution to achieve this. Thus, the thesis suggests a computational model that encompasses the flow theory and strengthens the existing computational models of motivation and engagement. The technique intends to promote an affordable and enjoyable computer-based learning system. It is important to recall that the thesis investigates learners' mental states (i.e., flow, boredom, and anxiety) in using computer-based learning; but not affective states, which are not easy to detect. Chapter 7 in this thesis describes the new technique in further detail.

3.4. Summary

This chapter described some important aspects related to computer-based learning experience. It is important that learners achieve an optimal experience in computer-based learning as it has some effects on their performance and the sustainability of such systems. The use of appropriate techniques or methods to achieve the optimal learning experience is a way to ensure the benefits of computer-based learning systems could be obtained by potential learners.

In the next chapter, a specific type of computer-based learning system is discussed, with the aim to understand the optimal learning experience in depth. The type of computer-based learning system is called dynamic curriculum sequencing systems (DCSS).

SECTION II: DESIGN AND DEVELOPMENT OF A DCSS

Section II explains the design, development, and usability evaluation of IT-Tutor, a dynamic curriculum sequencing system (DCSS) that serves as the main apparatus for conducting the empirical studies in this thesis. This section comprises Chapter 4.

CHAPTER 4: DEVELOPMENT AND EVALUATION OF IT-TUTOR: A DCSS

This chapter explains about curriculum sequencing systems (CSS), particularly the dynamic curriculum sequencing systems (DCSS). The purpose of this chapter is to *demonstrate how DCSS differs from other computer-based learning systems in terms of its learning content organisation and how it works*. An experimental DCSS, IT-Tutor is described, along with how it served as the main apparatus for conducting the empirical studies reported in this thesis.

Overview of the Chapter

This chapter is divided into two main sections. Section 4.1 provides an overview of CSS and DCSS. Section 4.2 presents the development of a DCSS known as IT-Tutor; an apparatus used for the experimental studies in this thesis. The section also describes the usability evaluation of IT-Tutor.

4.1. Curriculum Sequencing Systems (CSS)

4.1.1. An Overview to Curriculum Sequencing Systems (CSS)

The aim of current research in computer-based learning is to improve the major weakness of the "*one-size-fits-all*' approach found in traditional computer-based learning (Brusilovsky & Maybury, 2002) . The "*one-size-fits-all*" systems are no longer appropriate as many studies showed that learners differ in their learning styles, prior knowledge, learning goals and preferences (Chen, Liu, & Chang, 2006). A more personalised and adaptive learning system is required to accommodate learners' differences so that better learning performance could be obtained. An adaptive learning environment can be achieved through a type of computer-based learning known as a *curriculum sequencing system* (CSS).

CSS is categorised as an early type of intelligent tutoring systems (ITS). Most studies related to ITS in the 1990's fell into this category. However, nowadays, ITS comprise other types of systems, instead of CSS alone. There are some new types of ITS, such as *intelligent solution analysis* and *problem solving support* systems, which can also be referred to as ITS[11]. Figure 4.1 shows the three common types of intelligent tutoring systems as suggested by Brusilovsky and Maybury (2002). Studies related to curriculum sequencing in computer-based learning have been undertaken over the past three decades with some classic examples of curriculum sequencing systems such as ITEM-IP and SCENT-3 (Brusilovsky, 1998). This area had grown faster than expected in the late 1990s with some new improvements in sequencing behaviours, which aim to promote adaptive capabilities. Some examples of this type of systems include ELM-ART, (Brusilovsky *et al.*, 1996) CALAT (Nakabayashi *et al.*, 1997), InterBook (Brusilovsky & Schwarz, 1997), AST (Specht *et al.*, 1997), MANIC (Stern *et al.*, 1997), Medtec (Eliot *et al.*, 1997), and DCG (Vassileva, 1997).

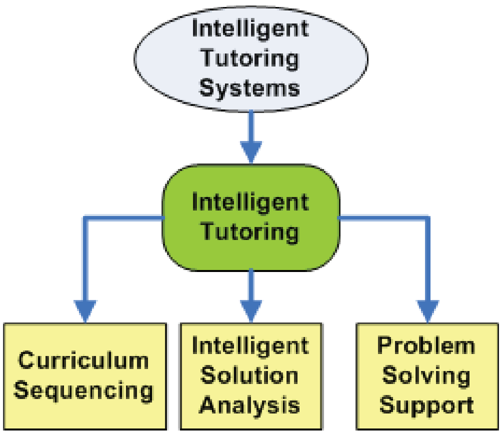

Figure 4.1: Intelligent Tutoring Systems by Brusilovsky & Maybury (2002)

[11] This thesis focuses on the CSS. The other types of intelligent tutoring systems (ITS) are beyond the scope of the thesis.

In the traditional teaching and learning settings (i.e., classroom and face-to-face), curriculum sequencing is organised and implemented by teachers. Generally, a teacher prepares a set of learning materials to all students and he or she organises the materials into an appropriate sequence of learning materials for a group of students manually. The major limitation of the traditional curriculum sequencing is that all students receive the same sequence of learning materials regardless of their prior knowledge about a particular subject or their learning progress. This method might be appropriate for a homogenous group of students. However, in reality, it is obviously difficult to have a group of students with a similar background, as they are distinct at their level of knowledge due to the differences in respect of prior learning experiences and progress. On the other hand, the one-to-one coaching approach to teaching and learning is no longer feasible as the number of students keeps increasing. It is also a non-cost effective approach for most educational institutions. For this reason, researchers in the area of computer-assisted instruction began to explore the potential of computer-based curriculum sequencing.

Computer-based curriculum sequencing is intended to provide learners with a computer-based learning environment, that is capable of organising learning materials appropriately, based on some learning parameters such as prior knowledge, cognitive styles, and preferences. CSS can be divided into two categories: static and dynamic. The major difference between the static and dynamic CSS is the *way learning materials are organised and presented to learners*. Static CSS (SCSS) organises learning materials statically, where learning materials are stored permanently in a fixed path of the learning course. This is similar to traditional curriculum sequencing. An example of a learning system that appears in this form is an electronic book (e-book).

Unlike the static CSS, a dynamic CSS (DCSS) provides learners with a non-linear path of learning materials (Stern & Woolf, 1998). Learning contents are dynamically organised based on individual learners' parameters. Hence, each learner will be presented with a set of learning contents, which meets his or her needs. Adaptive computer-based learning systems are examples of the DCSS. The next subsection describes the DCSS further.

4.1.2. Dynamic Curriculum Sequencing Systems (DCSS)

As briefly discussed above, the DCSS provide learners with the most suitable sequence of knowledge units to learn and the sequence of learning tasks to perform. Hence, key to the DCSS is to find an ”optimal learning path” for the learning contents (Weber *et al.*, 2002). The optimal learning path would maximise learner’s experience towards a meaningful learning process (H¨ubscher, 2000), which would foster better learning outcomes. The DCSS identify the relevant contents to match learners’ conditions, and then present the contents in an appropriate sequence to them (Brusilovsky, 1992; Chen*, et al.*, 2006; Darbhamulla & Lawhead, 2004; Guti´errez *et al.*, 2004; Limongelli *et al.*, 2009; Morales & Agüera, 2002; Stern & Woolff, 1998; Wan *et al.*, 2006; Zhu & Cao, 2008).

The potential to support adaptive learning is the main feature that differentiates the DCSS from other computer-based learning systems. It is able to provide similar supports as a human tutor does, wherein the system adapts to learners’ needs and individual differences when organising a learning session. Adaptation in the DCSS is achieved by the student model through investigation of learning parameters such as learners’ learning styles, levels of knowledge or skills and preferences. For example, learning or cognitive style has been used in providing adaptive learning in studies by Papadimitriou *et al*. (2009), Capuano *et al.* (2000), Jeremić *et al.* (2004), Conlan *et al.*(2002), Papanikolaou *et al.* (2003) and Peila *et al.*(2002).

Besides learning or cognitive styles, learners’ levels of knowledge (or skill) and preferences are the two common parameters which have been used to provide adaptive learning. This was found through the author’s extensive literature survey on fifteen DCSS as depicted in Table 4.1. From Table 4.1, 87% of the DCSS used levels of knowledge (or skill) as a main parameter to achieve adaptive learning, 73% used learners’ preferences, and 40% used learning (or cognitive) styles. About 26% used a combination of all three parameters.

In the case of this thesis, the author chose “*level of knowledge*” as the most important learning parameter to achieve adaptive learning. Level of knowledge can be divided into two categories: (i) prior knowledge before a computer-based learning session begins, and (ii) current knowledge just after the learners have completed a computer-based learning session. Learners' levels of knowledge are usually obtained through a set of questions related to the domain of study or a short questionnaire on the learners' levels of knowledge. For example, in the study by Darbhamulla & Lawhead (2004) a set of quizzes had been used to achieve adaptive learning. In another study by Chen *et al.* (2006), a very short and simple questionnaire had been used to obtain the difficulty levels that the learners wish to start.

Table 4.1: Learning parameters used to achieve adaptive learning

Curriculum sequencing systems	**Types of learner's parameters for achieving adaptive learning**		
	Learning/ cognitive style	Level of knowledge/ skills	Preferences (e.g., language, learning goals, modality, navigation, appearance, etc.)
ADAM (Wang *et al.*, In Press)	X	√	√
MATHEMA (Papadimitriou *et al.*, 2009)	√	√	√
Reinforcement Learning in an Adaptive and Intelligent Educational System (RLATES) (Iglesias *et al.*, 2004; Iglesias *et al.*, 2003)	X	√	√
Comprehensive Recommendation System (CRS) (Abbas & Juan, 2009)	X	√	X
Personalized Web-based instruction system (PWIS) (Chen, *et al.*, 2006)	X	√	X
ABITS (Capuano *et al.*, 2000; Gascueña & Fernández-Caballero, 2005)	√	√	√
Design Pattern Tutor (Jeremić *et al.*, 2004)	√	√	X
Adaptive Personalized eLearning Service (APeLS) (Conlan *et al.*, 2002; Conlan & Wade, 2004)	√	√	√
INSPIRE (Papanikolaou *et al.*, 2003)	√	√	√
MASPLANG (Peila *et al.*, 2002; Pena *et al.*, 2004)	√	√	√
AHA! (DeBra *et al.*, 2003)	X	X	√
Logic Tutor (Lesta & Yacef, 2002)	X	√	X
WLOG (Baldoni *et al.*, 2002)	X	X	√
ELM Adaptive Remote Tutor (ELM-ART) (Weber & Brusilovsky, 2001)	X	√	√
KBS Hyperbook System (Henze & Nejdl, 2000)	X	√	√

In order to understand the DCSS better, the author illustrated the DCSS components in Figure 4.2. It comprises four components, namely: a user interface, a student model, a domain knowledge repository, and a sequencing model (or engine). The *user interface* is the intermediary component between the learners and the DCSS. The major role of a user interface is to translate an input from users into an instruction that can be processed by the DCSS. It is also the medium for displaying learning contents or activities to learners. The *student model* is a component that stores information about learners such as personal information (e.g., user names and passwords), learning histories, and logs of usages. For each interaction that a learner makes with the DCSS, the student model keeps a record in its database.

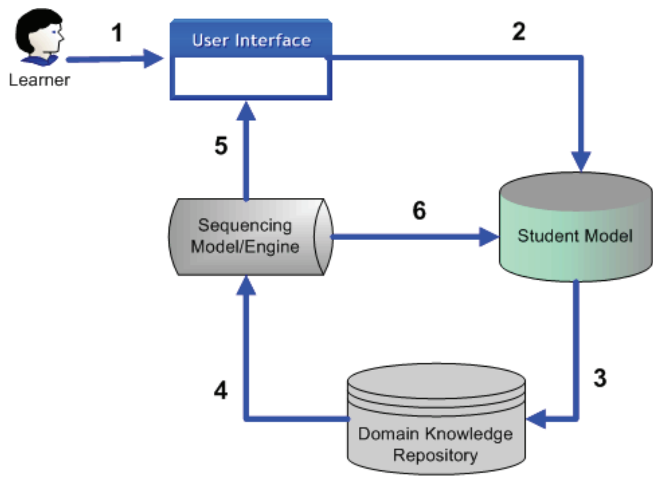

Figure 4.2: A generic architecture of DCSS

In addition, the *student model* evaluates learners' levels of knowledge and identifies the appropriate learning contents or activities for them individually. Then, the contents are obtained from the domain knowledge repository. The *domain knowledge repository* is a storage area for many types of learning materials such as explanations about theories, concepts, examples, assessment materials, and others. Learning materials are organised and sequenced by a *sequencing model or engine*. When learning materials have been organised, they will be presented to the learners through the *user interface*. From Figure 4.2, the flow of process in the DCSS is presented in a sequence of numbers (i.e., 1 to 6). The process is summarised in Figure 4.3.

(1) Learners communicate with the DCSS applications through the user interface component.
(2) The user interface sends information about the learners to the student model.
(3) The student model identifies the learners' levels of knowledge and identifies the appropriate learning contents for them individually.
(4) The domain knowledge repository sends the learning contents to the sequencing model or engine for further organisation.
(5) The organised contents are presented to the learners through the user interface.
(6) The sequencing model or engine sends information about the learning contents to the student model for keeping track of the learning activities.

Figure 4.3: Flow of process in DCSS

The learning process that learners will undertake is illustrated in a flow chart as depicted in Figure 4.4. A learning session in the DCSS could begin with an evaluation of the learners' prior knowledge. The prior knowledge is usually measured through a quiz related to the domain of study or a simple questionnaire asking about learners' background knowledge. In some DCSS where prior knowledge (pre-requisite) is not required (see Gascueña & Fernández-Caballero (2005) for an example), the systems simply present a sequence of learning contents to learners. In the case where pre-requisite knowledge is required (e.g., in advanced courses), a learning session starts with an evaluation of the learners' prior knowledge. Then, the learners are presented with a sequence of learning contents, which match with their individual levels of knowledge. After the learners undertake the learning session, their current knowledge will be evaluated through a quiz related to the contents that they have just learned.

The learners' current knowledge evaluation results will determine the next step of the learning process. If the learners meet the learning objectives (is able to answer the quiz or test and meet a certain standard), they can proceed to the next sequence of activities. If the learners do not achieve a certain standard of learning outcomes, they need to undergo a reinforcement session. The learning process can be repeated for a higher level of difficulty, which involves an iteration of the same processes.

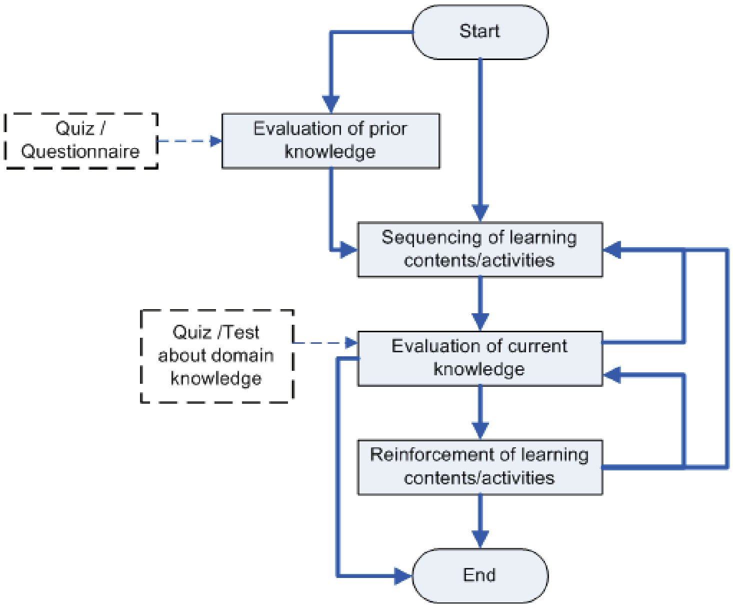

Figure 4.4: A generic flow of learners' learning process in DCSS

Generally, DCSS can be a good solution to lifelong learning and job training for employees. It can help students or employees to easily access the new information or knowledge that helps them to improve their skills at their convenience. By using DCSS, learners will be able to improve their performance in learning (Chen, 2008b; Weber & Brusilovsky, 2001).

However, performance is not the only outcome that a learning process attempts to achieve. There are other learning outcomes that computer-based learning research should consider, for example, learners' experiences, engagement, motivation, satisfaction, and the effects of computer-based learning on learners, organisations and society (O'Neil *et al.*, 2005). In this thesis, we intend to address learning experiences with the flow theory (Csikszentmihalyi, 1975, 1990, 1997).

In some research, computer-based learning caused frustration, anxiety, and confusion to learners (Hara & Kling, 2000; Zhang *et al.*, 2004). This claim is true for non-adaptive traditional computer-based learning systems, as they do not consider learners' differences in learning. Further, the systems are unable to accommodate learners' needs individually; consequently, they may obtain unsatisfying learning experiences from the systems' use. Unlike the traditional computer-based system, DCSS is adaptive to individual needs. For this reason, we are interested to understand whether the system can foster satisfying computer-based learning experience more effectively than a non-adaptive one. In the context of computer-based learning, experience is equally important because it helps learners to improve their psychological well-being, and obtain effective learning.

It has been mentioned in Chapter 3 that Csikszentmihalyi' flow theory is adapted to describe learning experiences. In this thesis, we attempt to understand the DCSS learning experiences through a series of empirical studies, which include a comparative study of the DCSS and non-DCSS learning experiences, and a study to understand how the DCSS learning experience evolves. The outcomes of these studies are intended to improve the design of the DCSS in particular.

4.2. IT-TUTOR: An Experimental DCSS

Prior to the evaluation of the learning experiences, the author developed an experimental DCSS (named IT-Tutor) which served as the main apparatus for the empirical studies reported in chapters 5, 6, and 7 of this thesis. In particular, IT-Tutor is a web-based dynamic curriculum sequencing system (DCSS) designed for learning "*Basic Computer Networks*" at a tertiary level. The aim of the system is to teach non-computer science (CS) students some general knowledge about computer networks. IT-Tutor can be used as a complement to the classroom lecture or for independent online learning. The key principle of IT-Tutor design is to provide learners with an adaptive computer-based learning environment for learning formal and technical courses.

4.2.1. The Architecture and Components of IT-Tutor

In general, the DCSS architecture comprises four components: a student model, a domain knowledge database, a user interface and, a tutoring module or pedagogical component (Virvou *et al.*, 2000). Like many other DCSSs, IT-Tutor shares some of the common features of DCSS with a few additional components. The architecture comprises the following components:

(1) *A Student Model (SM)* – A database for storing individual learners' information and records of interaction between the learners and IT-Tutor. The information includes personal information, records of usage, and learning activities log data.

(2) *A Domain Model (DM)* - A database for storing and keeping information about individual modules of learning or a course. Information about the modules includes structure, associations between lessons and sub-lessons, and associations between lessons with learning objects (LO).

(3) *A User Interface* – A user interface is a component that provides a platform for learners to communicate with IT-Tutor.

(4) *A Learning Object Repository (LOR)* – A set of databases for storing various types of learning objects (LO). It can be divided into two types:

   (a) *An Instructional Contents (IC) Database*- A database which stores the learning materials in the forms of explanations and examples

   (b) *An Assessment Items (AI) Database* - A database which stores the learning materials in the forms of exercise questions, quizzes and tests

(5) *A Sequencing Engine (SE)* – A set of production rules that performs dynamic sequencing approach (DSA) functionality (the next part of this section explains DSA). It also coordinates communications between other components.

Figure 4.5 shows the components and architecture of IT-Tutor. Some examples of IT-Tutor user interfaces are presented in Figure 4.6. The complete system of IT-Tutor can be accessed through the URL: http://it-tutor.net/Part2. The system runs on the .NET platform. Please refer to Appendix G for more screenshots.

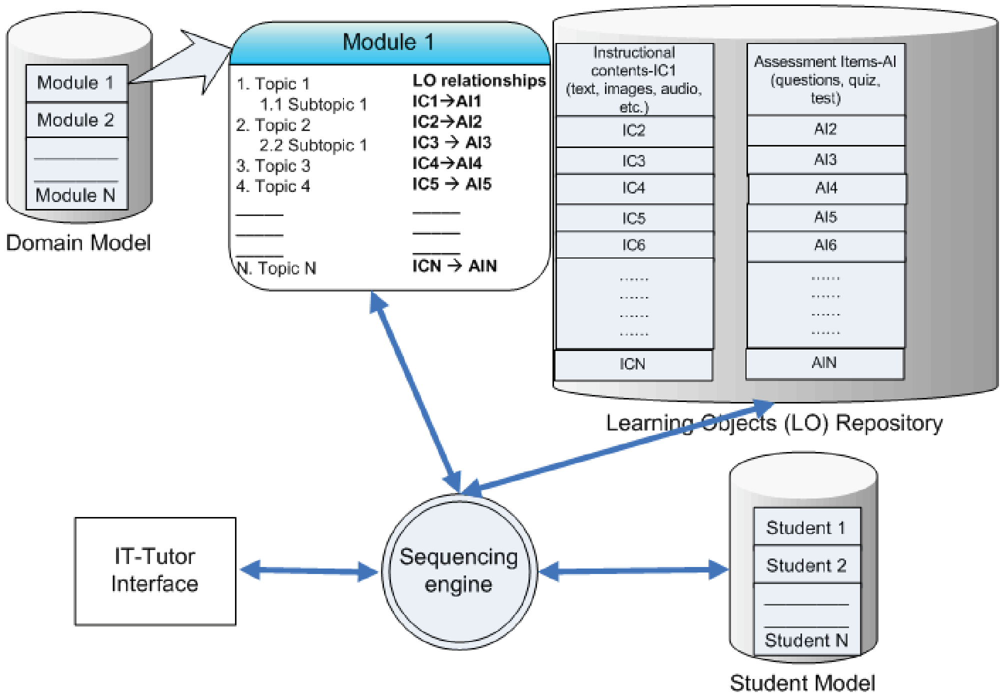

Figure 4.5: The components and architecture of IT-Tutor

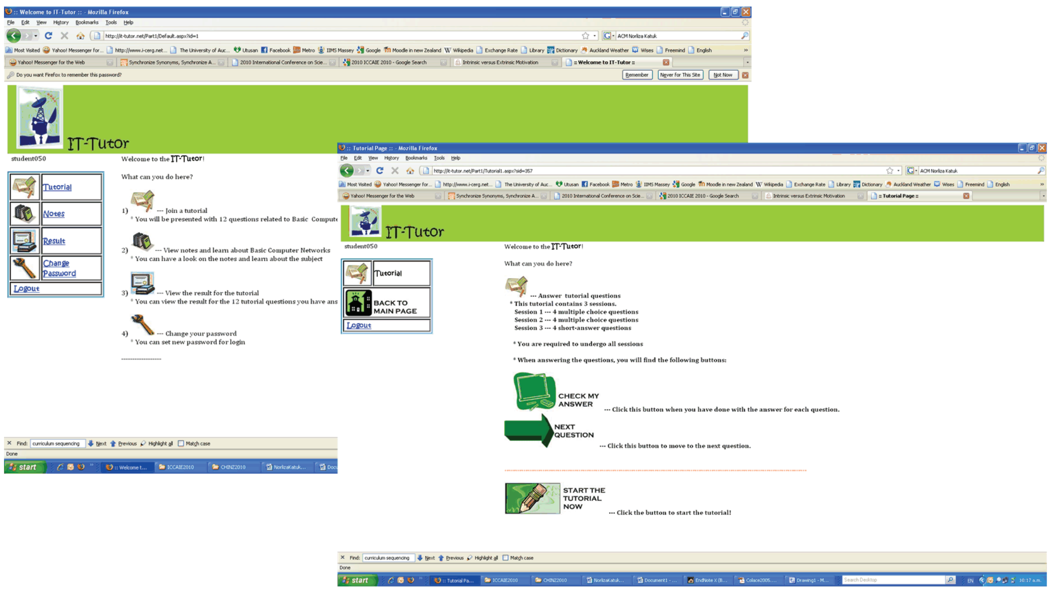

Figure 4.6: Screenshots of some IT-Tutor interfaces

4.2.2. Sequencing Technique in IT-Tutor

Sequencing approaches in DCSS aim to generate a personalised learning session for a targeted group of learners, which is tailored to the needs of that group. The sequencing approach in a particular DCSS is the most important component as it demonstrates how a computer-based system provides an adaptive learning environment to the learners. In IT-Tutor, sequencing of learning contents is accomplished by an approach known as *dynamic sequencing approach (DSA)* embedded in the *sequencing engine* (SE) component of the IT-Tutor architecture. DSA has been adapted from Morales & Agüera (2002) due to its simplicity in terms of the sequencing algorithm.

The approach consists of three main processes: (i) *composition of a learning module*, (ii) *association of learning objects,* and (iii) *automatic sequencing of lessons. Composition of a learning module* is the first process in which an experienced teacher defines a structure for a particular module. The structure of a module includes relationships between lessons and sub-lessons such as pre-requisites and co-requisites. As the structure of a module is prepared, the teacher needs to identify the contents of the module by selecting and matching learning objects with each of the lessons and sub-lessons of the module. This process is known as the *association of learning objects*. Learning objects (LO) are small reusable digital entities deliverable over the Internet (de-Marcos *et al.*, 2009; Wiley, 2002). The LO can be assembled to create a lesson which is a greater unit of instruction, while a set of lessons creates a module. Figure 4.7 shows an example of the hierarchy of LOs.

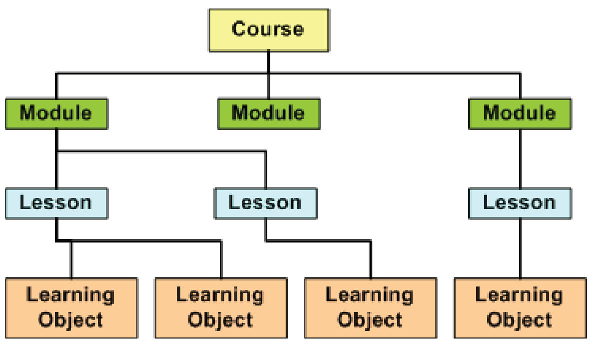

Figure 4.7: The structure of learning objects (Morales & Agüera, 2002)

Figure 4.8 shows the hierarchical structure of instructions in a module in IT-Tutor. It consists of two main lessons: (i) Introduction to Computer Networks, and (ii) Network Devices and Transmission Media (refer to Appendix E for the detail contents). Each of the lessons is made up of combinations of groups of LOs.

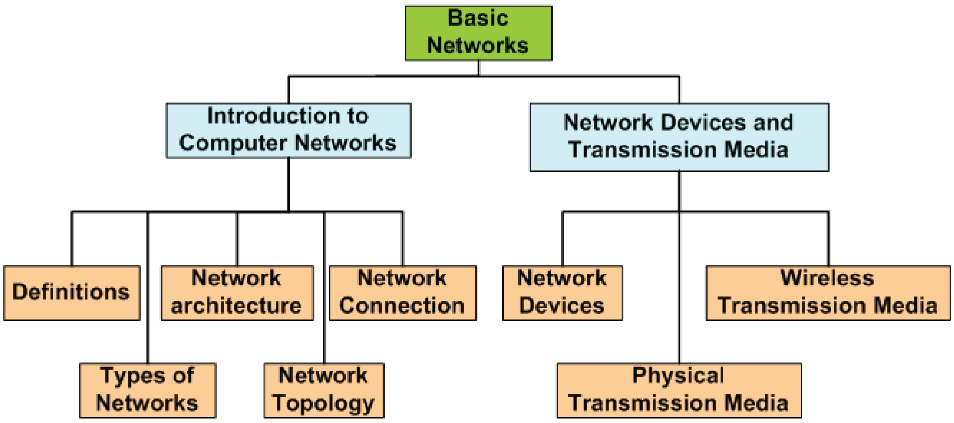

Figure 4.8: The structure of a module in IT-Tutor

In this study, each LO is comprised of quizzes (i.e., short-answer or multiple-choice questions), feedback (i.e., short text-based feedback), explanations (texts or combinations of texts, images or audio) and examples (i.e., texts, images, or audio). DSA in IT-Tutor is drawn upon the following procedure:

(1) First, a learner is presented with a quiz or a test in order to measure his or her background knowledge about the domain of learning;

(2) The learner receives a short feedback for each of the questions as he or she provides the system with an answer. At the same time, IT-Tutor observes the learner's answers and keeps track of each incorrect answer;

(3) For each of the incorrect answer(s), IT-Tutor identifies explanation(s), corresponding to the question(s), and presents the learner with further learning materials;

(4) The learner will be then presented with a new quiz or a test, when he or she successfully completes both procedure 2 and 3. This step will be repeated

until they show a certain level of learning performance. Figure 4.9 shows a process diagram of the automatic sequencing procedure.

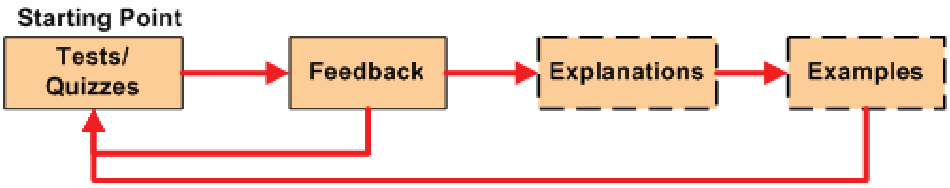

Figure 4.9: Dynamic Sequencing Approach (DSA) in IT-Tutor

The DSA is implemented through a set of rules which have been pre-programmed in the system (refer to Appendix F for the algorithm and rules). The rules consider the learner's prior knowledge and current knowledge levels in a learning session. At the beginning of a learning session, the learner's prior knowledge will be measured. If the learner's prior knowledge is insufficient, the learner is required to undergo an introductory sequence of learning contents. Otherwise, the learner can proceed to the next level of learning. During a computer-based learning session, the learner will be provided with feedback, evaluation of current knowledge, and reinforcement of learning.

4.2.3. Evaluation of IT-Tutor

IT-Tutor serves as a learning tool for the experimental studies in this thesis. IT-Tutor usability evaluation has been conducted to measure its suitability to be used as a learning tool.

4.2.3.1. Method

A usability test was performed using heuristic and formal evaluation approaches (Nielsen, 1994). The purpose of the heuristic evaluation was to find problems in the IT-Tutor interface and as well as to identify the suitability of the system to be used by learners as a computer-based learning system. On the other hand, the formal evaluation aimed to analyse the usability of IT-Tutor based on certain criteria as outlined by the computer-based learning usability questionnaire (Zaharias, 2004; Zaharias & Poylymenakou, 2009).

4.2.3.2. Participants

Five experts in usability and instructional design participated in the evaluation. Among them, three were experts in usability and the other two were experts in Computer Networks instructional design. The average years-of-experience in usability was 6.6 and 10 for instructional design. The minimum academic qualification was a Masters Degree. All of them are working with a public university in Malaysia and were identified through the directory of expertise published on the university's website.

4.2.3.3. Instruments

The evaluators were given a usability form to record the usability problems, as well as their comments about IT-Tutor. In addition, they were also given a usability questionnaire as proposed by Zaharias (Zaharias, 2004; Zaharias & Poylymenakou, 2009). The instrument was designed for evaluating the usability of computer-based learning systems. The reliability and validity of the instrument has been confirmed through a number of studies (refer to APPENDIX B for the usability evaluation form). Zaharias suggested eight dimensions of usability for computer-based learning systems; comprising content, learning and support, visual design, navigation, accessibility, interactivity, self-assessment and learnability, and motivation to learn. The e-learning usability questionnaire used a five-point Likert scale for rating.

4.2.3.4. Procedure

All evaluators were given a usability assessment comprising a cover letter, instructions to perform usability evaluation, and a usability report. Evaluators performed the usability evaluation independently at their own convenience. They were asked to browse the IT-Tutor interfaces thoroughly, identify usability problems and record the problems in the report. They were also asked to answer the e-learning usability questionnaire.

4.2.3.5. Results

The usability evaluation revealed that there were no major usability problems that had been encountered. The evaluators' comments had been reviewed, and appropriate actions had been taken to improve IT-Tutor. The evaluators' e-learning usability questionnaire data were analysed, and the results are discussed in this section. The Cronbach's Alpha coefficient for the nine items was 0.936 suggesting that the data were internally consistent. Table 4.2 depicts the means and standard deviations for the scores for each dimension of the usability questionnaire.

Table 4.2: The means (s.d.) for the e-learning usability questionnaire (n=5)

Component of usability	Mean score (s.d.)
Content	4.40(0.54)
Learning and support	4.00(0.71)
Visual design	4.80(0.44)
Navigation	3.80(0.84)
Accessibility	4.40(1.40)
Interactivity	4.00(0.00)
Self-assessment and learnability	4.60(0.89)
Motivation to learn	4.00(0.71)
Overall score	4.25(0.60)

From Table 4.2, the average rating for each dimension was acceptably high. In addition, the average of the evaluators' overall ratings was 85% suggesting that IT-Tutor was usable and acceptable to be used as an experimental system. All of the usability dimensions used in the usability evaluation were very important in optimising learners' experiences in learning through the DCSS. Thus, the reliability of IT-Tutor as an experimental apparatus has been confirmed through this usability evaluation.

4.3. Summary

This chapter discussed the fundamental aspects of the dynamic curriculum sequencing systems (DCSS). It has included discussions about the categories of the systems and some examples of the existing DCSS. The chapter has also described the systems' generic components and architecture, as well as how they work.

In this chapter, we emphasised the design and development of a DCSS, known as IT-Tutor. IT-Tutor has been developed following the sequencing technique proposed by Morales & Agüera (2002). Five experts in usability evaluation and Computer Networks instructional design had evaluated the usability of the system. They suggested that IT-Tutor was usable enough to be used as a learning tool.

IT-Tutor is the main apparatus for conducting experimental studies in this thesis. This will be further explained in Chapters 5, 6, and 7.

SECTION III: ANALYSIS OF THE DCSS LEARNING EXPERIENCE EVOLUTION

This section comprises two empirical studies that aim to understand how learning experience evolves in the DCSS. Chapter 5 explains an empirical study that compares learning experience with the DCSS and non-DCSS. It also predicts learners' cognitive states while interacting with the systems. In Chapter 6, learners' learning experiences are monitored progressively as they interacting with the systems. This chapter also studies cognitive load that the systems may impose to learners.

CHAPTER 5: A STUDY OF THE DCSS LEARNING EXPERIENCE

This chapter examines the learning experience of the dynamic curriculum sequencing system (DCSS). It aims to determine whether or not the DCSS learning experience and learning outcomes differ from the traditional computer-based learning system, i.e., the non-DCSS. Understanding the DCSS learning experience would help one to identify some important aspects of computer-based learning, and explain how the interaction between the student and the system happens. Therefore, we might be able to propose an effective computer-based instruction process.

An empirical study was performed to compare the learners' learning experiences and their learning outcomes in using the DCSS and the non-DCSS (i.e., a recommendation system). Further, this study investigates the effects of computer-based learning on different types of learners (i.e., high, medium, and low achievers). In this way, we would be able to identify the types of learners whom obtain the most satisfying DCSS learning experience, and use this information to develop more adaptive computer-based systems.

Additionally, the study predicts the learners' cognitive states (i.e., flow, boredom, and anxiety) while interacting with the computer-based systems. The prediction is used to evaluate how effective the systems are in maintaining the learners' optimal learning experience. More importantly, the prediction will determine the actual levels of the learning experience, which can strengthen their metacognitive skills. Again, the results of this study are expected to improve computer-based learning experience, especially in the context of human-computer interaction.

Overview of the Chapter

The chapter is divided into two sections. Section 5.1 discusses learning experiences in using computer-based learning systems with an emphasis on some prior studies. Based on the analytical stance in the literature review, Section 5.2 describes an empirical study of the DCSS.

5.1. Learning Experience in the DCSS

As discussed earlier in Chapters 2 and 3, learning experience would be a measure that generates positive influences on learning performance (Ho & Kuo, 2010). More importantly, learning experience plays an essential role in a larger perspective of education. In the contexts of independent learning, Alexander & Golja (2007) emphasised that learning experience would dictate the future of computer-based learning in higher academic institutions. They further claimed that the sustainability of computer-based learning is mainly influenced by the quality of the learning experience that the systems can offer to students. Thus, we anticipate that examining learning experience would practically contribute to the design of computer-based instruction, and this would make it possible for us to capture the benefits of computer-based learning.

There have been many studies that evaluated the experience of computer-based learning against that of traditional classroom pedagogy (see Johnson *et al.* (2000), Zhang *et al.*(2004), and Piccoli *et al.* (2001)). Johnson *et al.* (2000) reported that the learners, who used computer-based learning, had a lower level of satisfaction than the face-to-face group. This was mainly due to the effective role that human instructors played in the face-to-face mode, which was not available in the computer-based system. However, they emphasised that the learning quality was not much different and believed that the computer-based learning would have the same capability as the traditional one. Zhang *et al.* (2004) and Piccoli *et al.* (2001) also discussed similar results. In the context of this thesis, we believe that computer-based learning can be improved to support the higher educational sector in particular because it is capable of delivering instructions more economically and flexibly than traditional method.

Perhaps, the computer-based learning is not as good as the traditional learning environment. Nonetheless, the success of e-learning businesses has proved itself useful. This can be seen by the introduction of new learning paradigms using various pedagogy (e.g., mobile learning or ubiquitous learning). In particular, many novel computer-based learning systems have been introduced especially within higher educational institutions and professional training fields, thanks to their convenience and ease of maintaining the learning programmes. However, there are also many studies on the negative sides of computer-based learning (Hailey *et al.*, 2001; LaPointe & Reisetter, 2008; Shepherd & Bolliger, 2011; Tyler-Smith, 2006). In this respect, it is interesting to see what benefits computer-based learning systems would give the learners.

It is important to note that computer-based learning is primarily influenced by learners' past learning experiences with computers (Milligan & Buckenmeyer, 2008) or computer-based learning systems (Packham *et al.*, 2004). For example, students who had boring and stressful experiences are more likely to give up a computer-based learning activity or at the very least not interested in it and possibly will not return to the system in the future. For this reason, it is worthwhile to study what learning experiences that the computer-based learning systems can present so that a richer and more engaging learning experience could be fostered in the design and development of such systems.

As discussed in Chapter 3, we performed a comparative study about computer-based learning experience in the different types of computer-based learning systems. To our knowledge, the past experimental studies have focussed largely on learner performance rather than learner experience (for examples, see Ainsworth & Grimshaw, 2002 and Muntean & McManis, 2006). Further, some studies were carried out to investigate the effectiveness of new computational techniques (i.e., artificial intelligence techniques) in computer-based learning (Chen, 2008a; Chen, 2009; Chen, *et al.*, 2006), revealing that dynamic curriculum sequencing systems might be of greater value in terms of user satisfaction. However, there is still a lack of empirical evidence, which is central to this chapter. This empirical study would thus contribute to system developers and computer-based instructional designers for creating usable and acceptable computer-based learning systems.

In this chapter, the author attempts to understand learning experiences in a specific type of computer-based system named dynamic curriculum sequencing system (DCSS) from the context of cognitive engagement (i.e., as outlined by the flow theory).

Precisely, the author intends to study how learners cognitively undergo a learning session with the DCSS and what will be the outcomes derived from their learning process with the DCSS. The purpose of the empirical study is first to understand learning experience and then utilise the results to improve human-computer interaction toward a more adaptive DCSS.

5.2. Experiment 1: A Study about Learning Experience in the DCSS

This section explains an experimental study to understand the DCSS learning experience. In doing so, a DCSS system and a recommendation system (which is referred to as the non-DCSS in the remaining sections of this chapter) were used as a comparative learning tool, and in turn, their separate learning experiences were measured.

The two systems (i.e., the DCSS and the non-DCSS) were primarily different in terms of navigation style and control over the learning sequence. For this reason, the author predicts dissimilarity in the learning experiences that learners could obtain from the two different systems. This empirical study also categorises the learners into a few groups based on their post-test achievement to see the learning experience difference on their knowledge and skill levels. Then, it predicts the learners' cognitive states during the computer-based interactions.

5.2.1. Method

5.2.1.1. Participants

A total of 150 students from two universities, Massey University in New Zealand (66 students) and Northern University of Malaysia (84 students) volunteered to participate in this study. Only 78 participants (44 from New Zealand and 34 from Malaysia) completed all learning tasks, and these data were used for the following analyses. The participants were randomly assigned to one of the two groups: (i) 36 participants (26 females and 10 males) were in the experiment group, and (ii) 42 participants (22 females and 20 males) were assigned in the control condition. The average age of the participants was 29.13 years. Half of the participants were undergraduate students and the other half were postgraduates. More than 85% of the participants were non-CS (Computer Science) students. The participants were recruited through emails and advertisements on the university's notice boards during April to July 2010. The participants were automatically assigned to one of two fifty-dollar prize draws.

5.2.1.2. Apparatus

The apparatus used for the experiment comprised of four components: (i) two computer-based learning systems (i.e., the DCSS and the non-DCSS), (ii) a pre-learning quiz, (iii) a post-learning quiz, and (iv) a learning experience questionnaire.

The two computer-based learning systems were the main apparatus used to understand the learners' learning experiences. IT-Tutor (see Chapter 4 for more detail) was used to represent the DCSS. In contrast, the non-DCSS appeared in a form of a recommendation system based on IT-Tutor, which means the system simply suggested a learning path to the learners individually and allowed them to navigate the path independently. In the rest of the thesis, the recommendation system is referred to as the non-DCSS, for the descriptive purpose. Table 5.1 summarises the differences and the similarities of both systems. The DCSS and the non-DCSS served as the experimental and the control condition respectively.

Table 5.1: The features of the DCSS and the non-DCSS

	IT-Tutor (DCSS)	**IT-Tutor (non-DCSS)**
Evaluation of prior knowledge	Both versions evaluated learners' prior knowledge	
Sequencing of learning contents	Sequencing of learning contents were automatically enforced as soon as evaluation of prior and current knowledge were completed	The system suggested the learning contents that should be learned after the evaluation of the respective prior and current knowledge were completed
Learners' access to the learning path	Learners were automatically presented with the sequence of learning contents and should follow the given learning path	Learners were expected to browse the suggested learning contents independently from the "Notes page" in the system

The purpose of the pre-learning quiz was to evaluate the learners' knowledge and background about the domain of study (i.e., Basic Computer Networks). It was given as a control measure for the participants' equal variances in both groups. The pre-learning quiz contained ten multiple-choice questions.

As the participants completed the learning activity, they were asked to answer the post-learning quiz. The purpose of the quiz was to measure knowledge transfer and knowledge retention after a computer-based learning session. Knowledge transfer and knowledge retention are the common instruments for measuring learning outcomes (Mayer, 2005). The learners' ability in memorising the content is referred to as knowledge retention capability. On the other hand, the learners' ability to apply the new knowledge in a new context is seen as knowledge transfer capability. In this study, the knowledge retention capability was measured through five questions about the domain of study, and the knowledge transfer capability was also assessed through five short-answer questions.

Finally, another instrument was included to examine the learning experiences. A learning experience questionnaire was adopted from Park *et al.* (2010) based on Webster *et al.* (1993), which was designed to measure user experiences based on the flow theory (Csikszentmihalyi, 1990)[12]. The questionnaire consists of four dimensions of flow which measure: (i) control, (ii) attention focus, (iii) curiosity, and (iv) intrinsic interests. Webster *et al.* (1993) used this combination to characterise the state of flow in their studies.

This thesis adapted the above four dimensions of flow to describe learning experience from the context of cognitive states in computer-based learning. Apart from analysing the individual dimensions, the learner's ratings of all dimensions (i.e., control, attention focus, curiosity, and intrinsic interests) are combined to produce a single value that represents the learning experience quality as a whole. The following paragraphs define each learning experience dimension in the context of this thesis.

[12] The flow theory was explained in Chapter 3.

Control refers to the situation in which a learner feels in control of the learning activities. In this situation, the learner is capable of keeping the interactions between himself or herself with IT-Tutor on track. In the context of computer-based learning, control is a critical component that affects learner's motivation, performance and attitudes towards learning (Kopcha & Sullivan, 2008). In fact, several studies on learner control in computer-based learning have revealed that giving a learner control over learning activities leads to an improved academic achievement (Corbalan *et al.*, 2006; Shin *et al.*, 1994; Shyu & Brown, 1992). Hence, its effects on the DCSS learning experience are an interesting topic to be studied.

Besides control, the learning process also requires an optimal level of focus so that a meaningful learning can be obtained. *Attention focus* refers to the situation in which a learner is absorbed by the computer-based learning activities. That is, it actually measures learner's level of concentration in the given computer-based learning tasks. Saadé & Bahli (2005) defined this condition as cognitive absorption, which plays an important role in generating more positive attitudes towards learning and greater exploratory use of the system. With regard to this, the author attempts to understand: (i) how effective the DCSS is keeping learner's attention and focus towards the given learning activities, and (ii) how this would affect the learner's learning experiences.

Webster *et al.* (1993) confirmed the positive relationship between attention focus and curiosity. They defined *curiosity* as the situation in which a learner is excited and eager to know more about the domain knowledge. It is important to note that the state of curiosity is always inconsistent. Small & Arnone (1998) suggested that sufficient and relevant information can increase curiosity. They claimed that motivation could be increased when student is provided with the information that is required for learning; thus, encouraging the student to explore more about the topic. Consequently, in the context of computer-based learning, insufficient information or knowledge that a learner anticipates during a learning process may lead to a significant decrease or even extinction of curiosity. For this reason, it is crucial for us to study how effectively the DCSS increases learner's curiosity through its content presentation and sequencing.

The last learning experience dimension is *intrinsic interests,* which can be defined as a situation in which a learner feels enjoyment with the learning activities. This can be further described by the reasons that motivate the learner to learn. A learner with intrinsic interests engages in computer-based learning for the sake of the learning itself without apparent force (Benabou & Jean, 2003). Researchers in the area of computer-based learning acknowledge that a proper design of computer systems can help in stimulating intrinsic interests. On account of this, it is useful if we could have some information whether or not the DCSS fosters learning intrinsically.

The four learning experience dimensions discussed above are measured by a questionnaire. The questionnaire comprised of twelve items with three items for each dimension. A five-point Likert scale (i.e., one represented 'strongly disagree' and five represented 'strongly agree') was used for the questionnaire. Please refer to APPENDIX C for the complete set of the pre-learning quizzes, the post-learning quizzes, and the learning experience questionnaire.

5.2.1.3. Experimental Design

A one-way between-subject design was used for this experimental study. The independent variable was the type of computer-based learning system (i.e., the DCSS and the non-DCSS).

Two dependent variables were employed in this study. They were learning outcomes and learning experience. *Learning outcomes* was divided into two categories; knowledge retention and knowledge transfer capability. The knowledge retention capability measured the learners' capability in memorising the learning, whereas the knowledge transfer capability assessed how much each learner is able to apply his or her new knowledge to a new situation. The rating scales of the learning experience questionnaire assessed the *learning experience*.

In this study, it is noted that there are two additional variables to be controlled: the learners' *prior knowledge* and the *types of learners*. In many previous studies, it has been proven that *prior knowledge* affects the outcomes of computer-based learning (Jung & Park, 2004; Kalyuga, 2005; Kopcha & Sullivan, 2008; Mitchell *et al.*, 2005). In this regard, those studies found that high prior knowledge learners are more likely to have higher achievement than lower prior knowledge learners of the same domain of learning. Further, the different levels of achievement readily represent a few clusters of learners. In this thesis, the levels of achievement (i.e., high-, medium-, and low-performing achievers) characterised the *types of learners*. It makes sense to control these variables so that the effects of individual difference on the DCSS learning experiences can be monitored.

The learners' *prior knowledge* data were obtained from the pre-learning quiz scores. On the other hand, the *types of learners* were identified through a univariate cluster analysis on the post-learning quiz, which classified learners into *high achievers, medium achievers and low achievers*. Section 5.2.2 describes the analyses in details.

5.2.1.4. Procedure

The experiment was conducted in an online mode, which made the participants perform the experimental task at their own pace. As they attended the experiment, they were given an information sheet about the study, explaining how the experiment would be performed. Then, they were given a consent form. Each participant had to give consent to participate in the study. Following that, the participants were asked to answer the pre-learning quiz. As they completed the pre-learning quiz, the participants were randomly assigned[13] into one of the two experiment groups (i.e., IT-Tutor with DCSS and IT-Tutor without DCSS).

Next, the participants underwent a tutorial session with the corresponding computer-based learning systems at their own pace. Upon completion of the given tasks, the participants were required to answer a post-learning quiz, followed by the learning experience questionnaire. The whole procedure for conducting the experiment is illustrated in Figure 5.1. All the interactions between the participants and the computer programs were logged in a database, and in order to maintain the reliability of

[13] A computer random binary number generator was used to assign participants to the experiment groups and distributed males and females equally to both groups.

the data, the system was set to log off when a participant was inactive[14] for five minutes.

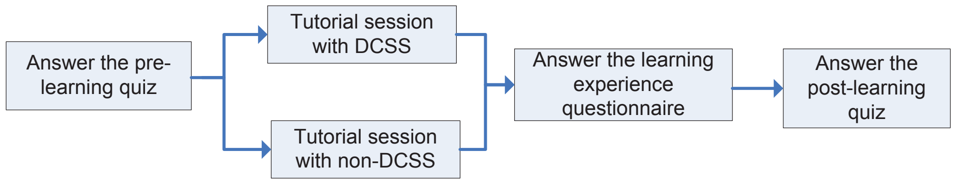

Figure 5.1: Procedure for conducting the experiment

5.2.1.5. Data Preparation

Prior to data analysis, a data screening procedure was performed to identify the integrity of data entry, missing values, outliers, and normality. The data collected were double-checked to ensure that all values were correct. Analysis of the data was performed using SPSS version 18. Missing values due to typing errors were also identified using the frequencies check provided by the "*descriptive statistics*" command. There were no outliers detected for these data. The *Kolmogorov-Smirnov* (K-S) test showed that the data were non-normal[15] in all cases, and all statistical tests for this experiment were thus performed using non-parametric[16] tests, instead. Please refer to Appendix H for the raw data of this experimental study.

[14] *Inactive* is defined by the situation in which there were no interactions had happened between the participants and the application for a period of time. The Interactions include mouse moving and clicking, scrolling down and up of a page and more.

[15] The significant values were between 0.00 and 0.04 which indicated that the data were non-normal. If the non-significant values ($p > 0.05$) were obtained through the K-S test, it showed that the data were in a normal distribution.

[16] The non-parametric statistical tests calculate the mean ranks and sum of ranks to evaluate the difference in two samples instead of the means and standard deviations (Sheskin, 2007).

5.2.2. Results

The analysis on the demographic data showed about 70% of the participants were non-English speakers and 98% of the participants had computer experience more than two years. Also, around 47% of the participants had used other kinds of computer-based learning systems, e.g., Blackboard and Moodle.

5.2.2.1. Learning Outcomes

Prior to the main statistical analysis, the reliability of the data was checked. The *Cronbach's alpha coefficient* for the two types of tests was 0.76 suggesting the items of the data had relatively high internal consistency. The *Mann-Whitney U* tests on the pre-learning scores showed no significant difference between the DCSS and the non-DCSS ($z=-0.32$, $p=0.752$) in terms of the learners' prior knowledge. Hence, an equal distribution of the learners was assumed. Table 5.2 shows the mean ranks for learning outcomes, i.e., the knowledge retention capability and the knowledge transfer capability, for the DCSS and the non-DCSS.

Table 5.2: The means and mean ranks for performance tests

	The DCSS (n=36)		The non-DCSS (n=42)		Statistical Significance
	Means	Mean Ranks	Means	Mean Ranks	
Retention Test	2.69	42.04	2.26	37.32	z=-0.935, p=0.350, n.s.
Transfer Test	1.42	43.04	1.07	36.46	z=-1.334, p=0.182, n.s.

The retention and transfer means for the DCSS learners were slightly higher than the counterpart. This information suggested that the DCSS learners memorised more knowledge and had better capability in applying the knowledge in a new context. However, the results of *Mann-Whitney U* tests revealed that there was no statistical difference between the groups in both types of the performance tests.

5.2.2.2. Learning Experience

Learning experience was measured through evaluation of the learners' questionnaire responses. The *Cronbach's alpha coefficient* for twelve questionnaire items was 0.849, suggesting that the data had relatively high internal consistency. The means and mean ranks for all learning experience dimensions were calculated and presented in Table 5.3.

Table 5.3: The means and mean ranks for the learning experience questionnaire

Learning experience dimensions	IT-Tutor with DCSS (n=36)		IT-Tutor with non-DCSS (n=42)		Statistical Significance
	Means	Mean Ranks	Means	Mean Ranks	
Control	3.44	39.43	3.44	39.56	z=-0.025, p=0.980, n.s.
Attention Focus	2.82	37.61	3.00	41.12	z=-0.686, p=0.492, n.s.
Curiosity	3.48	39.49	3.44	39.51	z=-0.005, p=0.996, n.s.
Intrinsic Interests	3.55	43.53	3.29	36.05	z=-1.469, p=0.142, n.s.
Overall Experience	3.32	41.14	3.29	38.10	z=-0.592, p=0.554, n.s.

The overall experience was higher in the DCSS (mean=3.32) compared to the non-DCSS (mean=3.29). Looking specifically at the individual dimensions of the DCSS learning experience, intrinsic interests received the highest ratings while attention focus received the lowest. In contrast, their attention focus had the lowest ratings in the non-DCSS. Control and curiosity were similar for the non-DCSS learners which of the highest ratings for the group. These descriptive statistics indicate that the DCSS provided the learners with a stimulating computer-based learning experience and quite a high level of control over the learning content. The system aroused the learners' curiosity better than the non-DCSS. In terms of focus, the non-DCSS learners were slightly better than the DCSS.

In general, it can be said that the DCSS learning experience was slightly more satisfying than the non-DCSS. However, the *Mann-Whitney U* tests revealed no significant difference (*z=-0.592, p=0.554*) in the learning experience between both systems.

5.2.2.3. The Learning Experiences Based on Different Types of Learners

This study also attempts to understand the effects of different "*types of learners*" on their learning experiences. In doing so, the author analysed the data to find some information about *who were really engaged in the computer-based learning session and gained the most satisfying experiences from it* and *who suffered from anxiety and boredom with the computer-based learning session.* A combination of some statistical methods was used to gather information for these questions. The process comprised of applying two advanced statistical methods known as a *univariate cluster analysis* (Zhang & Zhang, 2006) and a *discriminant function analysis* (Hair *et al.*, 1995).

A Univariate Cluster Analysis

A *univariate cluster analysis* was performed to classify the learners with homogenous performance into a few clusters. In this thesis, the learners were divided into three clusters based on their achievement in the post-learning quiz. The three categories were *low, medium, and high achievers*[17]. The clustering tasks were done using an add-on module of Microsoft Excel named XLStat[18] following Fisher's clustering algorithm (Fisher, 1958).

The post-learning quiz represents the learners cumulative knowledge obtained from the computer-based learning. Hence, the measure is reliable to be used for identifying different *types of learners*. The post-learning quiz comprised of ten marks and the learners' scores ranging from zero to ten. The univariate cluster analysis suggested three class-centroids (class-means); 6.8, 4.0 and 0.6 respectively for cluster 1 (i.e., the high achievers), cluster 2 (i.e., the medium achievers), and cluster 3 (i.e., the low achievers). The univariate cluster analysis had also suggested the lower and upper boundaries of each cluster. Information in Table 5.4 shows the classification results.

Table 5.4: Classification of learners based on the score of the post-learning quiz using univariate cluster analysis

Types of Learners	Range of Score	DCSS (n=36)	Non-DCSS (n=42)
Low achievers (Cluster 3)	0-2	10	18
Medium achievers (Cluster 2)	3-5	14	11
High achievers (Cluster 1)	6-10	12	13

Looking at Table 5.4, the number of the DCSS low achievers (27%) was smaller than the non-DCSS (43%). In contrast, the number of the DCSS medium achievers was

[17] The use of this categorization is very common in classifying learners into groups. See Konstantopoulos & Chung (2009) for an example.

[18] Refer to www.xlstat.com for further information about the software.

higher (38%) than the non-DCSS (26%). Nevertheless, the high achievers were distributed equally in both groups.

The *Kruskal-Wallis* tests calculated the mean ranks for the learning experience across different types of the learners (i.e., high, medium, and low achievers). Table 5.5 and Table 5.6 display the statistics values for the DCSS and the non-DCSS respectively in detail.

Table 5.5: The means and mean ranks for DCSS learning experience based on different types of learners

Learning experience dimensions	High Achievers (n=12)		Medium Achievers (n=14)		Low Achievers (n=10)		Statistical significance
	Means	Mean ranks	Mean	Mean ranks	Mean	Mean ranks	
Control	3.31	17.96	3.38	18.36	3.67	19.35	H(2)=0.102,*P*=0.95,n.s.
Attention Focus	2.92	19.25	2.86	18.18	2.83	18.05	H(2)=0.095,*P*=0.954,n.s.
Curiosity	3.42	18.25	3.12	14.14	4.07	24.90	H(2)=6.256,*P*=0.044,p<0.05
Intrinsic Interests	3.56	17.63	3.29	16.46	3.90	22.40	H(2)=2.019,*P*=0.364,n.s.
Overall Experience	3.30	16.63	3.16	17.71	3.61	21.85	H(2)=1.475,*P*=0.478,n.s.

Table 5.5 suggests that the high achievers rated intrinsic interests as the highest learning experience dimension. Control and curiosity were the highest dimensions rated by the medium and low achievers respectively. All categories of the learners rated attention focus the lowest. The descriptive statistics also suggests that the low achievers had a higher level of control, curiosity, and intrinsic interests compared to the medium and the high achievers. In fact, this type of learner rated the most satisfying learning experience. The *Kruskall-Wallis* tests suggest that the low achievers rated the highest in their curiosity compared to the other two types of learners (H(2)=6.256, p<0.05).

Table 5.6: The means and mean ranks for non-DCSS learning experience based on different types of learners

Learning experience dimensions	High Achievers (n=13)		Medium Achievers (n=11)		Low Achievers (n=18)		Statistical significance
	Means	Mean ranks	Means	Mean ranks	Mean	Mean ranks	
Control	3.43	21.15	3.27	19.73	3.56	22.83	H(2)=0.462,*P*=0.794,n.s.
Attention Focus	3.23	23.96	2.55	16.09	3.11	23.03	H(2)=3.002,*P*=0.223,n.s.
Curiosity	3.84	26.42	2.70	13.18	3.59	23.03	H(2)=7.563,*P*=0.023,p<0.05
Intrinsic Interests	3.67	28.04	2.67	12.77	3.39	22.11	H(2)=9.528,*P*=0.009,p<0.05
Overall Experience	3.55	25.81	2.80	13.45	3.41	23.31	H(2)=6.736,*P*=0.034,p<0.05

From Table 5.6, the high and the low achievers had the highest ratings in curiosity. Control had the highest ratings for the medium achievers. Similar to the DCSS, all categories of learners rated attention focus the lowest. Unlike the DCSS, the non-DCSS offered the high achievers the highest level of curiosity and intrinsic interests. Indeed, they obtained the best quality of experiences compared to others. The differences in curiosity, intrinsic interests, and the overall experience were significant as suggested by the *Kruskall-Wallis* tests.

A series of *Mann-Whitney U* tests were used to compare the learning experiences between different types of learner against the two types of systems. The test results revealed no significant difference in the learning experiences between the groups (i.e., the DCSS and the non-DCSS) in relation to different types of learner.

A Discriminant Function Analysis

A *discriminant function analysis* was performed to predict the learners' experiences with regard to three cognitive states of the *Flow Theory* (i.e., flow, boredom, and anxiety). The discriminant function analysis used five variables (i.e., post-learning quiz, control, attention focus, curiosity, and intrinsic interests) to predict the types of the learners' learning experiences.

Prior to this, *univariate cluster analyses* have been used to classify the learners into two clusters (i.e., low and high) based on the pre-learning quiz and learning experience scores. Regardless of the post-learning scores, the learners who had high learning experience ratings were assigned to the *flow group*. On the other hand, the learners with high post-learning scores but low learning experience ratings were categorised as *boredom*. In the case of the learners who had low scores in both post-learning quiz and learning experience, they were assigned to the *anxiety* group.

Then, these classifications were compared with the results derived from the discriminant function analysis as mentioned in the first paragraph of this section. Overall, 96.2% of cognitive states (i.e., flow, anxiety, and boredom) were correctly predicted. At the individual types of experience, 98.2% of the learners were correctly classified as flow, 100% of the learners were correctly classified as anxiety, and 85.7%

learners were correctly classified as boredom. This information is summarised in Table 5.7.

Table 5.7: Learners with different types of experience based on discriminant function analysis

Types of Learners	DCSS (n=36)	Non-DCSS (n=42)
Flow	30	32
Anxiety	0	5
Boredom	6	5

From Table 5.7, the number of the learners who achieved flow was higher in the DCSS group (i.e., 83%) in comparison to the non-DCSS (76%). None of the learners in the DCSS group suffered from anxiety; however, 17% of them were suffered from boredom. In the case of the non-DCSS learners, 12% of them suffered from anxiety and boredom respectively. Figure 5.2 shows the learning experience distribution of from the group centroids.

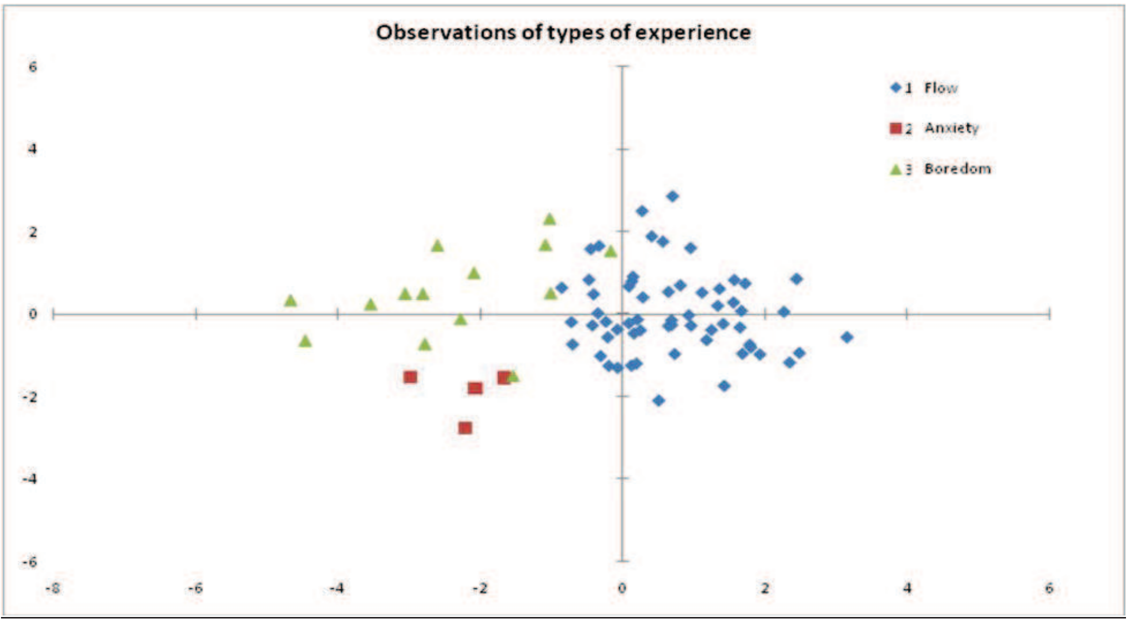

Figure 5.2: Types of learning experience using discriminant function

The discriminant function analysis also suggested two significant discriminant functions $\chi^2(10) = 88.73$, $p<0.001$ and $\chi^2(4) = 16.07$, $p<0.005$. The two discriminant functions accounted for 87.4% and 12.6%, respectively, of the between-group variability. Based on the statistical significance, both functions were used for further analysis.

The first discriminant function differentiated flow from boredom and anxiety, while the second function discriminates anxiety from flow or boredom. The learners who achieved flow were high in their intrinsic interests (*0.765*), curiosity (*0.757*), and control (*0.436*). On the other hand, the learners who suffered from anxiety were high in attention focus; however, they scored very low in the post-learning quiz. Table 5.8 depicts the correlation between the learning experience dimensions and the two canonical functions.

Table 5.8: Correlation of learning experience based on the discriminant function analysis

Variables	Function1	Function 2
Intrinsic interests	0.765*	0.238
Curiosity	0.757*	0.180
Control	0.436*	0.071
Attention focus	0.387	-0.728*
Post-learning quiz	-0.036	0.524*

** Largest absolute correlation between each variable and any discriminant function*

In order to identify who were experiencing boredom and anxiety particularly, the predicted cognitive states were analysed against the different *types of learners* (i.e., high achievers, medium achievers, and low achievers). The medium- and the high-achieving learners in the DCSS group mostly suffered from boredom with 11% and 6% respectively. Approximately 6% of the low achievers suffered from anxiety and 11% of the medium achievers suffered from boredom in the non-DCSS group. The categorisation is summarised in Table 5.9.

Table 5.9: Frequencies of the types of learning experience against types of learners

Types of Learners	DCSS (n=36)			Non-DCSS (n=42)		
	Flow	Anxiety	Boredom	Flow	Anxiety	Boredom
Low achievers	10	0	0	14	4	0
Medium achievers	10	0	4	5	1	5
High achievers	10	0	2	13	0	0
Total	**30**	**0**	**6**	**32**	**5**	**5**

The analysis suggests that the DCSS had caused boredom to some of the high and the medium achievers while the non-DCSS caused anxiety to the low achievers. In spite of this, both systems had led the medium achievers to suffer from boredom.

5.2.3. Discussions

This study was conducted to investigate three main objectives. Firstly, it aimed to determine whether or not the DCSS learning outcomes and learning experience were similar to the non-DCSS. Secondly, it examined the learners' types and their corresponding learning experiences resulted from the DCSS and the non-DCSS. Finally, the study was planned to predict the learners' cognitive states while interacting with the DCSS and the non-DCSS.

For the first objective, the result of this study suggests that the DCSS learning outcomes and learning experience were similar to the non-DCSS. In spite of the similarity, the study was able to show that the DCSS helped the low achievers to raise their curiosity level. On the other hand, the non-DCSS helped the high achievers to increase their curiosity; further, it stimulated their motivation to learn. The results can be justified by the learner's levels of control over navigation and sequencing of learning (Chou & Liu, 2005; DeRouin *et al.*, 2005; Hummel *et al.*, 2009; Kopcha & Sullivan, 2008; Shyu & Brown, 1992; Wan*, et al.*, 2006). It is well noted that high achievers prefer minimum navigation supports, while low achievers can work well with a fully-guided navigation. In the context of this study, the DCSS had been designed to offer a fully-guided computer-based learning which obviously improved the low achievers' learning experiences. On the opposite side, the freely-browsing non-DCSS improved the high-achievers' learning experiences. These results achieved the second objective of this study.

Apart from that, the study reported here also predicted the learners' types of cognitive states (i.e., flow, boredom, and anxiety) during the computer-based learning. The discriminant functions had successfully distinguished the learners who obtained flow with those who suffered from boredom and anxiety. It also separated the learners who suffered from anxiety from those who were in the flow and boredom state. Hence, the outcomes of the discriminant function analysis support the final objective of the study.

Generally, the results of the empirical study reported in this chapter have contributed some new knowledge to the fields of human-computer studies and computer-based learning instructional design. From these findings, the author has extracted some features of both systems that could be improved to give learners with rich and engaging learning experiences. The features take into account some important learning experience dimensions. Table 5.10 summarises these features.

Table 5.10: Feature analysis of DCSS and non-DCSS based on the Experiment 1's findings

Feature	DCSS	Non-DCSS
Control over learning process	DCSS are more suitable for low achievers as the predetermined learning path helps them to take control over their learning activities	Recommendation systems are more suitable for high achievers due to the given minimum supports of navigation
Attention and concentration	There is a need to improve the technique to regulate attention focus in DCSS	Recommendation systems help high achievers to be more focus
Learners' curiosity towards new knowledge	DCSS increase low achievers' curiosity about the domain of study	Recommendation systems help in arousing curiosity among high achievers
Enjoyable learning experience	DCSS stimulate low achievers' motivation to learn	Recommendation systems stimulate high achievers' motivation to learn

The features highlighted in Table 5.10 are used in designing a more adaptive computer-based learning that incorporates learning experiences. In conjunction with the results described herein, the author extends the study to understand how computer-based learning experience evolves. Specifically, the author aims to study whether computer-based learning experience is static or dynamic. The detail about this study is given in Chapter 6. In Chapter 7, the author explains a new technique for the DCSS user interface design that regulates learning experience more effectively.

5.3. Summary

This chapter explained a comparative study of the DCSS and the non-DCSS learning experiences and learning outcomes. It clustered the learners according to their achievement in the test and predicted their cognitive states while interacting with the systems. The study suggested that the low-achieving learners with the non-DCSS suffered from boredom more frequently than the DCSS. In terms of the high-achieving learners, they suffered from boredom more frequently with the DCSS than the non-DCSS.

The findings have shed some light on further research on how the DCSS learning experience is progressing.

CHAPTER 6: COGNITIVE LOAD AND PROGRESSIVE EVALUATION OF LEARNING IN THE DCSS

This chapter extends the previous empirical study described in Chapter 5. It is important to note that the results obtained from Experiment 1 suggested that the overall learning experience was similar between the DCSS and the non-DCSS (i.e., the recommendation system). In addition, when the learning experience was measured only at the end of the computer-based learning session, there was no clear evidence to indicate any changes in the learning experience that may take place throughout the learning activity in both groups. It was also unknown whether the learning experience quality was increasing or decreasing over the computer-based interaction period.

Inspired by Ceja & Navarro's (2009) research, the study reported here attempts to show that computer-based learning experience would change over time. For this reason, if it can be shown, we are further interested in how the DCSS can reshape the learning experience for each individual learner. In doing so, we measured the learner's learning experiences more than once, so that the learning experience temporal data can be analysed.

To understand further the learning activity in the context of DCSS, cognitive load is also studied. Cognitive load is considered important in this thesis due to the fact that a high-quality computer-based learning system must be able to reduce extraneous cognitive load that the system imposes on the learner. Consequently, the overall learning outcomes and experience can be improved when the available memory resources are allocated for processing new knowledge. This cognitive load aspect is important for computer-based learning designers and developers in order to fully understand the human-computer interaction issues in computer-based learning systems.

Overview of the Chapter

The chapter is divided into three sections. The first section describes briefly the progressive learning experience evaluation. The second section gives an overview of cognitive load and the last section discusses in detail the empirical study and the results.

6.1. Progressive Learning Experience

It is well known that learning is a dynamic process (Capello, 1999). Most importantly, its success is primarily determined by learner's motivation (Cole *et al.*, 2004) that also changes over time. Generally, motivation and engagement in learning are different between individuals (Ryan & Deci, 2000) and changeable over a period of time in unpredictable directions (Keller, 1999). The variance in motivation is influenced by many factors including environmental components such as technology and the way the instructional design is presented (Abrami, 2001). From the technological perspective, learners with computer-based learning systems have a self-regulated way of learning, which consequently makes motivation a more critical issue to be examined. Hence, it is important that computer-based learning systems foster the learners' motivation to learn.

Orvis *et al.* (2004) suggested that there is a positive correlation between motivation and learning experience in the context of computer-based learning. Seeing that motivation is inconsistent over a period of time, there is also a possibility to characterise learning experience in the same way. For this reason, this thesis aims to study computer-based learning experience over a certain period of time, and the learning experience is assessed at a few different learning stages.

The learning experience data that are collected during some stages of computer-based learning session would suggest how learning experience is changing over a period of a learning session. If changes happen more often than not, it is crucial to identify the types of changes (i.e., positive or negative) so that the source of these changes can be further articulated. To our knowledge, no studies had investigated the DCSS learning experiences progressively; therefore, this empirical study contributes a new knowledge to literature.

6.2. Cognitive Load in Computer-based Learning

Many cognitive psychologists suggested that computer-based instructional design should accommodate the learner's cognitive capability (Slabon, 2006; Sweller *et al.*, 1998). This is due to the fact that a human brain has a limited capacity to process information at one time, as suggested by cognitive load theory (CLT) (Chandler & Sweller, 1991, 1992; Paas *et al.*, 2003). Excessive amounts of information that need to be processed by a working memory at one time lead to high cognitive workload. In this respect, computer-based instruction must be designed in a way that allows information to be effectively processed within the manageable cognitive load (Kalyuga, 2009).

It is important to understand what factors would contribute to cognitive loads, so that appropriate measures can be taken to address these issues. Paas *et al.*(2003) outlined that cognitive load comprise three categories: *intrinsic* cognitive load, *extraneous* cognitive load, and *germane* cognitive load. Intrinsic cognitive load is described by the difficulty and complexity of knowledge that requires some space in a human working memory for its assimilation. Extraneous cognitive load involves the way that knowledge is presented to the learner, for example, content arrangement, and navigation styles. As to germane cognitive load, individual attributes in learning (e.g., prior knowledge, learning style, and motivation) contribute to this type of cognitive load. Paas *et al.* also highlighted that these three cognitive loads are additive to each other, hence, the total workload should not exceed the working memory resources that are available at the time of interaction.

In the context of computer-based learning, intrinsic cognitive load is hard to avoid or minimise as it is highly dependent on the domain of study and its levels of complexity (Gerjets *et al.*, 2004). On the other hand, there is a high potential to reduce or minimise extraneous cognitive load through some methods in human-computer interaction (Shi *et al.*, 2009), for example, by providing high degree of interactivity.

Reducing extraneous cognitive load provides more space for high intrinsic load, so the available resources in a working memory can be used effectively. This thesis attempts to determine whether learning with the DCSS would present high extraneous cognitive load or not.

In traditional computer-based learning systems, handling extraneous cognitive load has been overlooked. However, many computer-based learning designers are now conscious about the importance of minimising extraneous cognitive load. For example, Mayer & Moreno (2010) suggested that multimedia content in a form of text (i.e., verbal information) and images (i.e., visual information) is effective for the knowledge acquisition process. Another study by Kalyuga *et al.* (1998) suggested that the use of an integrated format of learning resources could reduce extraneous cognitive load among novice learners. They found that the combination of explanation and images for teaching electrical topics helped in reducing the learners' cognitive load, hence, improved their knowledge.

Indeed, extraneous cognitive load might be imposed by various factors such as inconsistent interface design (Mendel & Pak, 2009), poor navigation (van Merriënboer & Sweller, 2005), and excessive or lack of learner control over learning activities (Kirschner *et al.*, 2011). The individual level of knowledge influenced navigation and control over learning activities. Kirschner *et al.* (2011) suggested that advanced students are often comfortable with minimum navigation support so that they can gain higher control of their learning activities. In contrast, novice students require more guidance support in their navigation to prevent them from roaming freely.

6.3. Experiment 2: A Study on Progressive Learning Experience and Cognitive Load in the DCSS

Experiment 2 was conducted to determine changes in the learning experience at different stages of the DCSS learning. As we believe that learning experience would be dynamic, it is important to study this issue further, such as when and why learning experience would be varied.

6.3.1. Method

6.3.1.1. Participants

A total 77 students from the Department of Information Technology, Northern University of Malaysia were recruited through emails and advertisement notes in the lecture rooms. However, only 41 participants (19 males and 22 females) completed the experimental tasks. The average age of the participants was 24.17 years, ranging from 17 to 45 years. Approximately 75 percent of the participants were the students who took information technology (IT) programme. The participants were randomly divided into two groups. Twenty-one participants (9 males and 12 females) were assigned to the experimental condition (i.e., tutorial with the DCSS), while the rest of the participants (10 males and 10 females) were assigned to the control condition (i.e., tutorial with the non-DCSS).

6.3.1.2. Apparatus

The same apparatus as in the previous experiment (i.e., Chapter 5) was used in this experiment, apart from the simplified questionnaire comprising four items representing four dimensions of the learning experience (i.e., control, attention focus, curiosity, and intrinsic interests). This questionnaire was given at three stages of the computer-based learning session. Table 6.1 shows the dimensions used in this study.

Table 6.1: Simplified learning experience questionnaire

Number – Dimension of Experience	Questions
Q1 - Control	IT-Tutor allowed me to control the whole learning process
Q2 - Attention Focus	When using IT-Tutor, I was totally absorbed in what I was doing
Q3 - Curiosity	Interacting with IT-Tutor made me curious
Q4 – Intrinsic Interest	IT-Tutor was fun for me to use

To measure extraneous cognitive load, we adopted the NASA TLX test (Hart & Staveland, 1988). It was proposed to measure subjective workloads in using human-machine systems, comprised of six subscales; mental demands, physical demands, temporal demands, performance, effort, and frustration. The descriptions of the six subscales are presented in Table 6.2. NASA-TLX is believed to have high sensitivity and validity in measuring the cognitive load of human-machine systems (Rubio *et al.*, 2004).

Table 6.2: Descriptions of NASA-TLX subscales (Hart & Staveland, 1988)

Subscales	Description
Mental demand	The amount of mental and perceptual activity (e.g., thinking, deciding, calculating, remembering, looking, searching etc.) that is required to perform a particular task
Physical demand	The amount of physical activity (e.g., pushing and pulling the mouse, controlling the buttons etc.) that is required to perform a particular task
Temporal demand	The amount of time pressure that a person feel due to the rate or pace at which the task or task elements occurred
Performance	The individual successful level in accomplishing the task
Effort	The difficulty level (mental and physical) in accomplishing individual levels of performance
Frustration	The feeling of insecure against secure, discouragement against gratification, irritation against content, stress against relaxation and annoyance against complacent during performing a particular task

6.3.1.3. Experimental Design

The experimental study was a one-way between-subjects design with the types of computer-based learning systems (i.e., the DCSS and the non-DCSS) as the independent variable. The dependent variables comprised of rating scales of the learning experience at the different learning stages and cognitive load.

6.3.1.4. Procedure

The experiment was conducted in an unsupervised online mode. All materials were pre-programmed in a form of a web-based system. The participants were given a URL (web link) to access these materials.

The tasks for the experiment were arranged in the following sequence. First, the participants were given an information sheet, and were asked to sign a consent form digitally. Next, they were required to complete a computer-based learning tutorial (either with the DCSS or with the non-DCSS). The tutorial was divided into three stages. At the end of each stage, the learners were asked to self-report their learning experiences. Finally, the participants were asked to answer the cognitive load questionnaire. The procedure for conducting the experiment is illustrated in Figure 6.1.

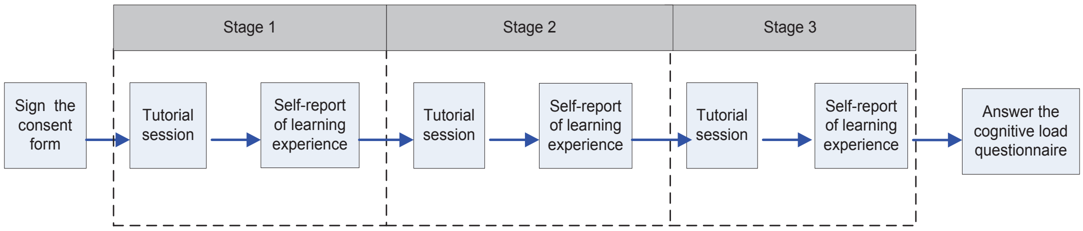

Figure 6.1: Procedure for conducting Experiment 2

6.3.1.5. Pre-processing Data

The raw data obtained from the experiment were kept in a database. They were screened for missing values and outliers using descriptive statistic commands in SPSS. In addition, we performed a normality test on the learning experience data using the *Kolmogorov-Smirnov (K-S)* method, revealing that the data were non-normal[19]. Hence, non-parametric statistical tests were used to analyse all data for this study. Please refer to Appendix H for the raw data of this experimental study.

6.3.2. Results

6.3.2.1. Progressive Learning Experience

The simplified learning experience questionnaire for the three stages (i.e., Stage 1, Stage 2, and Stage 3) was analysed. The reliability tests showed that the data had relatively high internal consistency with *Cronbach's alpha coefficient* for the questionnaire items being 0.949. The means for all constructs of the learning experience in each of the stages were calculated and presented in Table 6.3.

[19] Significant values for all items of learning experience questionnaire were less than 0.05 suggesting that the data were non-normal.

Table 6.3: The means for individual dimensions of progressive learning experience

Dimensions of learning experience	DCSS (n=21)			Non-DCSS (n=20)		
	Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3
Control	3.76	3.81	3.43	4.25	4.20	4.20
Attention focus	3.86	3.86	3.52	4.20	4.10	4.25
Curiosity	3.81	3.86	3.76	4.15	4.15	4.30
Intrinsic Interest	4.05	3.90	3.71	4.00	4.50	4.35
Overall Experience	3.87	3.85	3.61	4.15	4.24	4.28

Table 6.3 shows that the non-DCSS learners achieved higher scores in most of the learning experience dimensions compared to the DCSS. The overall learning experience scores for the three stages (i.e., Stage 1, Stage 2, and Stage 3) showed an increase in the non-DCSS. In contrast, the DCSS learning experience had declined in Stage 2 and Stage 3 respectively. A series of *Mann-Whitney U* tests were performed to determine the significance of these differences. Table 6.4 depicts the means and the mean ranks for the DCSS and the non-DCSS learning experience in all stages. At the beginning of the computer-based interactions, the learning experience of both types of systems was not statistically different. However, the Stage 3 mean ranks were significantly different ($z=-2.373$, $p=0.017$, $p<0.05$) with the non-DCSS learning experience score was higher than the DCSS.

Table 6.4: The means and mean ranks for the learning experience in the three stages

Stages of the tutorial	DCSS (n=21)		Non-DCSS (n=20)		Statistical Significance
	Means	Mean Ranks	Means	Mean Ranks	
Stage 1	3.87	18.45	4.15	23.68	z=-1.407, p=0.163, n.s.
Stage 2	3.85	17.62	4.24	24.55	z=-1.874, p=0.061, n.s.
Stage 3	3.61	16.71	4.28	25.50	z=-2.373, p=0.017, p<0.05

The patterns of the learning experience change are illustrated in a line chart in Figure 6.2. The line chart shows that there are two types of changes in the computer-based learning experience. First, the non-DCSS learning experience appears to have a positive change from the beginning towards the end of computer-based learning. In contrast, the DCSS learning experience had a negative direction of change.

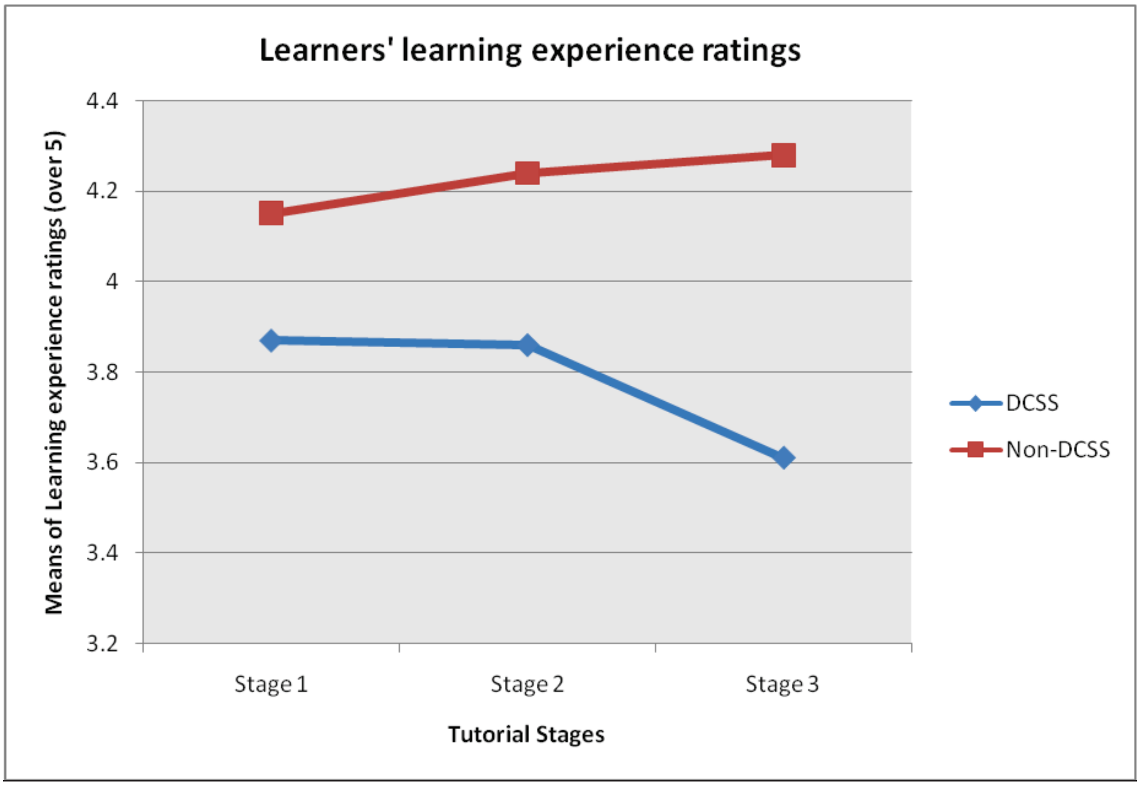

Figure 6.2: Progressive learning experience ratings for three stages

The difference in the learning experience patterns can be explained by the learners' background of knowledge. It is important to note that more than 75 percent of the research participants were recruited among students who took an Information Technology programme. Given that Basic Computer Networks is a fundamental course in the IT programme, the participants of the study had substantial prior knowledge about the course. Information in Table 6.5 shows the distribution of the IT and non-IT learners and their corresponding computer-based systems. The information also indicates that only three non-IT learners were assigned to the non-DCSS group; while the rest were assigned to the DCSS.

Table 6.5: Learners' background

	DCSS	Non-DCSS	Total
IT programme	14	17	31
Non-IT Programmes	7	3	10

Many past studies suggested that prior knowledge affects one's computer-based navigation and content organisation preferences (Amadieu *et al.*, 2009, 2010; Calisir *et al.*, 2008; Greene *et al.*, 2010; Jung & Park, 2004; Kalyuga, 2005; Kopcha & Sullivan, 2008; Mitchell*, et al.*, 2005; Shin*, et al.*, 1994). Those who have high prior knowledge prefer to create their own navigational learning paths; hence, learning activity is effective when they are given with high self-control over the learning content. In contrast, low prior knowledge learners require high navigational support and pre-organised learning content. The learning experience scores were split up into the IT- and non-IT students to validate this assertion. Table 6.6 shows the means and the mean ranks for the IT-students' learning experiences (i.e., high prior knowledge learners'). The information in the table confirms that the learning experience patterns were very similar with Table 6.4, i.e., the increasing pattern for the non-DCSS and the decreasing pattern for the DCSS.

Table 6.6: The means and mean ranks for the IT-students learning experience

Stages of the tutorial	DCSS (n=14)		Non-DCSS (n=17)		Statistical Significance
	Means	Mean Ranks	Means	Mean Ranks	
Stage 1	4.05	14.75	4.19	17.03	z=-0.702, p=0.493, n.s.
Stage 2	3.87	12.64	4.29	18.76	z=-1.901, p=0.064, n.s.
Stage 3	3.78	12.32	4.34	19.03	z=-2.070, p=0.040, p<0.05

In the context of the study described here, the difference in the learning experience patterns was due to the navigation and content organisation techniques used in the respective computer-based systems. Further, the study reveals the two-fold outcomes in relation to learners' prior knowledge. First, the freely-browsing non-DCSS gave a more satisfying learning experience than the fully-guided DCSS for those who have high prior knowledge (i.e., the IT-students). Second, the computer-based navigation and content organisation affected the learning experience patterns of the high prior knowledge learners. Specifically, the freely-browsing learning path improved the learning experience for those who have high prior knowledge. In contrast, the fully-guided learning path given by the DCSS decreased the learning experience of the high performing learners over time. These two patterns characterised the dynamics of computer-based learning experience for the high prior knowledge learners.

6.3.2.2. Cognitive Load

A computerised version of NASA-TLX was used in this experiment. The participants were asked to rate the individual subscales of the subjective workload that ranges from 0 (i.e., very low) to 100 (i.e., very high). Then, they were required to choose a subscale that contributed higher workload from fifteen pair-wise comparisons derived from the six subscales. The individual subscales of the fifteen pair-wise comparisons were tallied up and multiplied by the raw score of the corresponding subscale. All of the calculations were performed by some basic functions provided in Microsoft Excel spreadsheets. (Refer to APPENDIX D for an example of how the calculations were made).

Table 6.7: The means and mean ranks for unweighted NASA-TLX scores

NASA-TLX subscales	DCSS (n=21)		Non-DCSS (n=20)		Statistical Significance
	Means	Mean Ranks	Means	Mean Ranks	
Mental demand	72.24	21.76	69.15	20.20	z=-0.418 , p=0.684, n.s.
Physical demand	51.52	19.88	56.80	22.18	z=-0.614 , p=0.548, n.s.
Temporal demand	56.19	20.79	57.70	21.23	z=-0.118 , p=0.913, n.s.
Performance	75.86	21.00	75.45	21.00	z= 0.000, p=1.000, n.s.
Effort	64.76	21.19	67.15	20.80	z= -0.104, p=0.923, n.s.
Frustration	59.95	24.43	41.60	17.40	z=-1.879 , p=0.061, n.s.
Overall workload	63.42	21.57	61.31	20.40	z=-0.313 , p=0.762, n.s.

Table 6.7 shows the means and means ranks for the unweighted scores. From this table, the overall subjective workload in the DCSS was slightly higher (*63.42*) than the non-DCSS (*61.31*). In addition, the means for physical demand, temporal demand, and effort in the DCSS showed a lower value than that of the non-DCSS. However, the mental demand and frustration were higher in the DCSS. A series of *Mann-Whitney U* tests revealed that these differences were not statistically significant.

A series of *Spearman's Rank Order* correlation tests between mental demand and other NASA-TLX individual subscales for the distinctive groups of the computer-based learning systems were also carried out. The purpose of this correlation tests was to understand whether or not mental demand (i.e., cognitive load) correlated to the others. For the DCSS group, a few moderately positive correlations had been found between performance and mental demand ($r=0.566, p<0.01$). In the case of the non-DCSS, some positive correlations had also been shown between mental demand and physical demand

($r=0.578$, $p<0.01$) and effort ($r=0.721$, $p<0.01$) respectively. All of the correlation coefficients of the mental demand with other subscales are presented in Table 6.8.

Table 6.8: The correlation coefficients for the mental demand and other NASA-TLX subscales

Physical demand		**Temporal demand**		**Performance**		**Effort**		**Frustration**	
DCSS	Non-DCSS	DCSS	Non-DCSS	DCSS	Non-DCSS	DCSS	Non-DCSS	DCSS	Non-DCSS
0.104	***0.578****	0.161	0.428	***0.566****	0.356	0.354	***0.721****	0.029	-0.042

**.Correlation is significant at the 0.01 level (2-tailed)*

It is important to note that the aim of this study was to measure the cognitive load that the computer-based systems may impose on the learners. For this reason, we examined the mental demand subscale to see its relationships with other subscales of the subjective workload. The findings suggest that the DCSS learners who performed well in the learning tasks had used high cognitive resources. For the non-DCSS, the learners who used high cognitive resources had spent many effort and physical activities in learning. This is true because the non-DCSS required higher effort and extra physical activities (e.g., controlling the mouse, clicking hyperlinks, etc.) to navigate between learning contents since the system did not provide structured and guided navigation paths.

6.3.3. Discussions

The analyses in the previous section highlighted some important design guidelines that can be used to improve adaptive learning systems design, as shown in Table 6.9.

Table 6.9: Summary of results for Experiment 2

Variables	**DCSS**	**Non-DCSS**
Progressive learning experience	• The learning experience quality was decreasing throughout the computer-based learning session • A negative learning experience pattern was identified in this group	• The learning experience quality was increasing throughout the computer-based learning session • A positive learning experience pattern was identified in this group
Cognitive load	• The highly-imposed mental demand learners performed well	• The learners had high mental demand when they spent a lot of effort and physical activities for learning

The most important contribution of this study is to show how the learning experience changed from one point to another during the given learning activities. This study highlights that learning experience is inconsistent over the period of a computer-based learning session. This result confirms the finding of the Ceja & Navarro's (2009) study. Their study investigated the dynamics of experience in leisure and work activities, which had different situation with our study that focused on CBL activity. This highlights the contribution of our study to the body of knowledge. In the context of this research, the change in the learning experience quality was influenced by how the learning content is organised and presented to learners in conjunction with the learner's level of knowledge.

It is important to remember that a majority of the subjects recruited in this study were taking IT-related degree programmes. Kalyuga (2005; 2006; 1998; 2010) suggested that learners should be treated differently according to their level of knowledge when it comes to computer-based learning. Novice learners normally require full guidance in terms of their learning paths while advanced learners need more freedom in browsing and choosing their own learning paths.

The types of learner (i.e., experts and novices) and the types of learner control over the given learning activities would also affect the levels of cognitive load. Kirschner *et al.* (2011) argued that some learners may benefit from the opportunity of self-control. Further, they claimed that too much control or lack of control can cause extraneous cognitive overload during learning. Lack of control may cause cognitive overload to experts, whilst novices may experience the same when they are given high levels of control. Looking at our experimental tools, they used two different types of controls. The non-DCSS was higher in its levels of control compared to the DCSS. However, our findings have suggested that both types of computer-based systems (i.e., the DCSS and the non-DCSS) imposed about a similar level of mental demand; approximately 70 percent. With this figure, there is a potential to reduce the cognitive load by using a proper navigation and sequencing approach. This will be explained in the next chapter.

Although we cannot generalise the conclusions above with this single evaluation, this research seems to open some further research opportunities. In particular, the learners with the different level of knowledge had different needs when it comes to their learning paths, and the progressive learning experience is useful in creating flexible computer-based learning systems that manage learners differently according to their level of knowledge. The next chapter describes how an adaptive computer-based learning system can be created using learning experience variables based on the flow theory.

6.4. Summary

This chapter described a study about progressive learning experience in two different types of computer-based learning systems (i.e., the DCSS and the non-DCSS). In particular, the study found two different patterns of learning experience. The non-DCSS learners showed an improving pattern of learning experience from the beginning towards the end of the interaction. In contrast, the DCSS learners' experiences was decreasing. This pattern could be caused by the learners' prior knowledge where majority of them were advanced learners. In general, the non-DCSS improved learning experience of the high-prior knowledge learners.

The cognitive load of each system was also measured. However, there was no difference in cognitive load between learners with the DCSS and the non-DCSS. These research findings are used to create a technique to promote an adaptive computer-based learning environment to complement the findings from Chapter 5.

SECTION IV: IMPROVEMENT OF THE DCSS LEARNING EXPERIENCE

This section describes a technique to improve the DCSS learning experience and explains an empirical study to validate the effectiveness of the technique. Chapter 7 explains the technique and the evaluation in detail. In Chapter 8, the practical contributions of the thesis in the context of computer-based learning and human-computer interaction are discussed. It also concludes the findings of the research.

CHAPTER 7: INTEGRATION OF THE FLOW THEORY IN THE DESIGN OF DCSS

The DCSS learning experience studies discussed in Chapter 5 and Chapter 6 of this thesis showed some issues that require further research. The results suggested that in certain situation, the learners did not benefit from the DCSS. On the other hand, in a different condition, the non-DCSS gave the learners better learning experiences than the DCSS. Therefore, there is a need to improve the DCSS so that the system could foster learners' engagement and improve their learning experiences.

This chapter proposes a new technique to achieve adaptive learning in the DCSS. The technique is mainly formulated based on an assumption derived from the flow theory (Csikszentmihalyi, 1975, 1990, 1997). Earlier, the literature showed that the theory is robust to understand human psychological well-being in many areas of human tasks. It is likely that the theory could have potential to improve the overall computer-based learning process as well. Consequently, it has inspired the author to incorporate the theory in the design of the DCSS.

The theory suggested that an optimal learning experience is achieved when there is a balance between the individual's level of skill and the given levels of challenge. The skill-challenge balancing (SCB) instructional method was used for implementing this theory, by which computer-based learning allows the learners to have self-adjustment of the given levels of challenge to accommodate their current levels of skill.

Overview of the Chapter

The chapter is organised into three sections. The first section describes the connection between the flow theory and adaptive learning. In relation to that, the next section discusses the SCB technique. This includes the components and the implementation of the approach. The last section (i.e., Section 7.3) discusses the effectiveness of the SCB technique in relations to the learning experience.

7.1. The Flow Theory and Adaptive Computer-based Learning Systems

Adaptive computer-based learning is a prominent topic among many educators, instructional designers, and software developers. In the context of the DCSS, adaptive features are the most important element that determines the effectiveness of the computer-based learning system. In this thesis, the DCSS's adaptive features are discussed in terms of navigation and content organisation. The learning path that the DCSS generated dynamically according to individual learning parameters is expected to help learners to achieve the objectives of learning.

The ultimate aim of this thesis is to design an effective technique for the DCSS content organisation and navigation, so that learners could have a more engaging and enjoyable learning experience with computers. Chapter 5 and Chapter 6 have reported about computer-based learning experience studies with regard to the flow theory (Csikszentmihalyi, 1975, 1990, 1997). The findings of these studies suggested that the level of knowledge (i.e., prior knowledge and achievement) influenced learning content organisation and the way it should be presented to learners.

The important lesson learned from the previous chapters was that the DCSS was unable to handle learners with the different learning backgrounds. Simply put, the current version of the DCSS (i.e., IT-Tutor) is not adaptive enough to fulfil the learners' needs in conjunction with their background knowledge. Consequently, the lack of adaptivity of the DCSS had not improved learning experience, especially among learners who had high prior knowledge about the course. This finding further questioned how to improve the DCSS to be more adaptive which is central to this chapter.

In so doing, we adapted the flow theory in the design of DCSS. The flow theory is versatile and very useful in many aspects of adaptive computer-based learning. The flow theory suggests that an optimal experience is achieved when the right levels of challenge are given to a person. Specifically, when the person's level of skill is equivalent to the level of the given challenges of an activity, the person obtains an optimal learning experience. It is also suggested that the levels of challenge are increasing in conjunction with the improved levels of skill over time. Obviously, skill and challenge are the components of learning, while skill improvement is the objective or outcome of learning. From the computer-based learning perspective, adaptivity in the flow theory can be represented by a balanced adjustment of the levels of challenge to cope with the current skill set.

7.2. The Skill-Challenge Balancing (SCB) Technique for Adaptive Computer-based Learning

7.2.1. Introduction to the Skill-Challenge Balancing (SCB) Technique

The skill-challenge balancing (SCB) technique is proposed in this thesis with an aim to improve interactions between learners and computer-based learning systems. The SCB is designed based on one of the flow theory's assumptions. In performing a particular learning activity, the flow theory suggests that an optimal experience could be achieved when the level of the given challenge matches the individuals' levels of skill. It is also important to note that individual levels of skill are progressing over time and similarly for the level of the given challenges, as shown in Chapter 6.

The SCB technique is implemented by adjusting the *user interface module* and the *sequencing engine* of the DCSS architecture[20]. Before further discussion, it should be noted that the sequencing engine in the current version of IT-Tutor evaluates the learner's prior knowledge through a set of course-related quiz question to generate a

[20] Please refer to Figure 4.5 for the DCSS architecture.

learning path dynamically. Then, a sequence of learning material is identified based on the learner's answers to the quiz, and it will be automatically presented to the learner. Unfortunately, the results[21] derived from Experiment 1 and Experiment 2 suggested that this technique did not work effectively, and it imposed an unnecessary workload on learners especially those who had advanced knowledge about the course.

The main concept in the SCB technique is to allow a flexible adjustment of the given level of challenge. In the context of the DCSS, the levels of challenge are characterised by the increasing level of difficulty of the learning content. In order to keep the learners in an optimal cognitive engagement, the given levels of challenge must be always comparable to the learners' current level of knowledge. In other words, learners' current levels of knowledge (or skill) must be able to cope with the given levels of challenge. As described earlier in Chapter 2 and Chapter 3, the inequality in the levels of challenge and skill is the source of boredom and anxiety in learning.

The core of the SCB technique is to allow the learners to have self-assessments of their individual levels of knowledge throughout the computer-based learning session (i.e., self-determination theory). The learners are given a chance to self-evaluate whether the learning unit is too easy or too difficult for them. If the learners find that the learning unit is too easy, they can choose to move forward to a higher level of difficulty of the learning unit. On the other hand, if the learners find that the learning unit is too difficult, they are able to move backwards to a lower level of difficulty of the learning unit.

In this sense, the SCB technique improves the existing DCSS (i.e., IT-Tutor) by allowing the learners to self-adjust the individual learning path through self-assessment of their knowledge about the course. To implement the self-assessment capability, the SCB technique introduces "*flow buttons*" in the *user interface module* of the DCSS architecture. The buttons comprise two types; an "*anxiety"* button comes along with the tutorial questions and a "*boredom"* button appears with the explanation of the concept. The *sequencing engine* controls the interactions of these buttons with the *domain*

[21] Experiment 1 and Experiment 2 refer to the studies reported in Chapter 5 and Chapter 6 respectively.

knowledge repository. Manipulation of the "*flow buttons*" helps the learners to maintain their learning experiences at least in a consistent pattern. The SCB components, and how they work are further discussed in the next section.

There is some rationale to putting the "*flow buttons*" in the different parts of the tutorial components. First, when a learner finds that a particular tutorial question is too difficult, and he or she is not sure of the answer, the *"anxiety"* button helps the learner to browse the learning unit associated with the question. A learner may find that the learning unit has been learned before while browsing the explanation or the concept about a particular learning unit and may want to proceed to the next stage. In this case, the "*boredom"* button allows the learner to move forward to a tutorial question with a higher level of complexity. The process is illustrated in Figure 7.1.

The "*flow buttons*" in the SCB technique are designed to prevent boredom and anxiety when learners use the DCSS for learning. At the same time, the SCB aims to improve learning performance by bypassing some components of the original IT-Tutor sequencing technique such as the automatic sequencing and reinforcement. The flow buttons will be used wherever necessary, and the automatic sequencing of learning content would work otherwise.

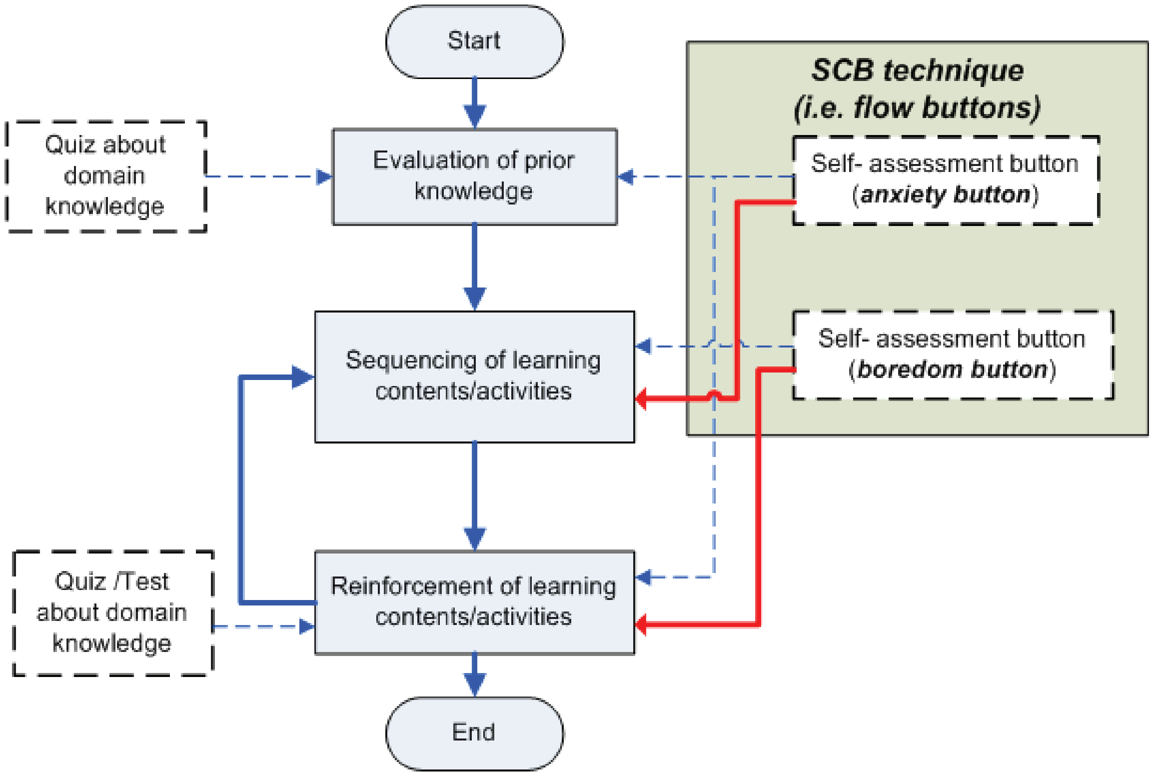

Figure 7.1: The SCB technique learning process

7.2.2. The Components of Skill-Challenge Balancing (SCB) Technique

As mentioned earlier, the SCB technique modifies the *user interface module* and the *sequencing engine* of the DCSS architecture. The other components such as the student model and the domain knowledge repository remain the same as the previous experimental settings. The integration of the SCB technique into the existing architecture of the DCSS is illustrated in Figure 7.2. The components within the dotted line represent the modification for the SCB technique.

Looking at Figure 7.2, a learner starts an interaction with the DCSS through the SCB user interface (i.e., number 1). Then, the user interface module communicates with the student model in order to obtain the learner's learning history (i.e., number 2). Next, the student model passes the information about the learner to the sequencing engine (i.e., number 3). After that, the sequencing engine looks up the appropriate learning materials for the learning path as stored in the student model (i.e., number 4). The learning material will be presented to the learner through the user interface module (i.e., number 5). The sequencing engine will update the information about the interactions in the student model (i.e., number 6). Iteration can happen in processes 3, 4, 5, and 6 especially when the learner uses the "*flow buttons*".

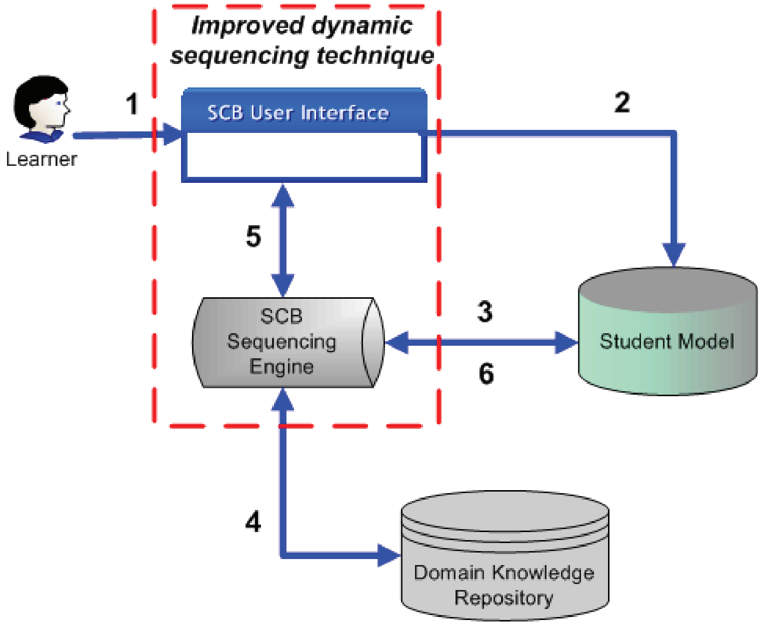

Figure 7.2: Integration of the SCB technique in the DCSS architecture

The "*flow buttons*" in the SCB technique that have been incorporated with the *user interface module* are linked to the sequencing engine. The functions of the "*flow buttons"* are described below:

(1) *The anxiety button*-A button for learners with low skill (knowledge)

The button appears with the tutorial questions. If the learners are not sure or have no idea of the answer for a tutorial question, they can click the button for reviewing the contents relevant to the particular question. In this way, it is expected to help the learners to avoid anxiety, thus keeping them in flow.

(2) *The boredom button*-A button for learners with high skill (knowledge)

The button appears with the learning contents. If the learners feel that the content is too easy for them, they can click the button to proceed to the next tutorial question.

In this way, it is expected to help the learners to avoid boredom, thus keeping them in flow.

The learners' self-assessment of their own level of skills provides information to the system (i.e., the DCSS) so that an appropriate challenge could be given to them. For example, when the "*anxiety*" button is pressed, the system will give a lower level of challenge to the learners, so that anxiety may be avoided. On the other hand, when a "*boredom*" button is pressed, the system will increase the difficulty level of the tutorial to avoid boredom. Figure 7.3 shows the high-level conceptual process of the SCB technique that appears to the learners.

From Figure 7.3, the straight arrows represent the actual flow of the computer-based learning session. The dotted arrows are the new flow when the "*flow buttons*" (i.e., the anxiety and the boredom buttons) are incorporated in the user interface module. The next section discusses the implementation of the SCB technique in a prototype of the DCSS.

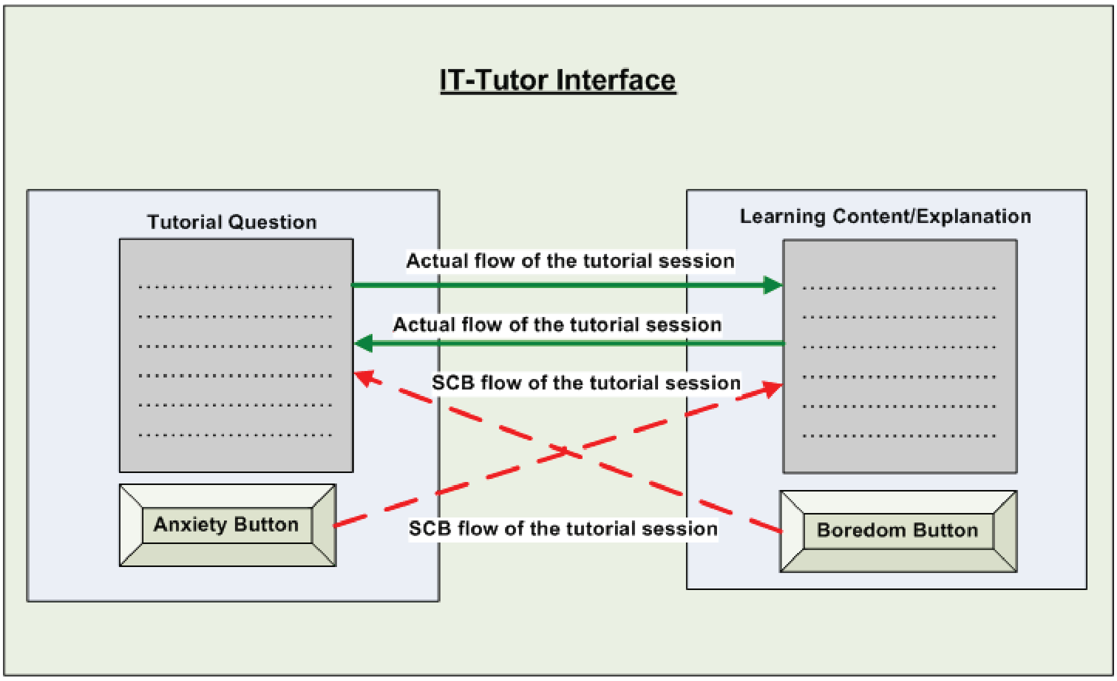

Figure 7.3: Anxiety and boredom buttons for adjustment of learning experience

7.2.3. Prototype Development of IT-Tutor with the Skill-Challenge Balancing (SCB) Technique

A prototype was developed to demonstrate how the SCB technique would work. In doing so, the author reused most of the software components of the current version of IT-Tutor system including the user interface layout, the databases, and the procedures and functions. The prototype was developed within the .NET platform, and set to be accessible through the Internet.

The implementation of the "*flow buttons*" is simplified to avoid confusion among the learners. In doing so, the text printed on the buttons was simplified to give a simpler and more understandable meaning to the learners. In the case of the "*anxiety*" button, the author used the text "*Click here if you do not know the answer*". For the "*boredom*" button, the text "*Click here if you think the section is too easy*" was used. The dotted line in Figure 7.4 and 7.5 show the "*anxiety*" button and the "*boredom*" button screenshots respectively.

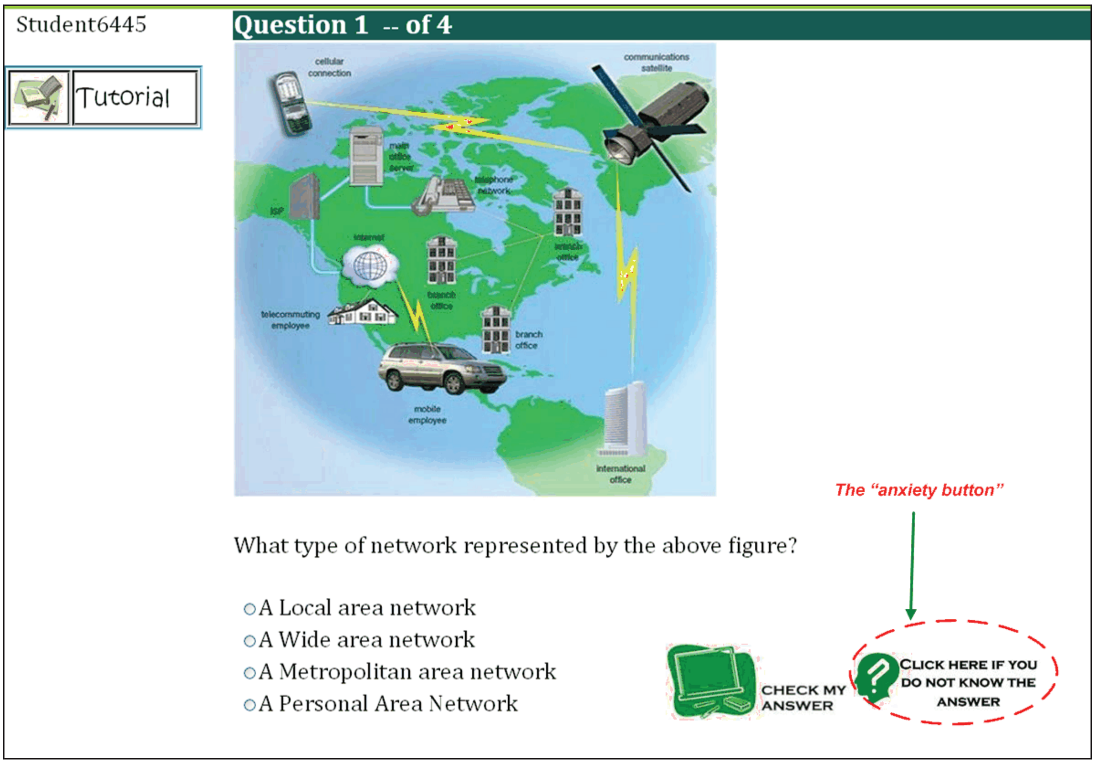

Figure 7.4: The "*anxiety*" button in the IT-Tutor interface

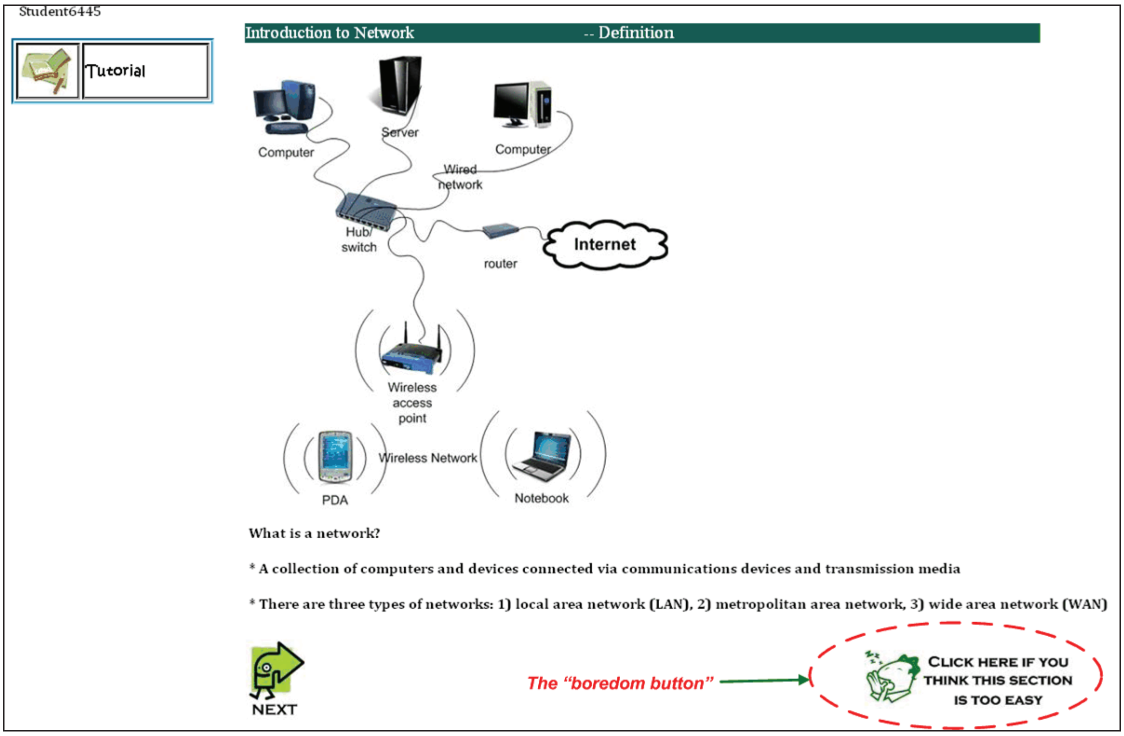

Figure 7.5: The "*boredom*" button in the IT-Tutor interface

The rules and algorithm used in the sequencing engine have been modified to incorporate the interactions generated by the "*flow button*". To implement the SCB technique, the algorithm presented in Figure 7.6 has been pre-programmed in a rule-based function. The algorithm mainly manages the "*flow button*" and it is iterated according to the number of levels of difficulty presented in a particular tutorial question.

```
Present the <tutorial questions>
If <the anxiety button> is pressed then
        Present the associated learning contents
        If <the boredom button > is pressed then
                Test <learners' current knowledge>
                If <learner's current knowledge> is <insufficient> then
                    Give feedback to learners
                    Present the sequence of learning contents
                    Test <learners' current knowledge>
                If <learners' current knowledge> is <sufficient> then
                    Give feedback to learners
                    Proceed to the next level of <tutorial questions>
        Test <learners' current knowledge>
        ......................................................
        ......................................................
```

Figure 7.6: The rules for performing the SCB technique

7.3. Experiment 3: An Evaluation of the Skill-Challenge Balancing (SCB) Technique

The aim of this empirical study is to evaluate the effectiveness of the proposed technique; i.e., the skill-challenge balancing (SCB) technique as described in the previous sections. This section describes in detail about the method used for conducting the study, the results derived from analysis of the data, and discussions about the findings.

7.3.1. Evaluation Method

7.3.1.1. Participants

The participants of this study were recruited from two universities; Massey University, New Zealand and Northern University of Malaysia. In doing so, advertisements were posted in the learning management systems of the corresponding universities for some selected courses. A number of 92 students participated on a voluntary basis. However, only 70 participants completed the given tasks. These participants comprised of 18 males and 52 females. Eighty-five percents of the participants were the Northern University of Malaysia students. About 80% of the participants were undergraduate students, while the remaining were postgraduate students.

Analysis of the demographic information showed that the average age of the participants was 25.20 years with approximately 85% of them were aged 17 to 30. About 75% of them had more than three years of experience in using the computer and at least 60% of them had used other computer-based learning systems before. Apart from that, about 64% of the participants classified themselves as beginners to the course, while the rest had learned about the course before. None of the participants classified themselves as experts in the area of Computer Networks.

The participants were randomly assigned into one of the two groups; i.e., the experiment group and the control group. This experimental study was conducted between March and April 2011.

7.3.1.2. Apparatus

Two types of computer-based learning systems were used in this experiment: IT-Tutor with SCB and IT-Tutor without SCB (i.e., the older version of IT-Tutor as described in Chapter 4 of this thesis). For the experimental purpose, the syllabus of the module (i.e., Basic Computer Networks) was reduced to cover only the first lesson, to make the experimental tasks simpler to the learners. By doing this, we could observe the effects of the SCB technique in a more systematic manner. The dotted line in Figure 7.7 shows the coverage of the lesson for the experimental study. The tutorial session in both types of computer-based learning systems comprised of four questions.

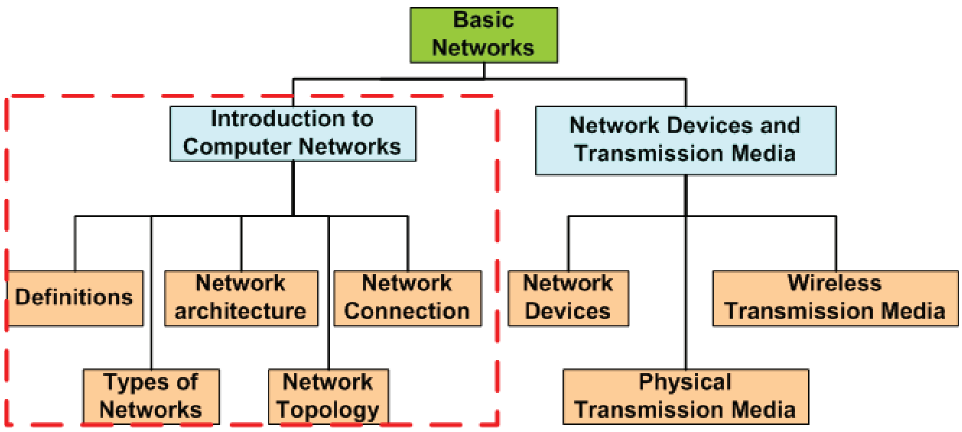

Figure 7.7: The coverage of lesson in Experiment 3

The questionnaire used in this study comprised of four components: demographic information (10 items), learning experience (12 items), usability (2 items), and cognitive load (1 item). The demographic questions asked the participants about their gender, age, the subject of study and year of study, native language, computer experience, past experience of computer-based learning, and so on. The same learning experience questionnaire with Experiment 1 and Experiment 2 was used.

The two items of usability questionnaire were adopted from Chiu *et al.* (2005). This dimension asked the participants whether the system they used was helping them in improving their learning performance and whether or not the system they used was suitable with their learning styles. The learners were asked to rate the learning experience and usability questionnaire using a five-point Likert Scale (i.e., one represented strongly disagree and five represented strongly agree).

In measuring the learners' cognitive load, a single-item question proposed by Paas (1992) was adopted. The item asked the participants how difficult working with the computer-based learning system using a nine-point scale in which one represented extremely very easy and nine represented extremely very difficult. The author chose the instrument because it is simpler and easier for the learners to understand and to answer the question as compared to NASA-TLX, which the author used in Experiment 2.

7.3.1.3. Experimental Design

A one-way between-subject design was used in this study. The independent variable was the two *types of computer-based learning systems* (i.e., IT-Tutor with the SCB and IT-Tutor without the SCB). The dependent variables comprised of three components: *learning experience, usability, cognitive load, and knowledge background*. For the case of IT-Tutor with the SCB, the author also measured the *SCB usage* in order to determine whether or not the "*flow buttons*" were effectively used by the learners.

7.3.1.4. Procedure

This study was conducted in an unsupervised online mode. All materials were pre-programmed in a form of a web system. The participants were given a URL to access the materials. First, they were given the research information sheet. As they consented to participate in the research, the system had randomly assigned the participants into one of the two groups of the computer-based learning systems. The learners were then asked to perform a tutorial session in the corresponding computer-based learning systems and follow the given instructions as they were interacting with the systems. As soon as the participants completed the tutorial session, they were given the questionnaire. All participants performed the tasks at their own pace and their own convenience. In order to retain the reliability of the study, the participants were logged off from the system if they were inactive[22] for five minutes.

7.3.1.5. Data Analysis

The raw data obtained from the study were kept in a database. The author performed a data screening procedure to ensure the accuracy and reliability of the data. All statistical tests reported in this chapter were performed using SPSS version 18. Pre-analyses of the data have been conducted to identify whether or not the data had a normal distribution pattern. The tests of normality following *Kolmogorov-Smirnov* on the individual items of the questionnaire data indicated that they were not normally distributed. Hence, non-parametric statistical tests were used in this study. Please refer to Appendix H for the raw data of this experimental study.

7.3.2. Results

7.3.2.1. Learning Experience & Usability

The learning experience was measured in four dimensions: control, attention focus, curiosity, and intrinsic interests[23]. The usability in this study measured the usefulness of the computer-based learning systems in improving the learners' performance, and investigated whether the corresponding systems would be suitable to the learners' learning styles.

[22] Inactive is the situation in which no interaction has happened (e.g., clicking buttons, moving mouse, etc.).

[23] Refer to Section 5.3.2.1 for explanation about these dimensions.

The learning experience and usability[24] data were relatively high in their internal consistency (Cronbach's Alpha coefficient = 0.828). The means and the mean ranks for each learning experience dimension and usability are shown in Table 7.1.

Looking at Table 7.1, the learners in the experiment group (i.e., IT-Tutor with the SCB) rated higher for all learning experience dimensions and as well as usability in comparison to the counterpart group. Intrinsic interests received the highest ratings (*3.90*), followed by usability (*3.87*), and curiosity (*3.68*). In contrast, attention focus (*3.25*) had received the lowest ratings among learners in this group. For the other group (i.e., IT-Tutor without the SCB), usability (*3.60*) had received the highest ratings, followed by intrinsic interests (*3.58*). The ratings for attention focus in the control group were also the lowest likewise in the counterpart group.

Table 7.1: The means and mean ranks for the individual learning experience dimensions

Dimensions of experience	**IT-Tutor with the SCB (n=35)**		**IT-Tutor without the SCB (n=35)**		**Statistical Significant**
	Means	Mean ranks	Means	Mean ranks	
Control (CO)	3.42	39.07	3.13	31.93	z=-1.498, p=0.136, n.s.
Attention Focus (AF)	3.25	40.36	2.86	30.64	z=-2.041, p=0.041, p<0.05
Curiosity (CU)	3.68	37.66	3.52	33.34	z=-0.902, p=0.371, n.s.
Intrinsic Interests (II)	3.90	40.34	3.58	30.66	z=-2.020, p=0.043, p<0.05
Average experience	3.56	41.70	3.27	29.30	z=-2.557, p=0.010, p<0.05
Usability	3.87	39.34	3.60	31.66	z=-1.613, p=0.108, n.s.

In order to understand whether or not the SCB technique was effective in improving the DCSS learning experience, a series of *Mann-Whitney U* tests (2-tailed) had been performed. The test results suggested that the mean ranks for attention focus and intrinsic interests of the IT-Tutor with the SCB were significantly higher than the IT-Tutor without the SCB. Although the ratings for control, curiosity, and usability were higher for IT-Tutor with the SCB, the differences were not statistically significant. Hence, it can be asserted that the SCB technique improved the learners' overall learning experiences specifically from the context of their attention focus and intrinsic interests.

[24] The reliability test for learning experience and usability questionnaire was combined because they used the same Likert scale.

7.3.2.2. Cognitive Load

Table 7.2 shows that the learners who used IT-Tutor with the SCB rated lower (*3.03*) for the cognitive load question than the counterpart (*3.74*). It demonstrates that the cognitive load imposed by IT-Tutor with the SCB was lower than the older version of the system. However, a *Mann-Whitney U* test suggested that the difference in the means was insignificant. Apart from this, the mean ratings for both versions of IT-Tutor were relatively low when considering the nine-point scale for the measure. For this reason, it can be said that the DCSS particularly with SCB imposed reasonably low extraneous cognitive load to learners.

Table 7.2: The means and mean ranks for the cognitive load question

Dependent variable	IT-Tutor with SCB (n=35)		IT-Tutor without SCB (n=35)		Statistical Significant
	Mean	Mean rank	Mean	Mean rank	
Cognitive Load (over 9)	3.03	31.01	3.74	39.99	z=-1.881, p=0.060, n.s.

7.3.2.3. Knowledge Background

At the beginning of the tutorial session, the participants were asked to classify themselves into one of the three groups according to their own prior knowledge about the lesson. The three options were; (i) learners who never learned about the course before (i.e., beginners), (ii) learners who had learned the course before, yet, in some way they may forget about the course (i.e., intermediate learners), and (iii) learners who specialised in the area of Computer Networks (i.e., advanced learners). The purpose of this classification is to understand whether or not learners with the different background of knowledge would have different learning experience.

Table 7.3 showed that approximately 64% of the participants had never learned about Basic Computer Networks beforehand, while the rest had some knowledge about the course. None of them classified themselves as experts in this domain of study.

Table 7.3: Number of learners according to their background of knowledge

Classification of learners	IT-Tutor with SCB	IT-Tutor without SCB	Total	Percentage
Beginners	20	25	45	64.3%
Intermediate learners	15	10	25	35.7%
Advanced learners	0	0	0	0%

The author reanalysed the learning experience and usability questionnaire in relation to the two categories of learners. The learning experience data were clustered according to the learners' background of knowledge. The means and mean ranks were calculated and presented in Table 7.4 and Table 7.5 for the SCB and without-SCB respectively.

Table 7.4: The means and mean ranks for IT-Tutor with SCB learning experience

Dimensions of experience	Beginners (n=20)		Intermediate Learners (n=15)		Statistical Significant
	Means	Mean Ranks	Means	Mean Ranks	
Control (CO)	3.48	18.84	3.33	17.37	z=-0.321, p=0.758, n.s.
Attention Focus (AF)	*2.93*	14.24	3.66	22.97	z=-2.534, p=0.010, p<0.05
Curiosity (CU)	3.65	17.27	3.71	18.97	z=-0.490, p=0.634, n.s.
Intrinsic Interests (II)	3.77	16.38	4.07	20.17	z=-1.099, p=0.279, n.s.
Average experience	3.46	16.18	3.69	20.43	z=-1.219, p=0.229, n.s.

Table 7.5: The means and mean ranks for IT-Tutor without SCB learning experience

Dimensions of experience	Beginners (n=25)		Intermediate Learners (n=10)		Statistical Significant
	Means	Mean Ranks	Means	Mean Ranks	
Control (CO)	3.09	17.70	3.23	18.75	z=-0.284, p=0.794, n.s.
Attention Focus (AF)	2.85	18.14	2.87	17.65	z=-0.131, p=0.904, n.s.
Curiosity (CU)	3.52	17.98	3.53	18.05	z=-0.019, p=0.995, n.s.
Intrinsic Interests (II)	3.55	17.30	3.67	19.75	z=-0.664, p=0.524, n.s.
Average experience	3.25	18.34	3.33	17.15	z=-0.312, p=0.766, n.s.

From Table 7.4, the SCB intermediate learners had rated higher scores compared to the beginners in most of the learning experience dimensions, except control. The *Mann-Whitney U* tests confirmed that their scores for attention focus (AF) were significantly higher ($z=-2.534$, $p=0.010$, $p<0.05$) than the beginners for the same computer system. However, the learning experience for beginners and intermediate learners in the IT-Tutor without the SCB group was relatively similar as depicted in Table 7.5.

7.3.2.4. SCB Usage

The IT-Tutor logged data were analysed in order to understand whether or not the SCB learners had effectively used the "*flow buttons*". The logged data suggested that 77% of the learners used at least one type of button. Nearly half of the learners used the "*anxiety"* button, one learner used the "*boredom*" button only, and about a third used both buttons. The bar graph in Figure 7.8 shows the information.

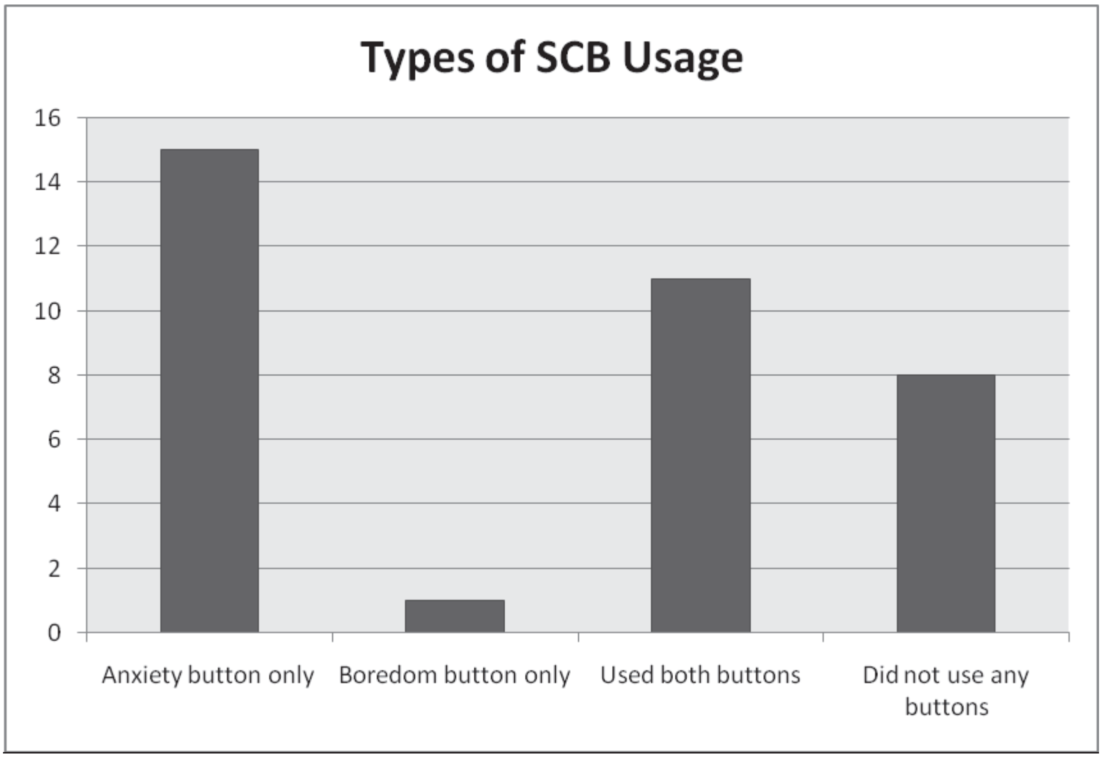

Figure 7.8: Types of the SCB buttons used by learners

The SCB usage according to the two stages of the tutorial was also analysed. About 26 learners used a total of 35 hits of the "*anxiety"* button with 9 and 26 hits for Stage 1 and Stage 2 respectively. The average hit of the "*anxiety*" button was 1.65 for every learner. For the "*boredom"* button, 20 hits were recorded with 3 and 17 for Stage

1 and Stage2 respectively. The average hit for the "*boredom*" button was 1.67. The bar graph in Figure 7.9 illustrates this information.

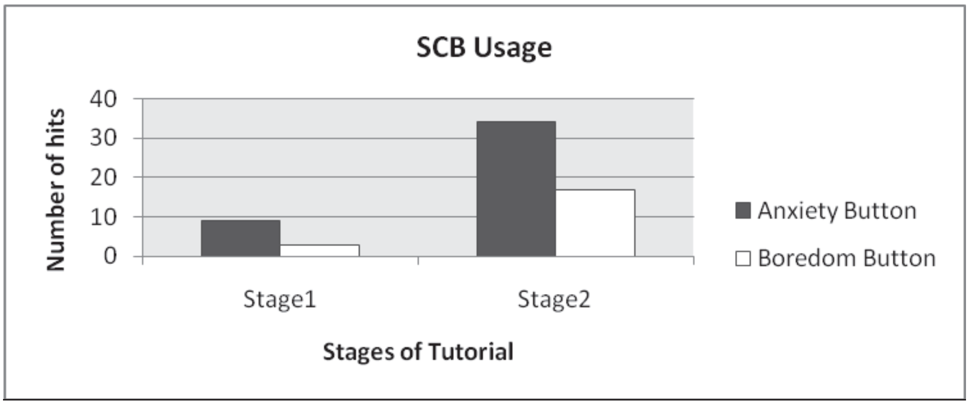

Figure 7.9: The "*flow buttons*" usage according to the two stages of tutorial

The analysis has also been extended to understand the SCB usage with regard to the learners' background of knowledge as depicted in Figure 7.10. The learners' access to SCB was clustered according to their background of knowledge. The analysis suggested that almost all of the beginners (17 out of 20) and more than half of the intermediate learners (9 out of 15) used the SCB buttons. About two third of the beginners used the "*anxiety*" button and only one of them used the "*boredom*" button. On the other hand, none of the intermediate learners used the "*boredom*" button only, whereas, nearly half of them used either "*anxiety*" button or combination of both buttons.

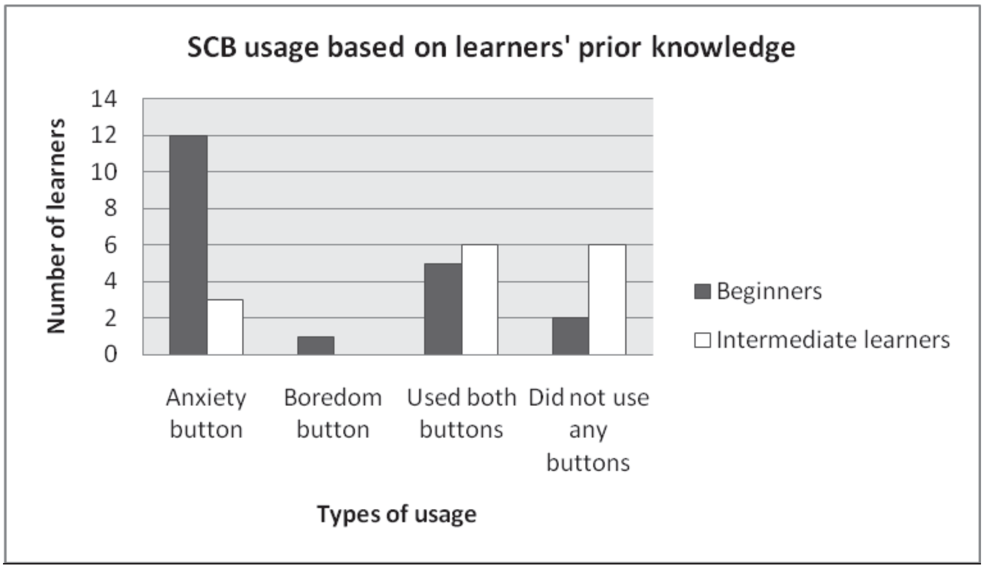

Figure 7.10: The SCB usage according to learners' prior knowledge

7.3.3. Discussions

This chapter proposed the SCB technique to provide learners with adaptive computer-based learning environment. The purpose of the SCB is to achieve a balance in skill and challenge so that the learners obtain an optimum learning experience. In doing so, the learners can make self-adjustment of the given levels of the learning activities to meet their current levels of skill or knowledge.

The experimental outcomes indicated some empirical points. It suggested that the DCSS learning experience was improved by using the SCB approach. Looking into the specific learning experience dimensions, the learners in the group were significantly better in their attention focus towards the given learning tasks and their intrinsic interests in computer-based learning. This is caused by the SCB learning path self-adjustment that gave greater flexibility. It can also be implied that the SCB had achieved a satisfactory level in terms of usability as the ratings were exceeding 70%. In addition, the cognitive load imposed by the SCB was considerably low with approximately 30%.

The effectiveness of the SCB approach has also been analysed from the viewpoint of usage. More than 75% of the learners had taken advantage of the existence of the "*flow buttons*" with approximately 30% of them using both of the buttons. The level of usage was considerably high which justifies their usefulness. The learners who used the SCB appeared to have a better learning experience than those who did not. The most important finding in this study is the fact that non-novice learners are more likely to prefer for a more flexible way of learning content navigation rather than a fully-guided learning path. This outcome validates a finding in a prior study by Mitchell *et al.*(2005).

7.4. Summary

The chapter described in detail the skill-challenge balancing (SCB) technique that aims to improve the DCSS learning experience. The approach was based on the flow theory, and it had been integrated into the DCSS user interface module. The balance in skill and challenge is obtained through learner's self-adjustment of the given levels of challenges so that they are equivalent to the learner's current level of skills. The self-adjustment of the levels of challenge is a simple and inexpensive method to achieve adaptive computer-based learning systems. The empirical study to understand the effectiveness of the SCB had suggested that the approach was effective in improving the DCSS learning experience. The SCB technique proposed in this chapter is the main contribution of the thesis.

CHAPTER 8: CONCLUSIONS AND DISCUSSIONS

The aim of this chapter is to summarise the research conducted for the entire thesis. This chapter comprises four sections: Firstly, it presents a reflection on the research objectives that underlie the thesis. Then, it summarises the findings of the thesis in Section 8.2. Next, it discusses the contributions of the studies in Section 8.3. Finally, it points out the limitations of the studies and potential future work.

8.1. Review of the Thesis Objectives

The aim of the thesis was to study the DCSS learning experience. On this basis, we identified five research questions central to the studies of this thesis as mentioned in Section 2.2. These research questions served as the detailed objectives that the author intended to achieve. The thesis evaluated the learning experience through the learners' cognitive states while engaging in a particular DCSS learning task. Further, the thesis aimed to improve the learning experience and engagement through a technique that integrates the flow theory into the DCSS design. The final objective was to measure how well the technique works in improving the students' learning experience and engagement in the DCSS. That is, the research questions were as follows:

- ***RQ1:*** Is there any difference in learning outcomes and learning experiences between learners who had used the dynamic curriculum sequencing system (DCSS) and the non-DCSS?
- ***RQ2:*** Do learning experiences change throughout a DCSS learning task?
- ***RQ3:*** Is there any difference in cognitive loads between learners who had used the DCSS and the non-DCSS?
- ***RQ4:*** How can the flow theory be incorporated in the design of the DCSS to improve the learning experience?

- ***RQ5:*** Is there any difference in learning experience between learners who had used the DCSS with the skill-challenge balancing (SCB) technique and the DCSS without the technique?

Experiment 1 in Chapter 5 was intended to answer RQ1. The basic statistical tests on the learners' post-learning quiz suggested that the DCSS and non-DCSS learning outcomes were similar. However, the advanced statistical tests (i.e., the cluster analysis and the discriminant function analysis) revealed that the DCSS and non-DCSS learning experiences were different. This was due to the learners' learning performances (i.e., high performing learners vs. low performing learners). The cluster analysis classified the learners into three clusters of cognitive states (i.e., flow, boredom, and anxiety) based on their performances and learning experience ratings. These clusters represented the learners' experiences and their cognitive states while engaging in the given DCSS and non-DCSS learning activities. The discriminant function analysis confirmed that this classification was highly accurate. This analysis also suggested that the low-achieving learners suffered from anxiety more frequently with the non-DCSS compared to the DCSS. These results answered RQ1.

Experiment 2 in Chapter 6 was intended to answer RQ2 and RQ3. The assessment of the learning experiences in a progressive manner showed that the DCSS and the non-DCSS leaning experiences were dynamic; this provided an answer for RQ2. A continuous assessment of the learners' learning experiences managed to demonstrate how the changes happened. In particular, the non-DCSS learning experience was improving from the beginning towards the end of the given tutorial session. However, the quality of DCSS learning experience was decreasing. A further analysis on the learning experiences revealed that the learners' background of knowledge could be the cause of the varied experiences. As majority of the participants enrolled in an IT-programme, they had advanced knowledge about Computer Networks. It seemed that the non-DCSS learners obtained improved learning experiences because the system gave them more flexibility during the learning process compared to the DCSS. Therefore, for RQ3, there was no difference in terms of cognitive loads between the DCSS and the non-DCSS learners.

These two empirical studies had suggested crucial information about the DCSS and non-DCSS learning experiences. First, it appears that the low-performing learners suffered from anxiety with the non-DCSS more frequently than the DCSS. Second, the advanced learners obtained improved learning experiences with the non-DCSS compared to the DCSS. These findings showed an urgent need to improve the DCSS so that the system could accommodate learners with different needs.

The author designed and proposed the skill-challenge balancing (SCB) technique to address the issue in RQ4. The early sections of Chapter 7 explained how the SCB technique could improve the DCSS learning experience and engagement. The basic idea of the SCB technique was to allow the learners to self-adjust the difficulty level of a learning activity to meet their current levels of knowledge. The SCB technique embedded in the DCSS design through modification of the system's user interface module and the sequencing engine. This produced a new version of IT-Tutor[25] with the SCB.

Experiment 3 in Chapter 7 described RQ5. The SCB technique was effective in improving the DCSS learning experience. The learners who had used the DCSS with the SCB rated significantly higher in their overall learning experiences compared to the learners who used the old version of DCSS. The integration of the SCB technique in the DCSS had significantly improved their learning experiences particularly in the learners' attention focus and intrinsic interests. Besides, the SCB usage rate was substantially higher with more than 80% of the learners using the proposed facilities. The results obtained from Experiment 3 have offered a conclusive answer for RQ5.

8.2. Summary of the Thesis

Learning experience is an important factor for the success of computer-based learning. It has been proven by a number of studies (Chan & Ahern, 1999; Konradt *et al.*, 2003; Lee, 2005; Liao & Lu, 2008; Lin, 2011; O'Brien & Toms, 2008; Paechter, *et al.*, 2010;

[25] IT-Tutor was the name of the DCSS as described in Chapter 4.

Sun *et al.*, 2008). However, these studies focused on the different CBL, and none of them had investigated learning experience in DCSS. Due to this fact, the thesis aimed to establish evidence of the importance of *learning experience* in the DCSS environment.

Chapter 2 established the theoretical basis that guided the implementation of the thesis. It explained the motivation for writing the thesis, the research questions, and the methodology for implementing the research.

Chapter 3 presented an extensive literature review concerning the computer-based learning experience. The literature review found a gap in the past CBL studies that needs further research. It showed that many past studies investigated the students' experiences through their perceptions, which were insufficient to understand how the students had engaged in the CBL activities.

Chapter 4 explained the dynamic curriculum sequencing system (DCSS); a specific instance of CBL system. The author developed a DCSS known as IT-Tutor that acted as the main apparatus for conducting the experimental studies in this thesis. The system teaches Basic Computer Networks, a common introductory course at university level. Five usability experts and Computer Networks instructional designers evaluated the DCSS usability. The usability test confirmed that the system was a usable learning tool.

Chapter 5 described the first empirical study to understand the DCSS learning experiences and learning outcomes. The empirical study used IT-Tutor as the main apparatus to investigate the DCSS learning experiences and learning outcomes. In order to deeply understand the DCSS learning experience, a freely-browsing computer-based learning system (i.e., the non-DCSS) was used in the study so that the students' learning experiences could be compared. The study found that the non-DCSS learners suffered from anxiety more frequently than the DCSS specifically for the low-performing learners.

Chapter 6 discussed the second empirical study that aimed to measure learning experiences at several points of the learners' interactions with the corresponding CBL systems. The results showed that the DCSS and non-DCSS learning experiences were dynamic with two main patterns throughout the given computer-based learning session. In the same experimental settings, the author also examined cognitive loads that the DCSS and the non-DCSS had imposed on the learners. The NASA-TLX analysis suggested a similar low overall workload for both types of computer-based systems.

Chapter 7 proposed the skill-challenge balancing (SCB) technique that aimed to improve learners' experiences and engagement in DCSS environment. The proposed SCB technique allows learners to adjust the difficulty level of DCSS learning material to cope with their individual level of skill. The third empirical study (i.e., Experiment 3) revealed the effectiveness of the technique. This study found that the SCB technique significantly improved the learners' experiences with the DCSS with substantial improvements in their attention focus and intrinsic interests.

8.3. Contributions

This thesis verified that learners' learning experiences are important to improve their engagement in CBL activities and helps them to enjoy a learning process with CBL. When learners have a stress-free CBL learning environment, they will have a motivating and stimulating learning, which later can improve their overall learning process. The studies in this thesis contribute to the field of computer-based learning, specifically for the DCSS learning environment, and human-computer interaction as described here:

1. The SCB technique improves learning experience

This thesis proposed a novel technique known as the SCB that aimed to improve the DCSS learning experience and engagement. The basic idea of the SCB is to allow learners to self-adjust the learning content difficulty levels based on their current levels of skill. The incorporation of the SCB technique in the DCSS had significantly improved the learners' experiences.

The empirical study had proven that the proposed technique is effective in improving the DCSS learning experience and helping learners to engage in CBL. Unlike other techniques used for monitoring affective states,[26] this new technique is theoretically practical and simple in its implementation. This technique is workable for the DCSS learning environment. It may also useful for other types of CBL such as problem-solving systems.

2. The DCSS can reduce anxiety among low-achieving learners

The thesis found that the low-achieving learners suffered from anxiety more frequently with the non-DCSS than the DCSS. It shows that the DCSS and non-DCSS could give different learning experiences to learners; however, the DCSS works more efficiently for the low-performing students as the system reduces their anxiety in CBL environment and helps them to engage in the given learning activity.

Identification of a very specific learning experience, particularly anxiety in DCSS environment, is a new finding in literature. This finding is useful for CBL designers and developers to design and develop a proper content sequencing system that suits the low-performing learners.

3. CBL experience is dynamic

Continuous assessment of the learning experience demonstrated that CBL experience was dynamic. The study observed two shapes of learning experience quality; intensified or weakened throughout the entire computer-based learning tasks. These results showed that students' experiences and engagement in the CBL activity could change throughout a given learning process. Students may keep engage or disengage in the CBL activity depending on their learning experiences during the CBL interactions.

To our knowledge, no empirical research has investigated CBL experience in a progressive manner as ours. This represents a new contribution to understanding of how the CBL experience evolves. The method that we employed to obtain the learning experience data could be useful for CBL developers to develop an adaptive technique for modelling students' behaviours. This method is simple yet practical. Subsequently, it could improve students' motivation and engagement in CBL.

[26] These techniques were discussed in Chapter 4.

4. *Self-evaluation is a tool to regulate learners' experiences in a continuous manner*

The SCB technique allows the learners to modify the difficulty level of the learning content at every stage of the DCSS learning. This means that the learners could proceed to a higher level of learning or return to a lower difficulty level at any time that they required. By modifying the difficulty level, the learners are actually evaluating their own levels of skill to match the given challenges. This technique helps the learners to engage in the DCSS activity and prevents them from becoming anxious or bored.

The use of self-evaluation in the DCSS as a way to regulate learning experiences is also a new contribution to the area of CBL. Many past studies tend to use intelligent techniques to evaluate the learners' experiences in an automatic manner. However, we believe that self-evaluation is more accurate and reliable to give information about the learners' states of learning. In addition, self-evaluation allows the learners to participate actively in identifying their own learning path by giving them the opportunity to decide on what they want to learn. This is also a good way to help them engage in their own leaning activities and take charge of the learning process.

5. *Background of knowledge is an important variable towards adaptive DCSS*

This thesis also confirms the results of past studies in the area of CBL. The findings of past studies suggested that learners with different backgrounds of knowledge have different quality of learning and require different instructional strategies. This claim is true. The thesis found that the advanced learners who used the freely-browsing learning system obtained improved learning experience in comparison to the same group of learners with a fully-guided content sequencing system. This means that a single instructional strategy that works for a group of learners is not necessarily works for other groups of learners. This finding confirms prior studies by Kalyuga (2006), Kalyuga & Renkl (2010), and Mitchell *et al.*(2005). This also indicates that background of knowledge is an important learning variable for achieving adaptive CBL environment.

8.4. Limitations

Although the thesis has answered the research questions mentioned in the earlier chapters, yet the works were carried out within certain limitations. We identified four limitations of this thesis as described in the following paragraphs.

Firstly, the sample size used for the studies was between forty to eighty students. This sample size could be questionable to represent all students at university level. A statistical analysis is needed to decide the sample size required if we know the population of students at tertiary level. In this case, it is impossible to know exactly the population of tertiary students. Hence, we used the sample sizes of similar studies reported in the literature. Apart from this, participation was voluntary; a reasonably high attrition rate in the respective experimental studies might be another limitation. Incentives in the form of monetary or course credits may increase students' participation and motivate the students to comply to the given research tasks (Tomporowski *et al.*, 1993). However, this is forbidden due to ethical reasons.

Secondly, these three experimental studies recruited subjects from two universities in Malaysia and New Zealand. There was a mixture of subjects from the two countries in Experiment 1 and Experiment 3. The results could be more generalised if a number of universities from more countries were involved. Apart from that, cultural differences from the two countries might be confounding some results in Experiment 1 and 3.

Thirdly, it is important to bear in mind that the experimental studies were conducted in the online mode where the subjects were allowed to carry out the learning tasks at their own convenient time and place. It is certain that this mode of experimental studies provides high external validity; however, it is also a limitation. The network speed and type of connections that the subjects had used in performing the tasks were not known. For this reason, we assume that the subjects used an acceptable network speed and it did not affect their quality of learning.

Finally, the outcomes of the thesis might be limited to the learning experience within the subject of the course used in this experiment, i.e., Computer Networks. This type of course is considered very formal, specialised, and technical. Courses that deliver non-technical content, less formal, and unspecialised may produce different learning experiences.

8.5. Future work

The effectiveness evaluation of the SCB technique as reported in Chapter 7 can be further extended by including multiple levels of learners' background. As the majority of the subjects of the study were novice learners, the author anticipates repeating the study among advanced learners so that the results could be compared in a more generalisable way.

The author also anticipates performing a study to understand the DCSS learning experience in the context of cultural differences between students from two or more different countries. If this is the case, the information about cultural effects on learning experience would help system designers to consider cultural aspects when designing computer-based systems.

Progressive evaluation of the learning experience that the author conducted and reported in Chapter 6 had some practical implications in the area of human-computer studies. The effectiveness of this method in monitoring users' experience can be further examined through a future comprehensive study. Research related to monitoring users experience is still at infancy level, hence more studies are needed to improve and strengthen the outcomes of experience variable particularly in a computer-based learning environment.

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Appendix A: Summary of Literature

Table A-1: Summary of learning experience approaches

Author/s	Dimension(s) of experience	Hardware approach	Software approach	Descriptions	Comments
Chou (2010)	Flow experience	√	√	• The research suggests an embedded system[27] design methodology that aims to produce flow experience to users while using online systems. • The embedded system design considered user experience as a component of user-centric design which implemented thorough analysis of workload variance to adapt to different types of user needs and workload variations effectively.	The design methodology is still at a pre-mature stage, thus, require more evaluations and validations.
Woolf *et al.* (2010)	Emotion Motivation	√		• The research suggests automatic learner's emotions recognition using wireless sensors that provide data about posture, movement, grip tension, facially expressed mental states and arousal for tutoring systems. • The devices used to detect learners' affective states include a mental state camera, a skin conductance bracelet, a pressure-sensitive mouse, and a pressure sensitive chair. • Learners' affective states that can be recognised by the sensor include frustration, confident, interest and excitement. • As learners' affective states are detected, the tutoring system responds to the conditions by providing empathy or supports as human tutors do so that	The research uses hardware sensor for recognising learners' emotions while using a tutoring system. The approach could accurately detect learners' affective states; however, it involves expenses on a number of devices to operate.

[27] An embedded system contains pre-programme software embedded in a microprocessor.

				learners are motivated to learn.	
Muldner *et al.* (2010)	Excitement Motivation	√		• The research suggests the use of sensor devices to track learners' excitement as a sign of positive affect in using the intelligent tutoring systems (ITS). • The sensor devices include a posture chair, a skin conductance bracelet, a pressure mouse, and a Tobii eye tracker. • The study shows that, excitement in learning always followed by correct solution steps; however, correct solution steps do not necessarily followed by excitement. The excitement also happens when student invested a lot of effort, and it pays off.	The research uses similar devices as found in Woolf *et al.* (2010), except that, it specifically investigates learners' excitement in using ITS.
Kaklauskas *et al.* (2009)	Emotions	√		• The research studied users' emotions and their correlation with labour productivity. • Biometric mouse was used to measure biometric parameters such as physiological, psychological, and behavioural correlate with the user's emotional states (anger, fear, sadness, disgust, happiness, and surprise) and labour productivity.	The study is at the initial stage of system development. Further experimental studies on the effectiveness of the biometric mouse are needed.
Leontidis *et al.* (2009)	Emotions Cognition		√	• The research suggests the use of ontologies and Bayesian Networks to model learners' emotional and cognitive states. It also suggests a method called Affective Tactic; which intended to provide cognitive and emotional guidance, and to support learners. • The method is implemented in an adaptive educational system (AES) known as MENTOR.	The study did not specifically describe the types of emotional states that have been investigated (e.g., sad, anger, fear, anxiety, happy, etc.).
Sabine (2008)	Flow experience Quality of experience		√	• The research suggests the use of a method called *strategy modularisation and merger* in order to achieve the maximum quality of experience (QoE) in learning. • Generally, the method suggests the authoring of hypermedia systems through modularization of	It is a theoretical framework; further evaluation and validation have not been found.

				complex tasks into smaller one, which could be reuse and apply in other hypermedia system conditions.	
van den Hoogen *et al.* (2008)	Game experience Emotions	√		• The research suggests that behavioural expression can be used to measure players' experience in computer games. • The evaluation of behavioural expression used a pressure-sensitive mouse for measuring force. The study found that more pressure was exerted on a game pad's button as the difficulty level increased and it serves as indicators of human's level of arousal.	The difference between behavioural expressions in playing games and learning through computer-based has not been confirmed.
Ryoo *et al.* (2008)	Engagement Flow experience		√	• The research suggests design principles of a motivational e-learning environment (MELE). • The design principles were formulated based on *Flow Theory*: (i) focused attention, (ii) clear set of goals, (iii) immediate and appropriate feedback, (iv) potential control, (v) balance of skills and challenges, and (vi) ease of use.	The design principles are intended to motivate learners to use e-learning. The design principles are very general to be implemented. More specific design principles and guidelines are required.
D'Mello *et al.* (2007)	Emotions Flow experience Cognition	√		• The research suggests the use of automatic affective states detection in an intelligent tutoring system called Auto-Tutor. • AutoTutor tries to detect learners' affective states (e.g., boredom, confusion, delight, flow and frustration) and try to engage learners with learning in a human-like manner. • It uses devices such as a body-pressure-sensitive chair and an eye-tracking camera.	The use of device sensors can accurately predict learners' affective states; however, it needs some investment on the devices, which might not available to everyone.
D'Mello *et al.* (2006)	Affective states		√	• The research suggests the use of dialog conversation in the detection of learners' affective states (e.g., confusion, eureka, frustration) in ITS. • The research found that the way of conversation expressed by the tutor and the type of feedback given	The use of conversation in detecting learners' affective state allows inexpensive and simple approach for the implementation of computer-based learning.

				can significantly predict the learners' affective states, so that the tutor can take appropriate actions in order to maximise the learning experience.	
Sweetser & Wyeth (2005)	Flow experience Playfulness Enjoyment		√	• The research suggests a set of flow design criteria for computer game systems known as GameFlow. • The criteria are concentration, challenge, skills, control, clear goals, feedback, immersion, and social interaction. • The research suggests that concentration is the most important criteria that helping game player to achieve enjoyment in playing games, hence helps them to achieve flow. • The current form (as reported in the article) of the design criteria is useful for identifying issues during the design of computer games but not intended to serve as an evaluation tool.	The flow design criteria for game systems could be adapted in the design of computer-based learning systems as it outlines some basic features that should be available to achieve flow.
Georgouli (2002)	Motivation		√	• The research suggests a computational model of motivation in the design of ITS. The model has the capability to adapt itself to the learners' aptitudes and motivational states. • It evaluates learners' motivational characteristics (e.g., time taken to respond to an activity, number of attempts to solve a problem, and number of activities given up), and decides whether to offer help and to proceed to the sequence of learning path.	The computational model is simple and very cost effective to create a *motivational* ITS.

Appendix B: Materials for the Usability Evaluation

Dear Evaluators,

We invite you to perform a usability study of an e-learning system, known as IT-Tutor. The system is intended to support teaching and learning at higher institutions. The module is designed for learning Basic Computer Networks.

We seek you support and expertise in evaluating the usability of the system.

Thank you.

Kind Regards,
Liza Katuk

INSTRUCTIONS TO EVALUATORS:

1) Please visit the website http://it-tutor.net/Part2.
2) Click on the "Sign Up" button on the left side of the page.
3) Create your own user name and password, and complete other information required for creating an account with IT-Tutor. After an account is successfully created, you will automatically be log on to IT-Tutor.
4) As you log on to IT-Tutor, please browse the system thoroughly and complete the "**Usability Evaluation Report**" attached at the end of this document.

AN OVERVIEW TO IT-TUTOR

IT-Tutor helps learners by providing a tutorial session about Basic Computer Networks. The tutorial session in divided into three stages:

- **Stage 1 – Evaluation of prior knowledge**
  It consists of 4 multiple-choice questions (MCQ). Learners who manage to answer all the questions correctly, they will proceed to Stage 2. Incorrect answer(s) will lead them to a learning activity where they have to review the concepts and theories they were wrong. Then, they will be asked again with the same question they were wrong as a way to reinforce learning at the early stage.
- **Stage 2 – Sequencing of learning materials**
  Stage 2 consist the same number of questions and the same flow as in Stage 1. However, questions in this stage are higher in their difficulty levels as compared to Stage 1.
- **Stage 3 - Reinforcement**
  Stage 3 comprises of 4 short-answer questions. The purpose of this stage is to reinforce the whole learning.

Learners are able to browse lecture notes independently, change password of IT-Tutor account and preview tutorial(s) records.

USABILITY EVALUATION REPORT

SECTION 1: USABILITY CRITERIA

Instruction: Please mark **[X] on a rating** in the appropriate box (**1-strongly disagree** to **5 strongly agree**) based on your experience and judgement in using IT-Tutor.

Criteria	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
	1	2	3	4	5
Content Concepts are illustrated with concrete and specific examples in IT-Tutor					
Learning & Support- IT-Tutor offers tools that support learning (e.g., notes, quizzes etc.)					
Visual Design Fonts are easy to read					
Navigation Learners are always know where they are in IT-Tutor					
Accessibility IT-Tutor is free from technical problems (e.g., hyperlink errors, programming errors)					
Interactivity IT-Tutor provides appropriate response and feedback to learners					
Self-assessment and Learnability Learners can start using IT-Tutor by themselves without specific training on the system					
Motivation to Learn IT-Tutor simulates further inquiry and enjoyable					

SECTION 2: GENERAL COMMENTS

Please provide comment (if relevant).

SECTION 3: EVALUATOR'S BACKGROUND

Note: This section is intended to obtain background information about the evaluators. Identity of all evaluators will not be revealed in any reports.

Name	**:**
Highest level of education	:
Experience in teaching	: (please mention in the number of years)
Experience in usability evaluation (if relevant)	: (please mention in the number of years)

SECTION 4: APPRECIATION

Thank you for your support and expertise in evaluating the usability of IT-Tutor.

Appendix C: Materials for Experiment 1

These materials were used in Experiment 1:

1) Information Sheet
2) Consent Form
3) Pre-learning Quiz
4) Post-learning Quiz
5) Learning Experience Questionnaire

Information Sheet

Institute of Information and Mathematical Sciences (IIMS)

EVALUATION OF INTELLIGENT TUTORING SYSTEM
INFORMATION SHEET

Who are the researchers?

The principal researcher of this study is Liza Katuk who is currently a PhD student at IIMS. The main supervisor of this study is Dr. Hokyoung Ryu. Should you have any questions regarding the study, you can contact us at:

	Liza Katuk	Dr. Hokyoung Ryu
Email	n.katuk@massey.ac.nz	h.ryu@massey.ac.nz
Phone	+64 9 414 0800 ext. 9249	+64 9 414 0800 ext. 9140
Physical and Courier Address	QA 2.20, Albany Campus, Massey University, State Highway 17, Albany, Auckland, New Zealand 0632	QA 2.02, Albany Campus, Massey University, State Highway 17, Albany, Auckland, New Zealand, 0632
Mailing Address	Institute of Information and Mathematical Sciences (IIMS), Massey University, Albany Campus, Private Bag 102-904, North Shore Mail Centre Auckland, New Zealand	Institute of Information and Mathematical Sciences (IIMS), Massey University , Albany Campus, Private Bag 102-904, North Shore Mail Centre Auckland, New Zealand

What is the research about?

We cordially invite you to participate in this research. The research is intended to evaluate the learning outcomes of a computer-based learning system.

What should you do for the experiment?

Participants who wish to participate in this study will undergo a laboratory experimentation in which they need to:

- *Read and sign the consent form*
- *Answer a short quiz about Basic Computer Networks*
- *Use a computer software for learning the topic independently*
- *Answer a questionnaire on how you feel about the software*
- *Answer a short post-quiz related to the topic*

*The experiment will take about **30 minutes**.*

How do we use data you have provided?

There is no way your identity will be revealed as the research will conclude on group result. Each participant will be treated as anonymous. All answer-sheets of the quizzes and questionnaire will be kept in locked drawer. We will dispose the data completely following Massey University procedure of disposal confidential documents when the thesis of this study has been published. During the period of research, the data will also be published in conference proceedings and journals.

What are your rights?

You are under no obligation to accept this invitation. If you decide to participate, you have the right to:

- *decline to answer any particular question;*
- *withdraw from the study within two(2) weeks from the date of experiment;*
- *ask any questions about the study at any time during participation;*
- *be given access to a summary of the project findings when it is concluded.*

Consent Form

Massey University

Institute of Information and Mathematical Sciences

EVALUATION OF INTELLIGENT TUTORING SYSTEM

PARTICIPANT CONSENT FORM

1. *I have read the Information Sheet and have had the details of the study explained to me.*
2. *My questions have been answered to my satisfaction, and I understand that I may ask further questions at any time.*
3. *I understand that I am free to withdraw from the study at any time, or to decline to answer any particular questions in the study.*
4. *I agree to provide information to the researchers under the conditions of confidentiality set out on the information sheet.*
5. *I agree to participate in this study under the conditions set out in the Information Sheet.*

* ☐ *I would like to receive my score for pre-test and post-test.*
** ☐ *I would like to receive the summary of study.*

Signature :________________________ *Date:* ________________________

Full Name :____

Email :____

**** Mark X if you wish to receive your score for pre-test and post-test through email***
***** Mark X if you wish to receive the summary of the study.***

Pre-learning quiz

Instruction: Choose the correct answer for the following questions

1) The layout of computers and other devices in the network is referred to as:
   A. Network architecture
   B. Network type
   C. Network topology
   D. Network distribution
2) A network can be described as a collection of computers and devices connected via __________ and ________________.
   A. Communications --- transmission
   B. Communications devices --- transmission media
   C. Communications agent --- transmission agent
   D. Communications setting --- transmission agent
3) A type of communications device that connects a communications channel to a sending or receiving device.
   A. Mainframe
   B. Computer
   C. Server
   D. Modem
4) A network that connects computers and devices in a limited geographical area.
   A. MAN
   B. LAN
   C. WAN
   D. BUS
5) ________________ is a simple network that connects fewer than 10 computers. Each computer has equal capabilities
   A. Client/server
   B. Router
   C. Peer-to-peer
   D. GPS
6) In _________________ network, all devices connect to a central device.
   A. Bus
   B. Ring
   C. Star
   D. Hybrid
7) _____________ is a temporary connection using telephone line for communications
   A. ISDN line
   B. Intranet
   C. Dedicated line
   D. Dial-up line
8) _____________________ is a central communications device that allows computers and devices to transfer data wirelessly among themselves or wirelessly to a wired network
   A. cable modem
   B. wireless modem
   C. wireless access point
   D. network card
9) ___________________ consists of dozens or hundreds of thin strands of glass or plastic for carrying data at fast speeds.
   A. Twisted-pair cable
   B. Fiber-optic cable
   C. Coaxial cable
   D. Phone cable
10) ______________________ is a space station that receives microwave signals from earth-based station, amplifies signals, and broadcasts signals back to any number of earth-based stations
    A. Radio station
    B. Microwave station

C. Communications satellite
D. Cellular station

Post learning quiz

INSTRUCTION: The test comprises of two sections; Section A and Section B. Answer ALL sections

SECTION A: Fill-in the blank with correct answer.

1) ______________________________ is a network that covers a large geographic area using many types of media.
2) ______________________________ is a type of network in which one or more computers act as host computers and other computers access the host computer.
3) ______________________________ network uses a cable that forms closed loop with all computers and devices arranged along the cable.
4) ______________________________ allows access to the Web wirelessly from a notebook computer, a smart phone, or other mobile device.
5) ______________________________ consists of a single copper wire and often used for cable television wiring.

SECTION B: Read each of the scenarios carefully and identity the best communications and networks solution to each of the scenarios.

6) "A network officer at a primary school has been assigned by the school principal to create a computer network for the new computer laboratory. There are 12 computers, which need to be connected to each other. The network officer needs a type of network which can be easily expandable in the future and has better performance in routing data, instructions and information among the computers."
What type of network topology is the best for the computer laboratory?______________

7) "A network officer is required to setup a small network consists of four computers. He needs to create a network so that all computers can share files and resources among them and as well as sharing access to the Internet. To enable this setting, he must ensure that each computer has equal capabilities and responsibilities."
What type of network architecture that he needs to choose? ______________________

8) "A network consultant is required to setup a small office network consists of two computers. Each of the computers has been installed with modem, but no network cards. All computers should have access to the internet."
What type of network connection appropriate for this setting? ______________________

9) "A network consultant is required to setup a network for a public library in North Shore. There are ten computers within 100 square meters of the library building. All computers have been installed with TCP/IP standard network cards. He needs to think of the cheapest cable which appropriate for connecting all computers in the building. The cable must also thin and easy to string between walls."
What type of network cable appropriate for this setting? ______________________

10) "A network consultant is required to setup a wireless network at the ground level of Westfield Mall in Albany. Customers who are having their meals at the food court area of the mall will use the wireless network. The new wireless network will be connected to the existing local area network (LAN) in the building. He is thinking of investigating a network device for the wireless network.
What is the most appropriate wireless network device he should think of?

____

Learning experience questionnaire

Instruction: Please mark 'X' in the corresponding box for each of the statement.

	1	2	3	4	5
	Strongly disagree				Strongly agree
When using IT-Tutor, I felt in control over everything					
I felt that I had no control over my learning process with IT-Tutor					
IT-Tutor allowed me to control the whole learning process					
When using IT-Tutor, I thought about other things					
When using IT-Tutor, I was aware of distractions					
When using IT-Tutor, I was totally absorbed in what I was doing					
Using IT-Tutor excited my curiosity					
Interacting with IT-Tutor made me curious					
Using IT-Tutor aroused my imagination					
Using IT-Tutor bored me					
Using IT-Tutor was intrinsically interesting					
IT-Tutor was fun for me to use					

Please complete the demographic information OR mark X in the appropriate box.

1) I am currently doing *(your programme of study at Massey, e.g. Bechelor in Education, Diploma in Business*)
____

2) I am in the ____________________ of my study.
☐ First year ☐ Second year ☐ Third year ☐ Final year

3) English is my _____________ .
☐ First language ☐ Second language

4) I have been using computer____________________________ .
☐ Less than a year ☐ 2 to 3 years ☐ more than 3 years ☐ Never used the computer

5) I have been using e-learning system before.
☐ Yes ☐ No ☐ Not sure

Comments:

Appendix D: NASA-TLX Example

This section gives an example of how NASA-TLX score is calculated. Figure D-1 and D-2 show the computerised version of the tool. First, participant is required to score the individual subscales of the subjective workload that ranged from 0-100. Then, the participant is asked to choose a subscale that has lower workload each of fifteen pair-wise subscales. Example 1 shows how the calculation is done manually.

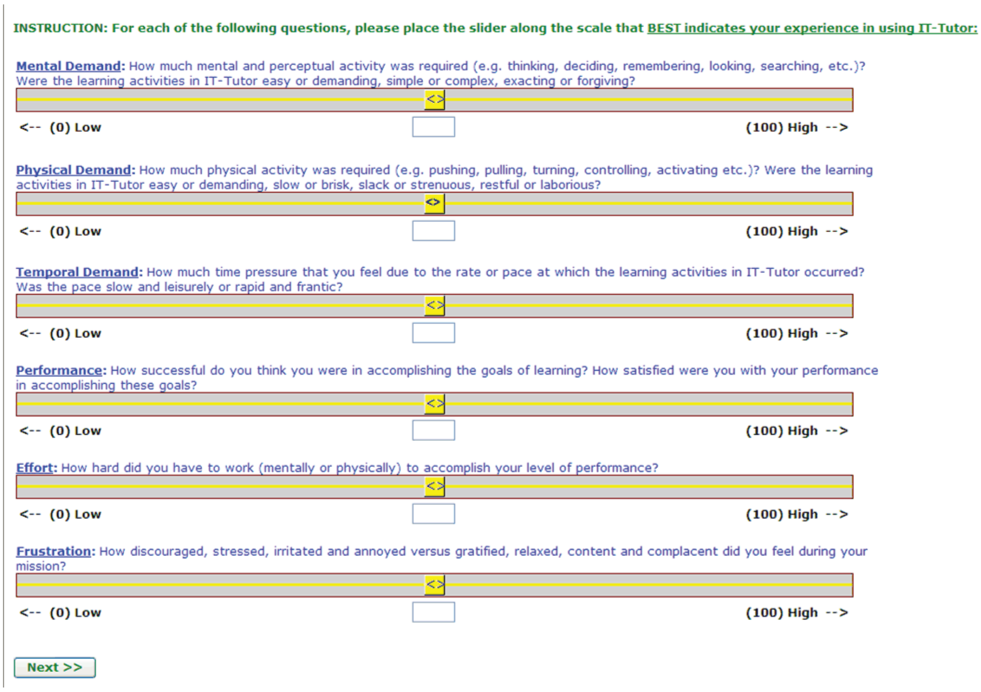


Figure D-1: Scales used to rate subjective workload

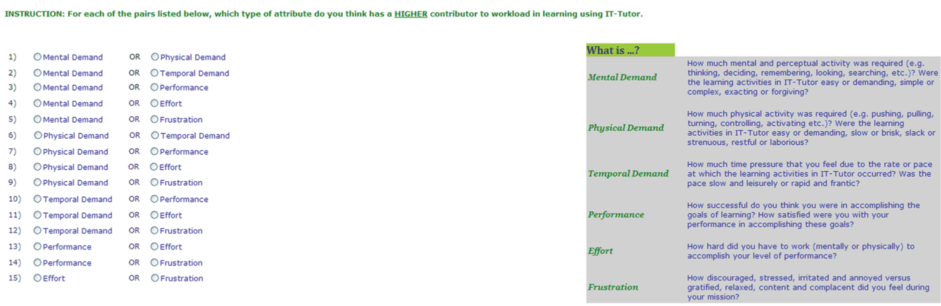


Figure D-2: Fifteen pair-wise of source of subjective workload

Example 1:

Let's assume the participant's ratings on the individual subscales as in Table D-1 and source of workload in Table D-2.

Table D-1: Example of a participant's scores on the in individual subscales

NASA-TLX subscales	Participant's Score
Mental demand	70
Physical demand	35
Temporal demand	10
Performance	90
Effort	43
Frustration	36

Table D-2: Example of a participant's choices on the source of workload

NASA-TLX subscales	Participant's Choice
Mental Demand OR Physical Demand	Mental Demand
Mental Demand OR Temporal Demand	Mental Demand
Mental Demand OR Performance	Performance
Mental Demand OR Effort	Mental Demand
Mental Demand OR Frustration	Mental Demand
Physical Demand OR Temporal Demand	Physical Demand
Physical Demand OR Performance	Performance
Physical Demand OR Effort	Effort
Physical Demand OR Frustration	Frustration
Temporal Demand OR Performance	Performance
Temporal Demand OR Effort	Effort
Temporal Demand OR Frustration	Frustration
Performance OR Effort	Performance
Performance OR Frustration	Performance
Frustration OR Effort	Frustration

Calculation Process:

1) Tally up the number of subscale that contributed the most to workload from Table D-2. Table D-3 shows the tallied number of the high workload source.

Table D-3: Source of workload tally sheet

NASA-TLX subscales	Tally	Weight
Mental demand	IIII	4
Physical demand	I	1
Temporal demand		0
Performance	~~IIII~~	5

Effort	II	2
Frustration	III	3
Total Count (must always equal to 15)		**15**

2) Calculate the weighted ratings. The individual weight for the subscale as in Table D-3 is used to calculate adjusted ratings (i.e., weight multiply by raw rating) and the overall weight rating for the participant in this example. The calculations are shown in Table D-4

Table D-4: Weighted rating worksheet

NASA-TLX subscales	Weight	Raw Rating	Adjusted Rating (Weight X Raw rating)
Mental demand	4	70	280
Physical demand	1	35	35
Temporal demand	0	10	0
Performance	5	90	450
Effort	2	43	86
Frustration	3	36	108
Sum of Adjusted Ratings			959
Weighted Rating (divide by 15)			**63.93**

Appendix E: Learning Contents of IT-Tutor

This document contains the learning contents and the set of quiz used in IT-Tutor.

Basic Computer Networks

Lesson Content & Tutorial Questions

This document contains domain knowledge for learning Basic Computer Networks. It is the main resource for developing IT-Tutor

Adapted from Shelly, G. B. & Vermaat, M. E. (2009) *Discovering Computers 2010: Living in a Digital World, Fundamentals*. 6th. Course Technology Press.
4 March 2010

Contents

1.0 Introduction to Network
1.1 Definition
1.2 Types of Networks
1.3 Network Architecture
1.4 Network Topology
1.5 Network Connections
2.0 Network Devices and Transmission Media
2.1 Network Devices
2.2 Physical Transmission Media
2.3 Wireless Transmission Media

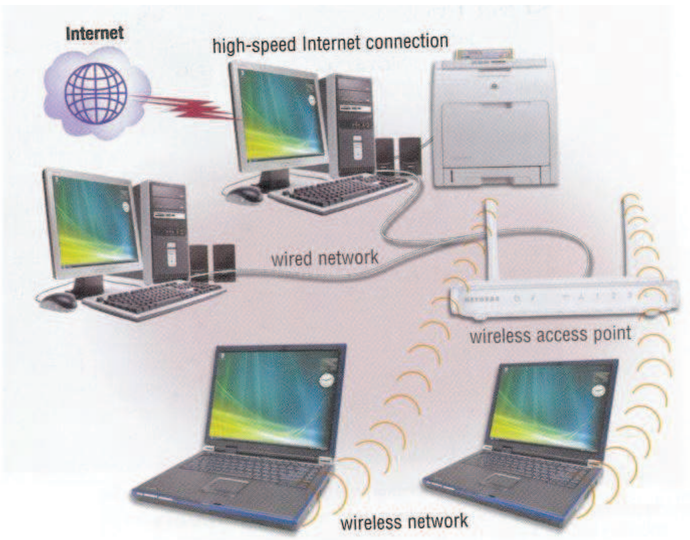
1.0 Introduction to Network

1.1 Definition

What is a network?

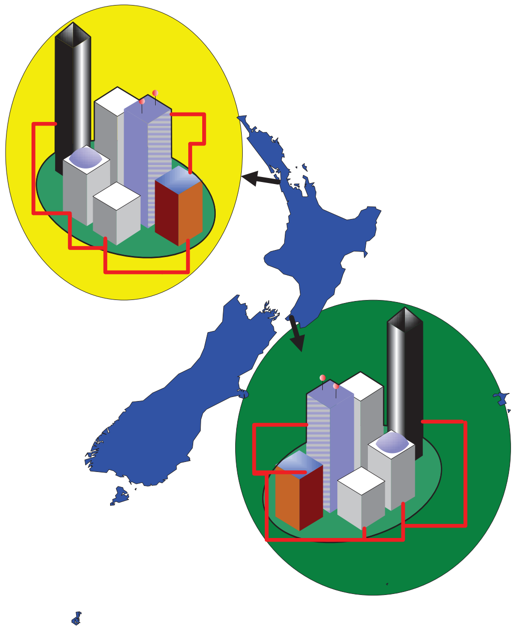
- Collection of computers and devices connected via communications devices and transmission
  media
- There are three types of networks: 1) local area network (LAN), 2) metropolitan area network, 3) wide area network (WAN)

1.2 Types of Networks



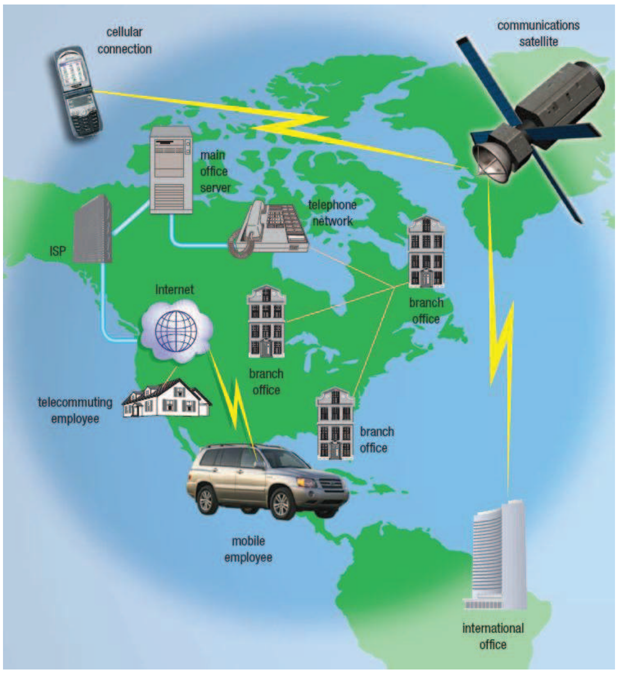
What is a local area network (LAN)?

- Is a network that connects computers in limited geographical area such as home or office building.
- A wireless LAN (WLAN) is a LAN that uses no physical wires.



What is a metropolitan area network (MAN)?

- A high-speed network that connects local area networks in a metropolitan area such as city or town and handles the bulk of communications activities across that region.



What is a wide area network (WAN)?

- Network that covers large geographic area using many types of media. Internet is world's largest WAN

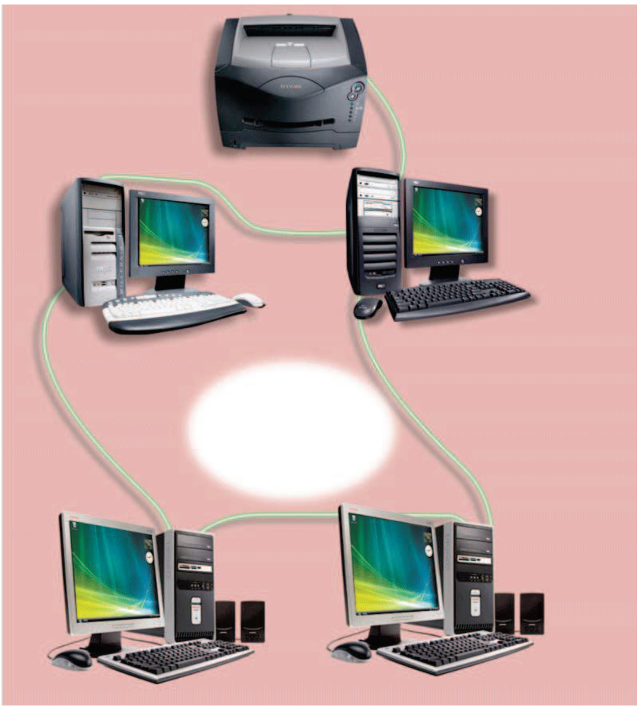
1.3 Network Architecture

What is network architecture?

- Network architecture is the design of computers, devices and media in a network.
- Two types of network architecture; 1) client/server and 2) peer-to-peer

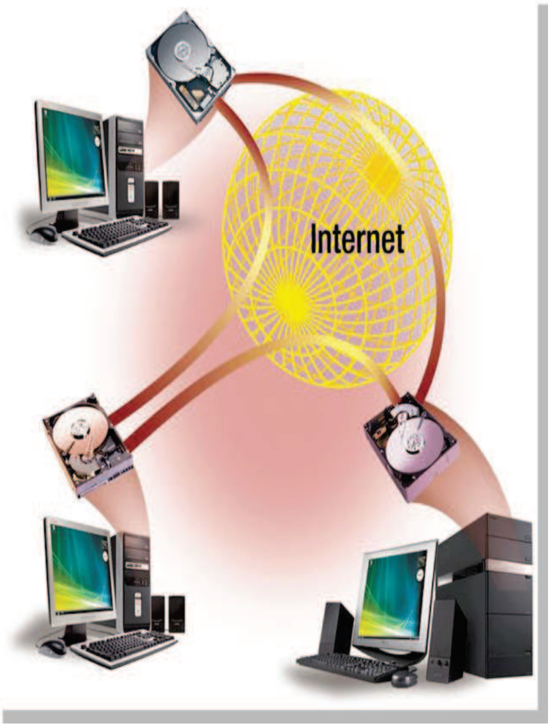
What is a client/server network?

- One or more computers act as a server; the other computers on the network request services from the server.
- A server controls access to the hardware, software and other resources on the network and provides a centralized storage area for programs, data and information.
- The clients are other computer and mobile devices on the network that rely on the server for its resources.



What is a peer-to-peer network?

- Simple network that connects fewer than 10 computers
- Each computer, or peer, has equal responsibilities and capabilities.
- Each computers store files on its own storage devices.



What is Internet peer-to-peer (P2P)?

- Enables users to connect to each other's hard disks and exchange files directly

1.4 Network Topology

What is network topology?

- Layout of devices in a network. Popular topologies are bus, ring, and star

What is bus network?

- All computers and devices connect to a single central cable, or known as bus. The bus is the physical cable that connects the computers and other devices. The bus transmits data, instructions, and information in both directions.

What are the advantages of bus network?

- Inexpensive and easy to install.
- Computers and other network devices can be attached and detached at any time without disturbing the rest of the network.
- Failure of one device does not affect the rest of the network.

What is the disadvantage of bus network?

- If the bus cable is faulty, the whole network is inoperative until the bus is back in working order.

What is ring network?

- A type of topology where a cable forms a closed loop (ring) with all computers and devices arranged along the ring.
- Data transmitted on a ring network travel from device to device around the entire ring, in one direction until it reaches its destination.

What is the advantage of ring network?

- A ring network can span a larger distance than bus network.

What is the disadvantage of ring network?

- If a device is malfunctioning, all computers before the device are working however other devices after the failed device cannot function.
- Ring network is difficult to install.

What is star network?

- All computers and devices (called as nodes) on the network connect to a central device, thus forming a star.
- Two types of devices that provide a common central connection point for nodes in the networks are: 1) a hub and 2) a switch.
- Data that travel from one node to another will pass through the hub/switch.

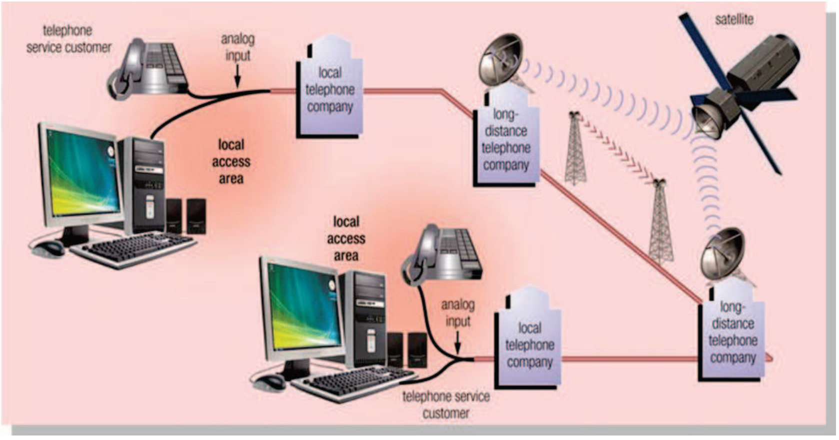
What is the advantage of star network?

- Easy to install and maintain.

What is the disadvantage of star network?

- *If the hub/switch fails, the entire network is inoperable until the device is repaired.

1.5 Network Connections



What is the public switched telephone network (PSTN)?

- Worldwide telephone system that handles voice-oriented telephone calls
- Data, instructions and information are transmitted over the telephone network using dial-up lines or dedicated lines

What is a dial-up line?

- Temporary connection using one or more analog telephone lines for communications
- Costs no more than making regular call
- Computers at any two locations can establish a connection using modems and telephone network

SPEEDS OF VARIOUS INTERNET CONNECTIONS

Type of Line	Approximate Monthly Cost	Transfer Rates*
Dial-up	Local or long-distance rates	Up to 56 Kbps
ISDN	$10 to $40	Up to 144 Kbps
DSL	$13 to $70	128 Kbps to 8.45 Mbps
Cable TV (CATV)	$20 to $50	128 Kbps to 36 Mbps
FTTH and FTTB	$35 to $180	5 Mbps to 30 Mbps
Fixed Wireless	$35 to $80	256 Kbps to 10 Mbps
Fractional T1	$200 to $700	128 Kbps to 768 Kbps
T1	$400 to $1,600	1.544 Mbps
T3	$5,000 to $15,000	44.736 Mbps
ATM	$3,000 or more	155 Mbps to 622 Mbps, can reach 10 Gbps

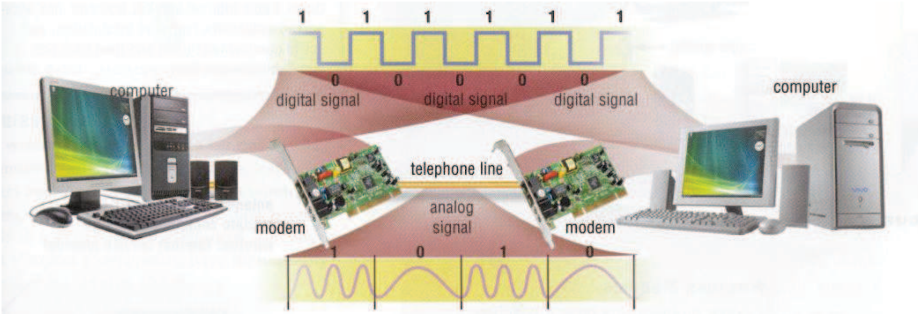
*Kbps = thousand bits per second
Mbps = million bits per second
Gbps = billion bits per second

What is a dedicated line?

- Always-on connection between two communications devices
- Five types are ISDN line, DSL, FTTB and FTTH, T-carrier line, and ATM

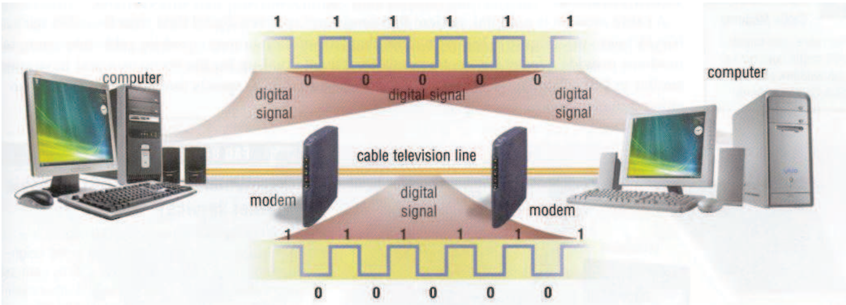
2.0 Network Devices and Transmission Media

2.1 Network Devices



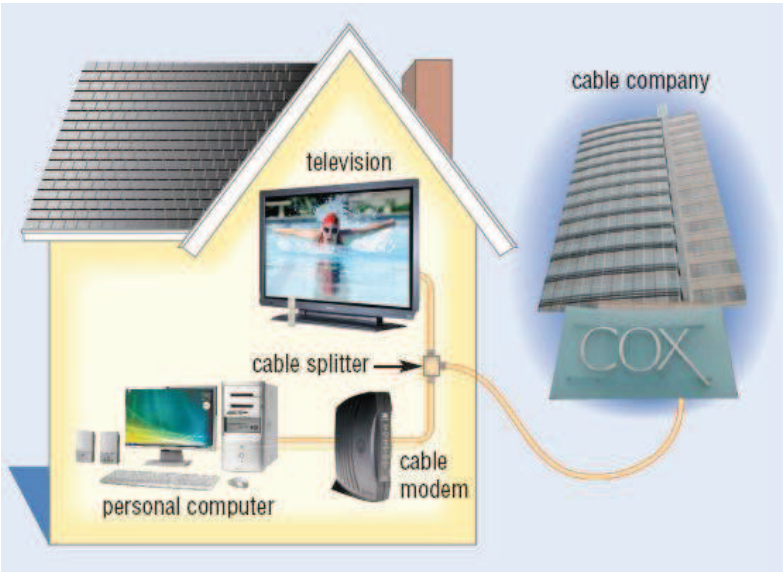
What is a dial-up modem?

- A communication device that converts digital signals to analog signals and vice versa
- The word modem is derived from the word MOdulatorDEModulator



What are ISDN and DSL modems?

- Communications devices that send and receive digital ISDN and DSL signals
- Usually external devices in which one end connects to a telephone line and the other end connects to a port on the system unit

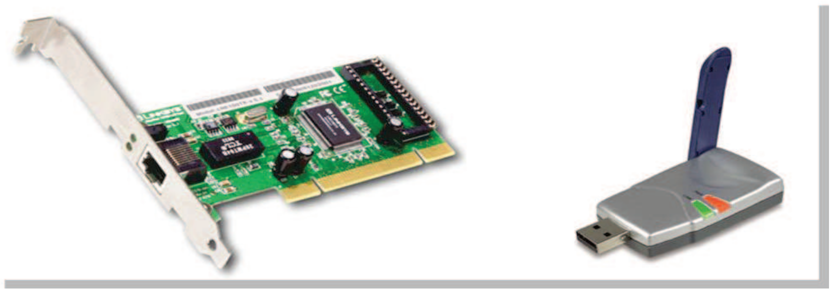


What is a cable modem?

- Sends and receives data over cable television network
- Much faster than dial-up modem or ISDN

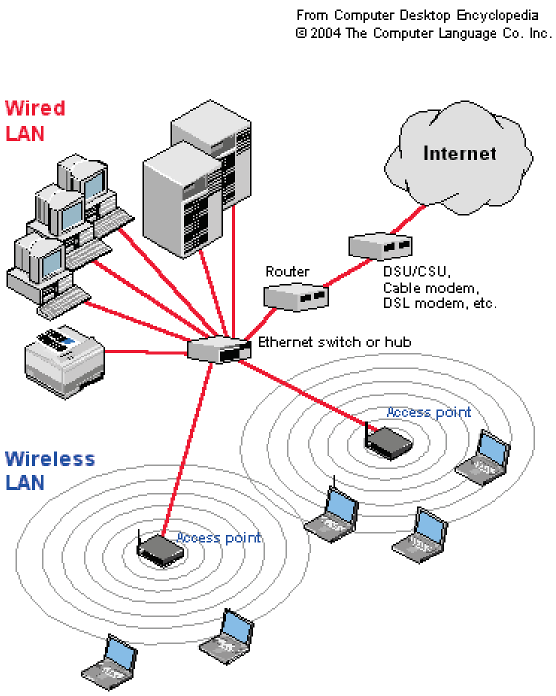
What is a wireless modem?

- Allows access to the Web wirelessly from a notebook computer, a PDA, a smart phone, or other mobile device
- Typically use the same waves used by cellular telephones



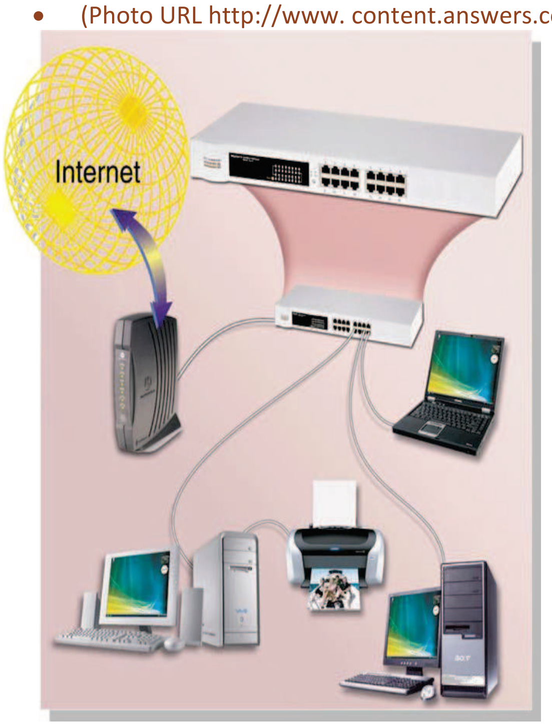
What is a network card?

- Adapter card, PC Card, ExpressCard module, USB network adapter or flash card that enables a computer or device to access a network



What is a wireless access point?

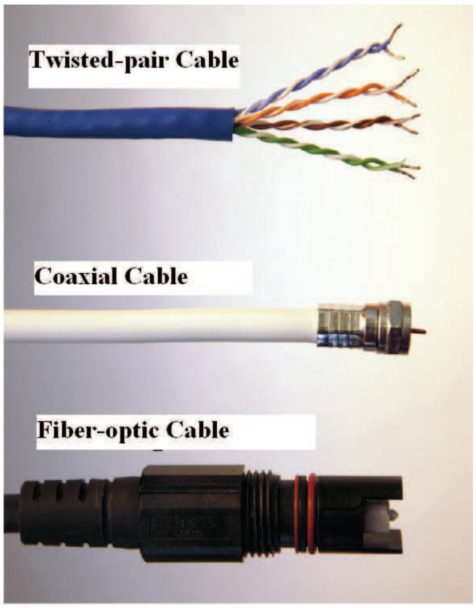
- Central communications device that allows computers and devices to transfer data wirelessly among themselves or to wired network
- (Photo URL http://www. content.answers.com/main/content/img/CDE/WLAN.GIF)



What is a router?

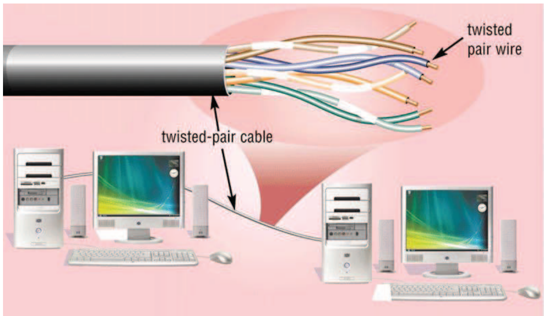
- Connects computers and transmits data to correct destination on network
- Routers forward data on the Internet using fastest available path

2.2 Physical Transmission Media



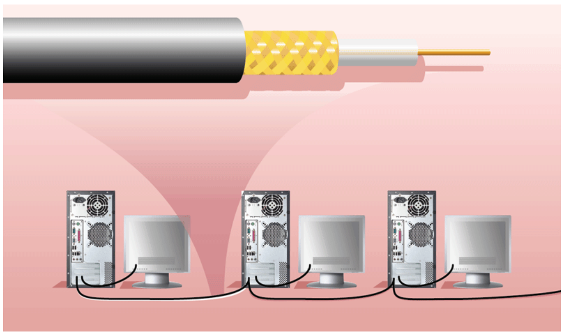
What is physical transmission media?

- Physical transmission media refers to transmission medium that present in the form of cables such as twisted-pair, coaxial cable and fiber optics.
- (Photo URL: http://www.fairfaxcounty.gov/cable/channel16/connecting/dsc_0901_color.jpg)



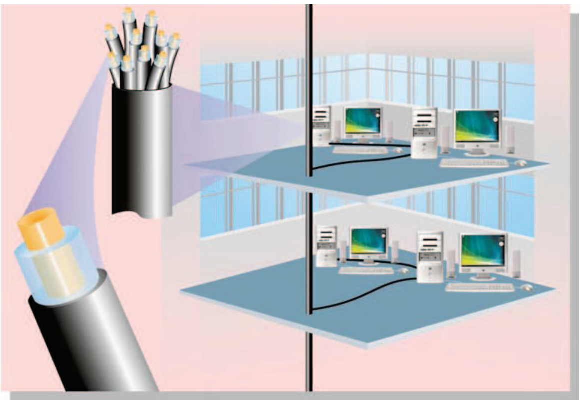
What is twisted-pair cable?

- A type of network cable which made up of one or more twisted-pair wires bundled together.
- Each twisted pair wire consists of two separate insulated copper wires that are twisted together to reduce noise (an electrical disturbance that can degrade communications)



What is coaxial cable?

- A network cable which made up of a single copper wire surrounded by at least three layers: 1) an insulating material, 2) a woven or braided metal, and 3) a plastic outer coating
- This type of cable is usually used for cable television (CATV) network wiring.



What is fiber-optic cable?

- A network cable that contained dozens or hundreds of thin strands of glass or plastic, which uses light to transmit signals. Each strand (optical fibre) is as thin as a human hair.
- Inside the fibre optic cable, an insulating glass cladding and a protective coating surround each optical fibre.

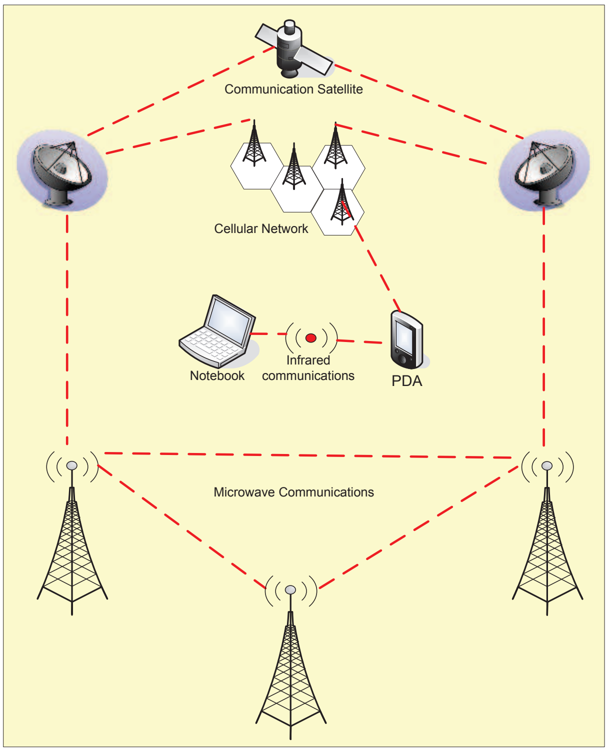
What are the advantages of fibre-optic cable?

- Higher capability in carrying signals than other cables
- Faster data transmission
- Less susceptible to noise
- Better security for signals during transmission because they are less susceptible to noise
- Smaller size (much thinner and lighter weight)

What are the disadvantages of fibre-optic cable?

- Expensive in cost
- Difficult to install and maintain

2.3 Wireless Transmission Media



What is wireless transmission media?

- Used when inconvenient, impractical, or impossible to install cables
- Includes infrared, broadcast radio, cellular radio, microwaves, and communications satellites

What is broadcast radio?

- Broadcast radio distributes radio signals through the air over long distances

What is cellular radio?

- Cellular radio is form of broadcast radio used for mobile communications
- A cellular telephone is a telephone device that uses high-frequency radio waves to transmit voice and digital data messages

What is a microwave station?

- Earth-based reflective dish used for microwave communications
- Must transmit in straight line with no obstructions

What is a communications satellite?

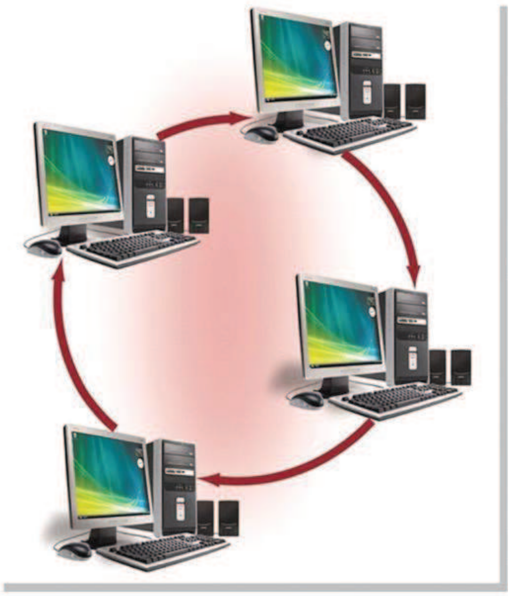
- Space station that receives microwave signals from earth-based station, amplifies signals, and broadcasts signals back over a wide area to any number of earth-based stations

TUTORIAL QUESTIONS

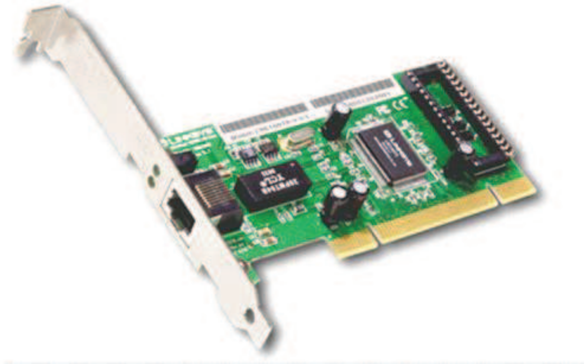
SESSION 1

1) What type of network represented by the figure?
Answer: wide area network
MCQ: Local area network, Wide area network, Metropolitan area network, Personal Area Network

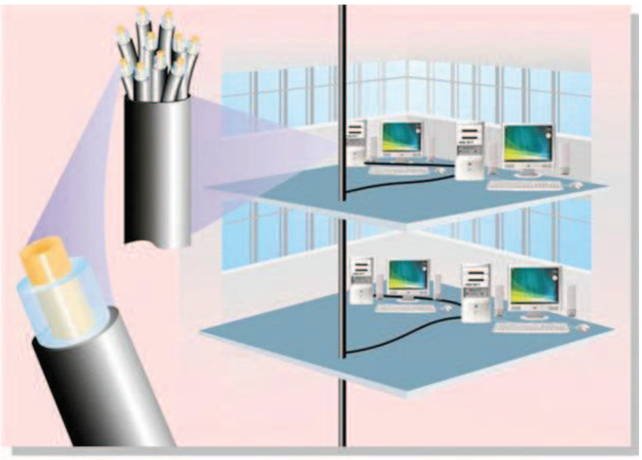
2) What type of topology presented in this figure?
Answer: Ring
MCQ: Bus, Ring, Star, Hybrid



3) The purpose of the device is to enable access to a network. What is the device name?
Answer: Network Card
MCQ: Cable modem, Wireless Modem, Router, Network Card

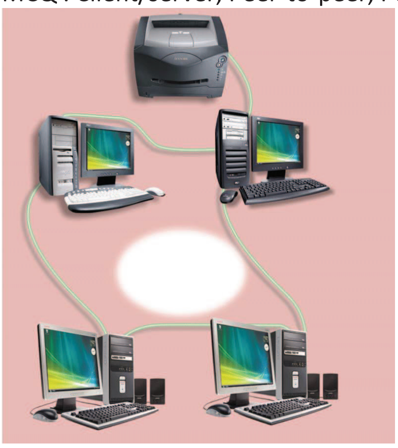


4) What type of cable presented by this figure?
Answer: fiber-optic
MCQ: Twisted-pair, Fiber-optic, Coaxial cable, Ribbon Cable

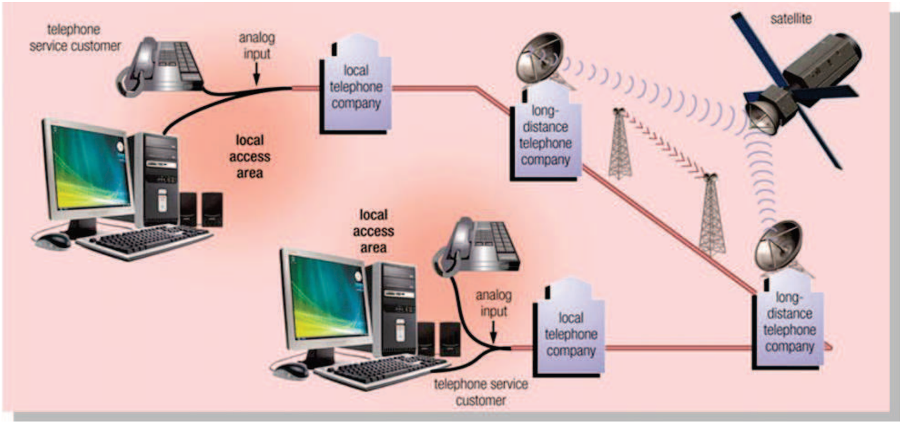


SESSION 2

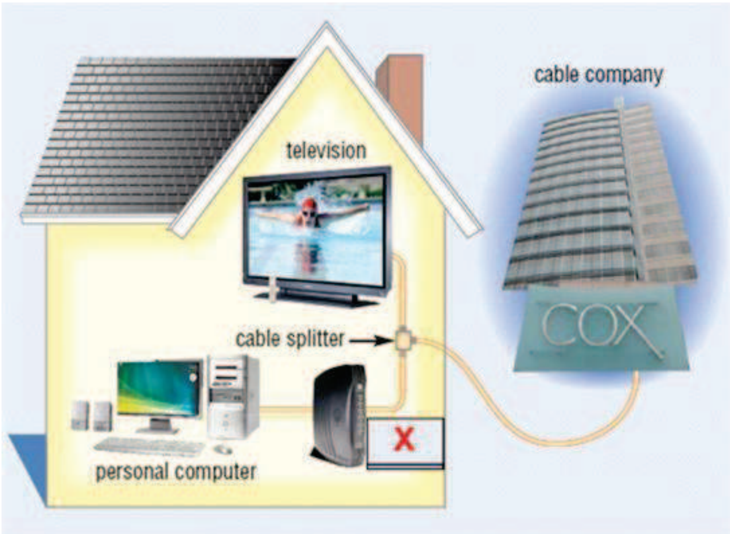
5) The figure shows and example of a network architecture in which each computer has equal responsibilities and capabilities. What is the type of architecture?
Answer: Peer-to-peer
MCQ : Client/server, Peer-to-peer, Point-to-point, Server/Client



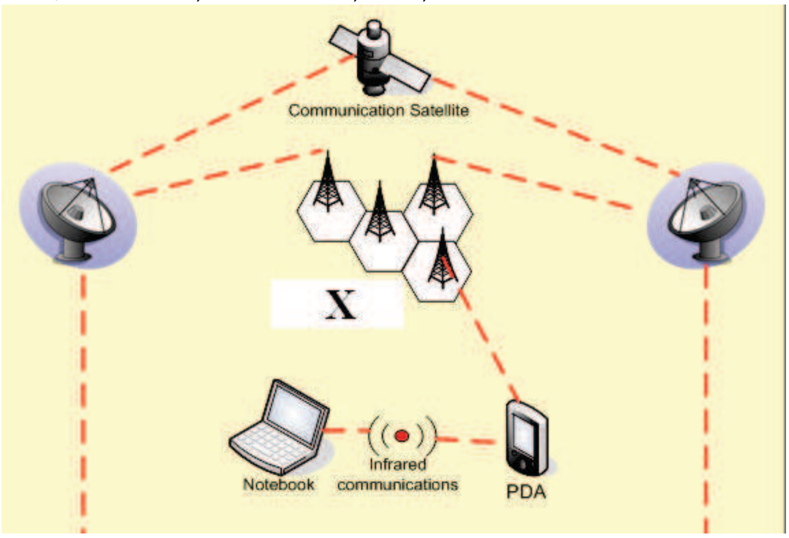
6) The existing telephone network is possible to establish network connection as in the figure. This connection is always referred to as ______________________.
Answer: public switched telephone network
MCQ : Broadband, **Integrated Services Digital Network (ISDN)**, Public switched telephone network (PSTN), ***Digital Subscriber Line(DSL)***



7) X in the figure is _________________________________.
Answer: cable modem
MCQ : TV modem, Cable modem, Entertainment Modem, Router



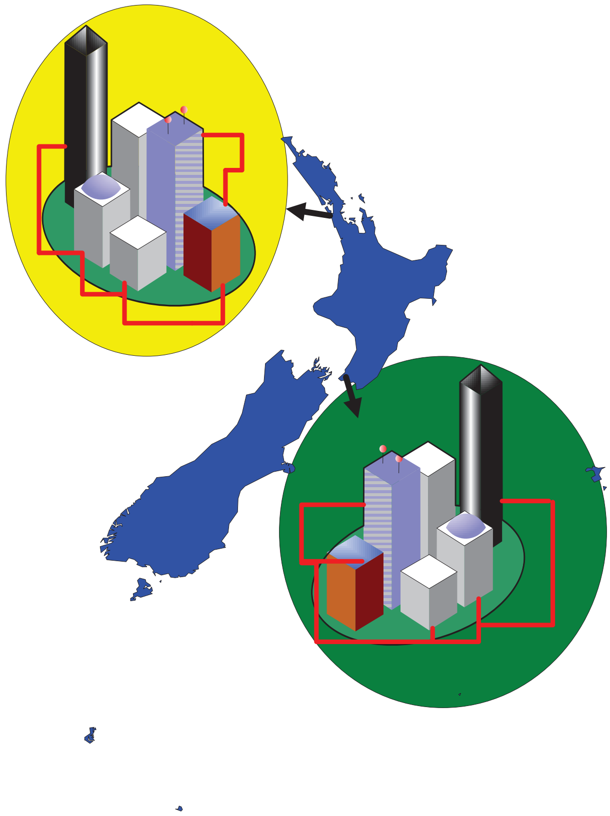
8) What type of wireless network represented by X?
Answer: cellular radio
MCQ : Microwave, Cellular radio, Wi-Fi, IRDA



SESSION 3

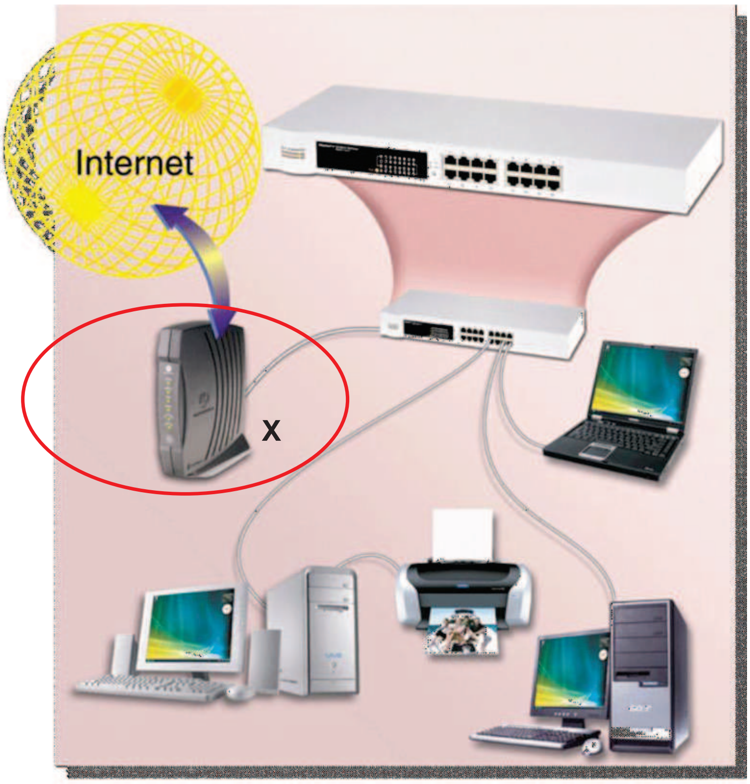
9) X in the figure shows a central controlling device in a star network. What is the device?
Answer: hub, switch

10) The figure shows a type of network in which it spans throughout a city. What type of network the figure is referring to?
Answer: metropolitan area network (MAN)



11) X is the most common wired transmission media used in a computer network. What is X?
Answer: twisted-pair

12) The role of X in the figure is to forward data in the internet using the fastest available path. What is X?
Answer: Modem



Appendix F: IT-Tutor Algorithm & Rules

This section contains two parts. The first part explains the algorithm for sequencing the learning contents and second part shows the code snippet for the rules that has been used in IT-Tutor system.

Algorithm

The following algorithm shows the sequencing procedure in IT-Tutor. The algorithm analyses learners' prior and current knowledge to identify the appropriate learning contents.

```
If <learner's prior knowledge> is <insufficient> then
    Give feedback to learner
    Present the sequence of learning contents
    Test <learner's current knowledge>
    Give feedback to learner
    If <learner's current knowledge> is <sufficient> then
        Proceed to the next level of learning
    Else
        Reinforce the current sequence of learning contents
If <learner's prior knowledge> is <sufficient> then
    Proceed to the next level of learning
    Present the sequence of learning contents
    Test <learner's current knowledge>
    Give feedback to learner
    If <learner's current knowledge> is <sufficient> then
        Proceed to the next level of learning
    Else
        Reinforce the current sequence of learning content
```

Code Snippet for the rules

The algorithm above has been pre-programmed as a set of rules in Visual Basic as presented in the following code snippet. The code was written in a VB sub routine and also called other sub routines in the programme.

```
'*****RULES FOR GENERATING A SEQUENCE **************
Sub DisplaySession1Result()
Using myConnection As New
SqlConnection(ConfigurationManager.ConnectionStrings("ConnectionString2").ConnectionString)

Const SQL1 As String = "SELECT * FROM TutorialSession WHERE [TutorialId] =@ID"
Dim myCommand1 As New SqlCommand(SQL1, myConnection)

Dim Question1 As String
Dim Question2 As String
Dim Question3 As String
Dim Question4 As String

myConnection.Open()
myCommand1.Parameters.AddWithValue("@ID", CInt(TutorialID.Text))
Dim myReader1 As SqlDataReader = myCommand1.ExecuteReader()
If myReader1.Read Then
Question1 = myReader1("Q1Answer")
Question2 = myReader1("Q2Answer")
Question3 = myReader1("Q3Answer")
Question4 = myReader1("Q4Answer")

If Question1 = "Wrong" And Question2 = "Correct" And Question3 = "Correct" And Question4 = "Correct"
Then ' -------------wrong in question 1 only
    Dim myAlert As String = "alert('Question 1 was wrong. You need to study the concept for Question
1.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
   Label11.Text = "Question 1 was wrong"
```

```
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(1)
    Label13.Text = 7
    Label24.Text = 1 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

 ElseIf Question1 = "Correct" And Question2 = "Wrong" And Question3 = "Correct" And Question4 = "Correct"
Then ' -------------wrong in question 2 only
    Dim myAlert As String = "alert('Question 2 was wrong. You need to study the concept for Question
2.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 2 was wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(8)
    Label13.Text = 12
    Label24.Text = 2 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Correct" And Question2 = "Correct" And Question3 = "Wrong" And Question4 = "Correct"
Then ' -------------wrong in question 3 only
    Dim myAlert As String = "alert('Question 3 was wrong. You need to study the concept for Question
3.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 3 was wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(13)
    Label13.Text = 19
    Label24.Text = 3 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Correct" And Question2 = "Correct" And Question3 = "Correct" And Question4 = "Wrong"
Then ' -------------wrong in question 4 only
    Dim myAlert As String = "alert('Question 4 was wrong. You need to study the concept for Question
4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 4 was wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(20)
    Label13.Text = 24
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Wrong" And Question3 = "Correct" And Question4 = "Correct"
Then ' -------------wrong in question1 and 2 only
    Dim myAlert As String = "alert('Question 1 and 2 were wrong. You need to study the concept for Question
1 and 2.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 1 and 2 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(1)
    Label13.Text = 12
    Label24.Text = 2 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Correct" And Question3 = "Wrong" And Question4 = "Correct"
Then ' -------------wrong in question1 and 3 only
```

```
     Dim myAlert As String = "alert('Question 1 and 3 were wrong. You need to study the concept for Question 1 and 3.\nClick OK to proceed.');"
      ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
      Label11.Text = "Question 1 and 3 were wrong"
      MultiView1.SetActiveView(View2)
      DisplayDomainKnowledge(1)
      Label13.Text = 7
      Label20.Text = "1"
      DisplayDomainKnowledge1(13)
     Label14.Text = 13
     Label19.Text = 7
     Label24.Text = 3 ' Revision question ID
     Dim RevisionQuestion As Integer = CInt(Label24.Text)
     displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Correct" And Question3 = "Correct" And Question4 = "Wrong" Then ' -------------wrong in question1 and 4 only
     Dim myAlert As String = "alert('Question 1 and 4 were wrong. You need to study the concept for Question 1 and 4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 1 and 4 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(1)
    Label13.Text = 7
    Label20.Text = "1"
    DisplayDomainKnowledge1(20)
    Label14.Text = 20
    Label19.Text = 5
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Correct" And Question2 = "Wrong" And Question3 = "Wrong" And Question4 = "Correct" Then  ' -------------wrong in question 2 and 3 only
     Dim myAlert As String = "alert('Question 2 and 3  were wrong. You need to study the concept for Question 2 and 3.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 2 and 3 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(8)
    Label13.Text = 19 ' 20-8 =12
    Label24.Text = 3 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Correct" And Question2 = "Wrong" And Question3 = "Correct" And Question4 = "Wrong" Then  ' -------------wrong in question 2 and 4 only
     Dim myAlert As String = "alert('Question 2 and 4 were wrong. You need to study the concept for Question 2 and 4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 2 and 4 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(8)
    Label13.Text = 5 'Number of content for this section
    Label20.Text = "1" ' 2 different views combined into 1
    DisplayDomainKnowledge1(20)
    Label14.Text = 20 'Content ID start with 20
    Label19.Text = 5 ' number of content
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)
```

```
ElseIf Question1 = "Correct" And Question2 = "Correct" And Question3 = "Wrong" And Question4 = "Wrong"
Then ' -------------wrong in question 3 and 4 only
    Dim myAlert As String = "alert('Question 3 and 4 were wrong. You need to study the concept for Question
3 and 4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 3 and 4 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(13)
    Label13.Text = 24 ' = 24-12 -- 24 is the total number of contents
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Wrong" And Question3 = "Wrong" And Question4 = "Correct"
Then ' -------------wrong in question 1, 2 and 3
    Dim myAlert As String = "alert('Question 1, 2 and 3 were wrong. You need to study the concept for
Question 1, 2 and 3.\nClick OK to proceed.');"
   ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
   Label11.Text = "Question 1, 2 and 3 were wrong"
   MultiView1.SetActiveView(View2)
   DisplayDomainKnowledge(1)
   Label13.Text = 19
   Label24.Text = 3 ' Revision question ID
   Dim RevisionQuestion As Integer = CInt(Label24.Text)
   displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Wrong" And Question3 = "Correct" And Question4 = "Wrong"
Then ' -------------wrong in question 1, 2 and 4
    Dim myAlert As String = "alert('Question 1, 2 and 4 were wrong. You need to study the concept for
Question 1, 2 and 4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 1, 2 and 4 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(1)
    Label13.Text = 12 'Number of content for this section
    Label20.Text = "1" ' 2 different views combined into 1
    DisplayDomainKnowledge1(20)
    Label14.Text = 20 'Content ID start with 20
    Label19.Text = 5 ' number of content
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Correct" And Question3 = "Wrong" And Question4 = "Wrong"
Then ' -------------wrong in question 1, 3 and 4
    Dim myAlert As String = "alert('Question 1, 3 and 4 were wrong. You need to study the concept for
Question 1, 3 and 4.\nClick OK to proceed.');"
    ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
    Label11.Text = "Question 1, 3 and 4 were wrong"
    MultiView1.SetActiveView(View2)
    DisplayDomainKnowledge(1)
    Label13.Text = 7 'Number of content for this section
    Label20.Text = "1" ' 2 different views combined into 1
    DisplayDomainKnowledge1(13)
    Label14.Text = 13 'Content ID start with 20
    Label19.Text = 12 ' number of content
    Label24.Text = 4 ' Revision question ID
    Dim RevisionQuestion As Integer = CInt(Label24.Text)
    displayRevisionQuestion(RevisionQuestion)
    'Label13.Text = 5
```

```
 ElseIf Question1 = "Correct" And Question2 = "Wrong" And Question3 = "Wrong" And Question4 = "Wrong"
Then ' -------------wrong in question 2, 3, and 4
      Dim myAlert As String = "alert('Question 2, 3, and 4 were wrong. You need to study the concept for
Question 2, 3 and 4.\nClick OK to proceed.');"
      ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
      Label11.Text = "Question 2, 3 and 4 were wrong"
      MultiView1.SetActiveView(View2)
      DisplayDomainKnowledge(8)
      Label13.Text = 24 '24-8
      Label24.Text = 4 ' Revision question ID
      Dim RevisionQuestion As Integer = CInt(Label24.Text)
      displayRevisionQuestion(RevisionQuestion)

ElseIf Question1 = "Wrong" And Question2 = "Wrong" And Question3 = "Wrong" And Question4 = "Wrong"
Then ' -------------wrong in question 1, 2, 3 and 4
      Dim myAlert As String = "alert('Question 1, 2, 3 and 4 were wrong. You need to study the concept for
Question 1, 2, 3 and 4.\nClick OK to proceed.');"
      ClientScript.RegisterStartupScript(GetType(String), "loadScript", myAlert, True)
      Label11.Text = "Question 1, 2, 3 and 4 were wrong"
      MultiView1.SetActiveView(View2)
      DisplayDomainKnowledge(1)
     Label13.Text = 24
     Label24.Text = 4 ' Revision question ID
     Dim RevisionQuestion As Integer = CInt(Label24.Text)
     displayRevisionQuestion(RevisionQuestion)

Else ' -------------All correct
     MultiView1.SetActiveView(View1)
End If
End If

 myReader1.Close()
 myConnection.Close()
RadioButtonList1.Enabled = True
RadioButtonList1.Visible = True
End Using
End Sub
```

Appendix G: IT-Tutor Screenshots

This section explains how IT-Tutor works. It contains information about the flow of the system through screenshots.

IT-Tutor Screenshots

IT-Tutor is available through http://it-tutor.net/Part2.

1) Homepage

Users (students) will be presented with IT-Tutor homepage as in Figure G-1 at the beginning. It contains three menus: (i) Login, (ii) Sign-up, and (iii) Forgot password. It also explains the lesson covered by the system.

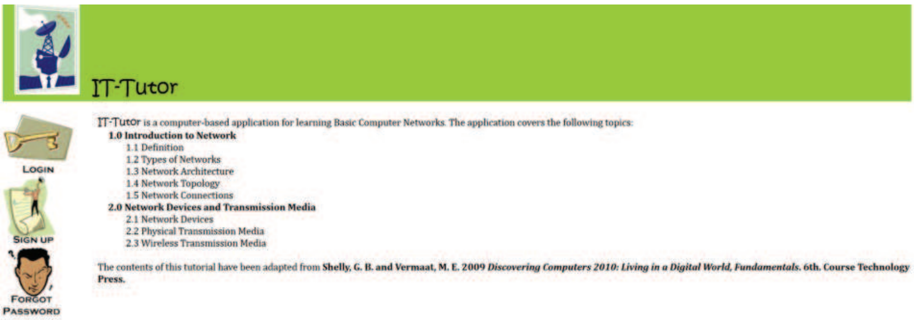


Figure G-1: IT-Tutor homepage

2) Login

Existing users are required to provide their user name and password to login. The login page is as in Figure G-2.

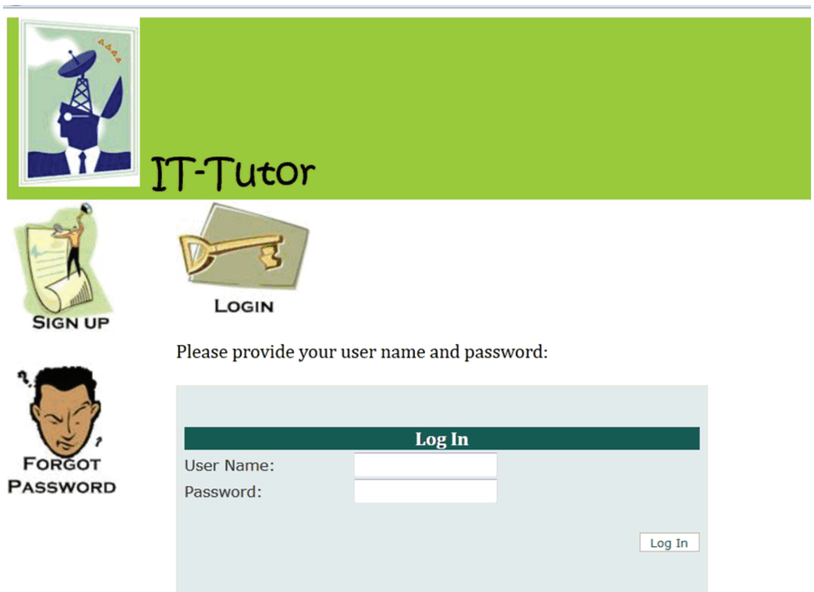


Figure G-2: Login Page

3) Sign-Up

A new user can sign up to use the system by providing some information including a preferred username and password, gender, age, email and security Q&A. Figure G-3 shows the screenshot of the page.

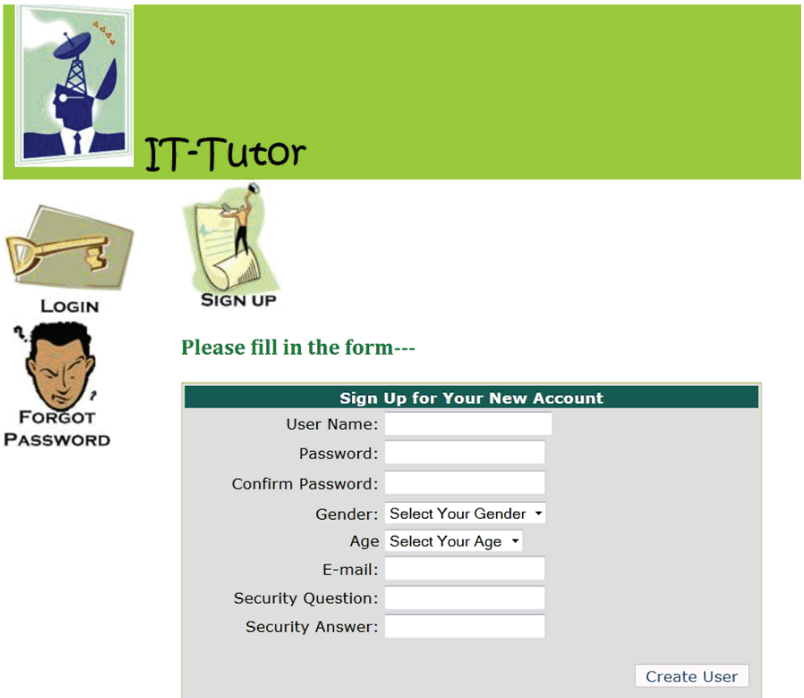


Figure G-3: Sign-up page

4) Forgot Password

Password could be retrieved back by providing the user name. The user name and password will be sent through email. Figure G-4 is a screenshot of the interface.

Figure G-4: Forgot Password page

5) Main menu

Upon successful login, a user will be presented with the main menu as in Figure G-5. The main menu contains four options: (i) Tutorial, (ii) Notes, (iii) Result, and (iv) Change password.

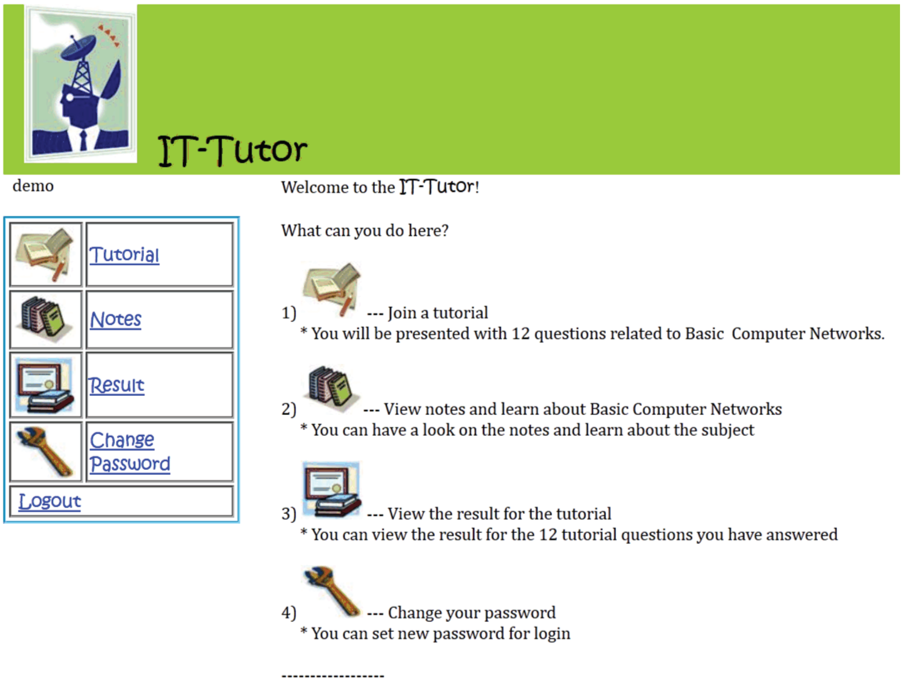


Figure G-5: Main menu

6) Tutorial

Figure G-6 shows the screenshot of the tutorial page. A user can proceed to the tutorial section by clicking the “Start the Tutorial Now” button.

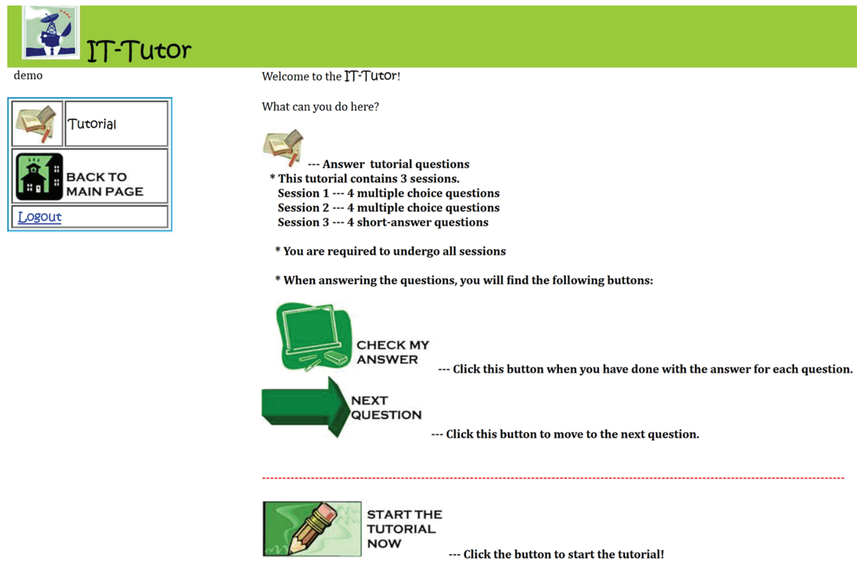


Figure G-6: Tutorial page

Figure G-7 shows an example of the tutorial questions.

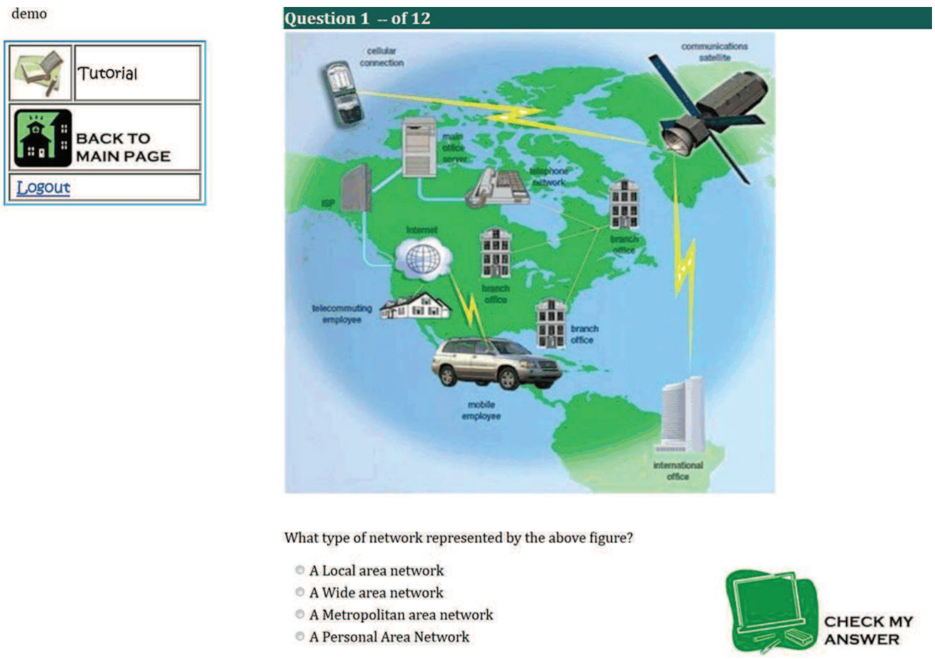


Figure G-7: Example of the tutorial questions

Figure G-8 shows the example of feedback when a user gives a correct answer.

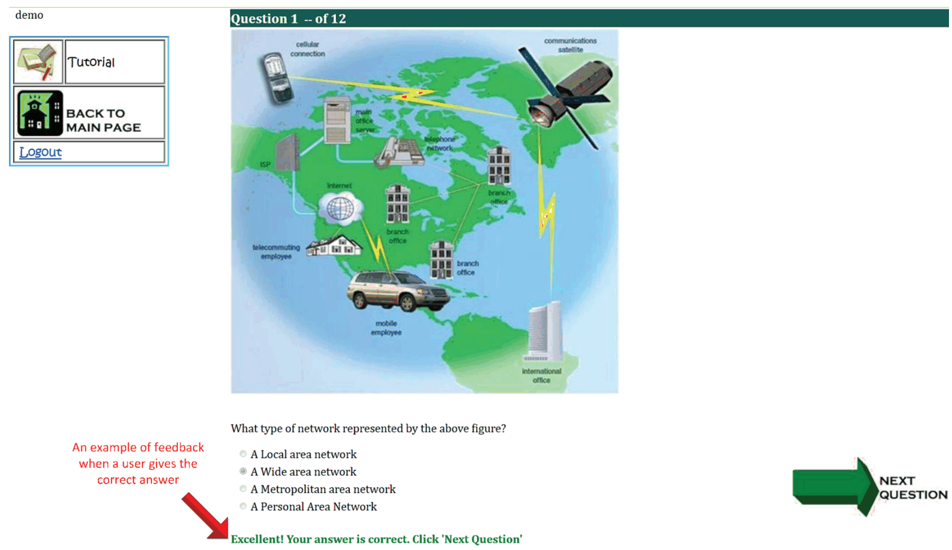


Figure G-8: Example of feedback of a correct answer

Figure G-9 shows the example of feedback when a user gives a wrong answer.

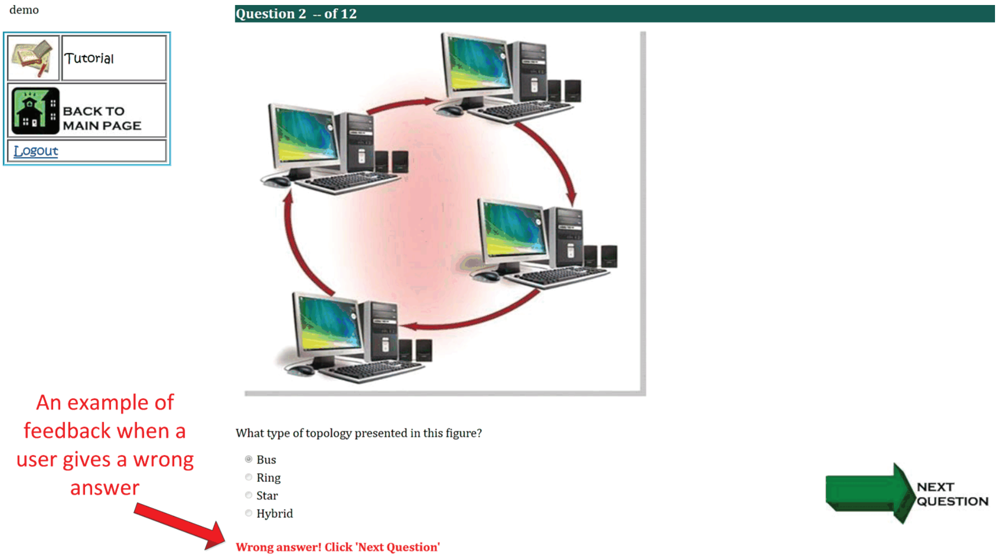


Figure G-9: Example of feedback of a wrong answer

IT-Tutor will redirect the user to explanation page associated with the tutorial questions. Figure G-10 shows an example of the page.

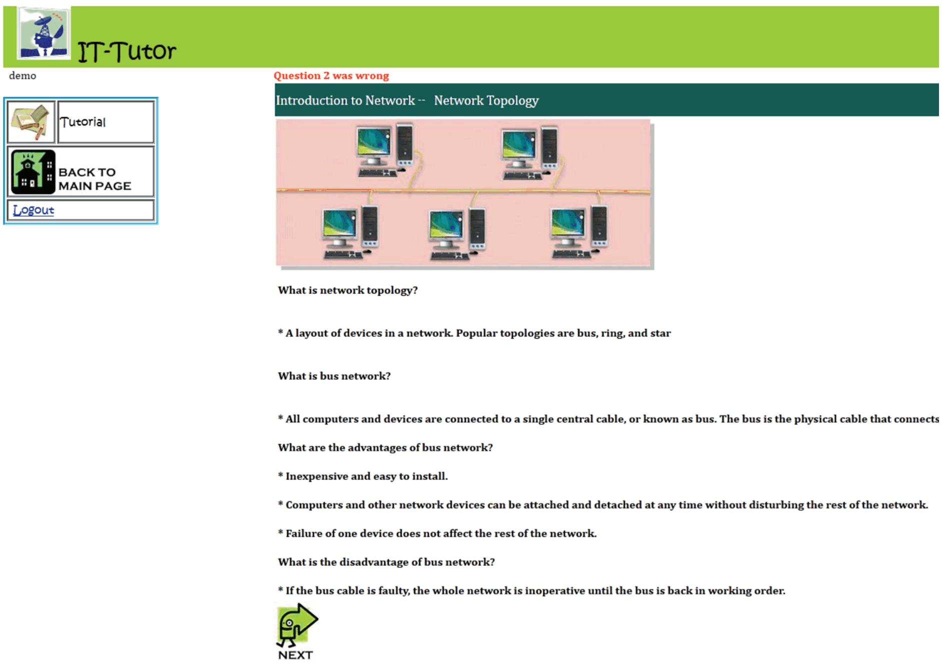


Figure G-10: Example of explanation page

7) Notes

The Notes page contains the learning notes in web pages and portable document format (pdf). Figure G-11 shows the screenshot of the interface.

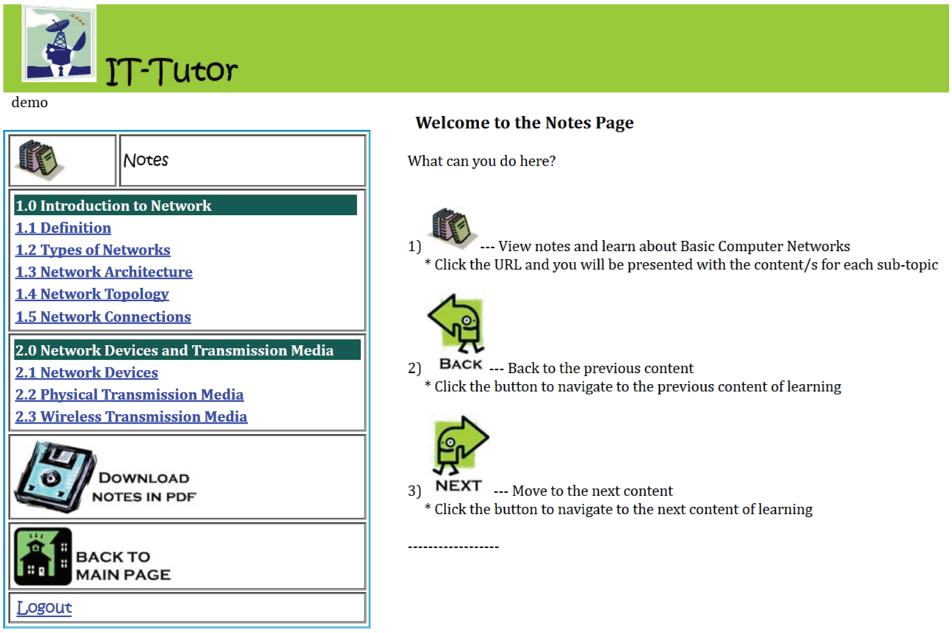


Figure G-11: Notes page

8) Results

A user can view the result of the tutorial session from the Result menu as in Figure G-12.

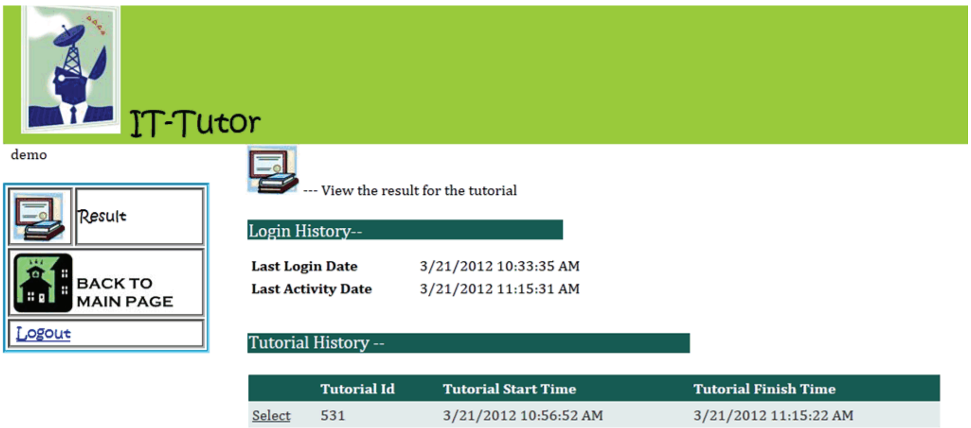
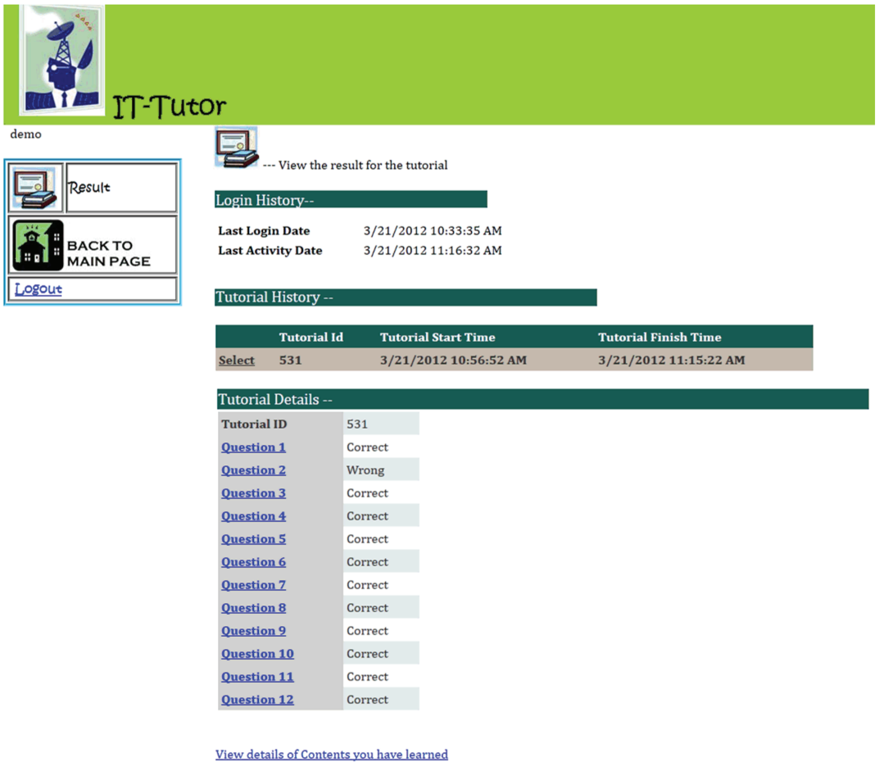


Figure G-12: Result page

A user can view the detail to his or her tutorial session by clicking the given link as in Figure G-13 and G-14.



Last Login Date	3/21/2012 10:33:35 AM
Last Activity Date	3/21/2012 11:16:32 AM

Tutorial History --

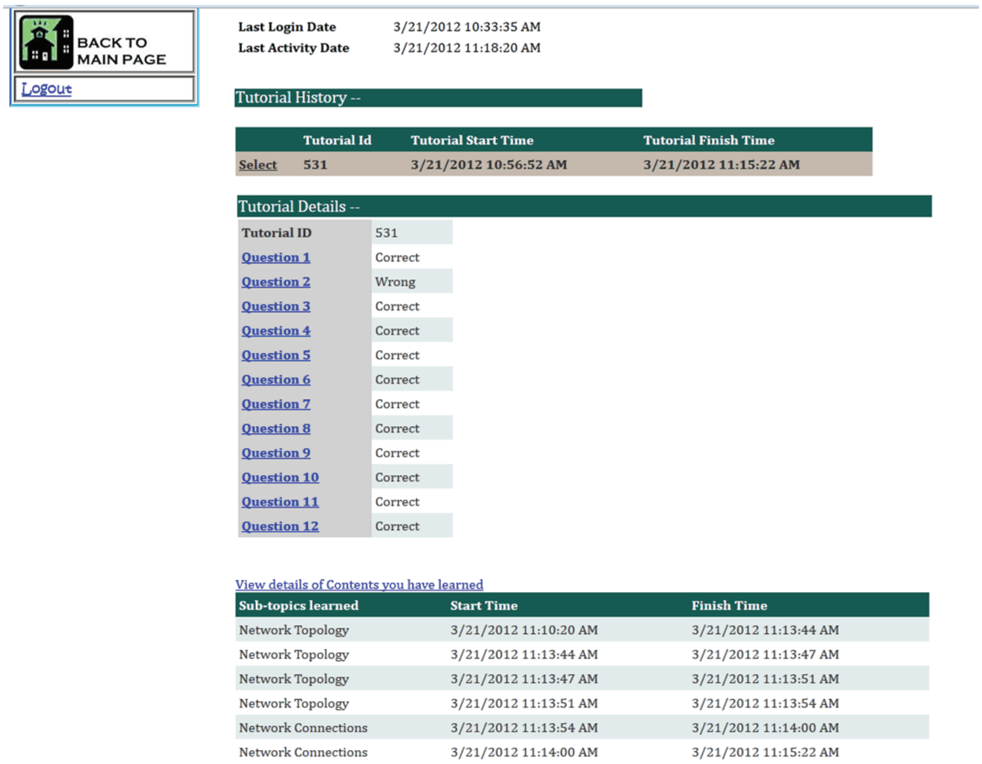
	Tutorial Id	Tutorial Start Time	Tutorial Finish Time
Select	531	3/21/2012 10:56:52 AM	3/21/2012 11:15:22 AM

Tutorial Details --

Tutorial ID	531
Question 1	Correct
Question 2	Wrong
Question 3	Correct
Question 4	Correct
Question 5	Correct
Question 6	Correct
Question 7	Correct
Question 8	Correct
Question 9	Correct
Question 10	Correct
Question 11	Correct
Question 12	Correct

View details of Contents you have learned

Figure G-13: Result page



Last Login Date	3/21/2012 10:33:35 AM
Last Activity Date	3/21/2012 11:18:20 AM

Tutorial History --

	Tutorial Id	Tutorial Start Time	Tutorial Finish Time
Select	531	3/21/2012 10:56:52 AM	3/21/2012 11:15:22 AM

Tutorial Details --

Tutorial ID	531
Question 1	Correct
Question 2	Wrong
Question 3	Correct
Question 4	Correct
Question 5	Correct
Question 6	Correct
Question 7	Correct
Question 8	Correct
Question 9	Correct
Question 10	Correct
Question 11	Correct
Question 12	Correct

View details of Contents you have learned

Sub-topics learned	Start Time	Finish Time
Network Topology	3/21/2012 11:10:20 AM	3/21/2012 11:13:44 AM
Network Topology	3/21/2012 11:13:44 AM	3/21/2012 11:13:47 AM
Network Topology	3/21/2012 11:13:47 AM	3/21/2012 11:13:51 AM
Network Topology	3/21/2012 11:13:51 AM	3/21/2012 11:13:54 AM
Network Connections	3/21/2012 11:13:54 AM	3/21/2012 11:14:00 AM
Network Connections	3/21/2012 11:14:00 AM	3/21/2012 11:15:22 AM

Figure G-14: Result page

9) Change password

A user can change his or her password using the given menu. Figure G-15 shows the screenshot of the page.

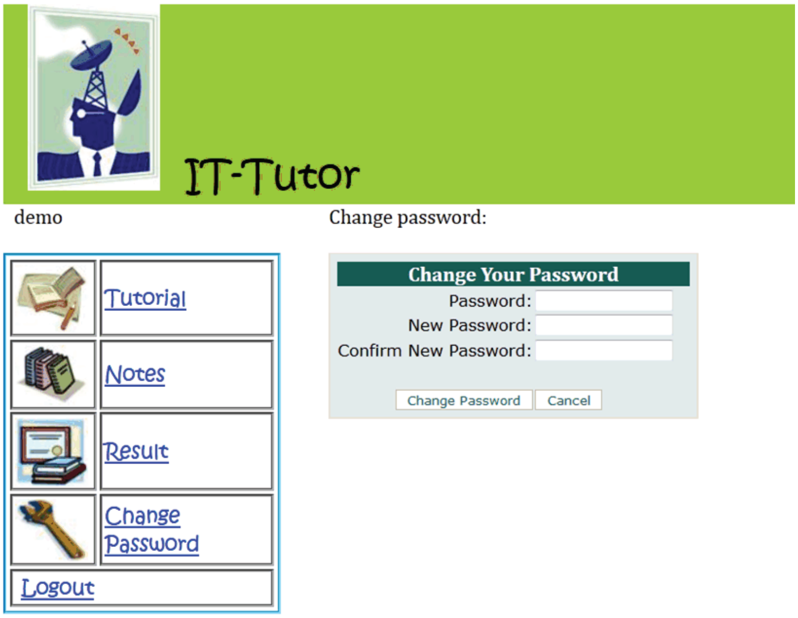


Figure G-15: Result page

Appendix H: Raw Data

This section contains raw data of the three experimental studies as reported in Chapters 5-7. Experiment 1 represents Chapter 5, Experiment 2 represents Chapter 6, and Experiment 3 represents Chapter 7.

Experiment 1(Chapter 5)

Questionnaire

Table H-1: Questionnaire Data

ID	Cat	Programme	Year of Study	English	Comp. Exp.	E-learning	CO1	CO2	CO3	AF1	AF2	AF3	CU1	CU2	CU3	II1	II2	II3
101	1	BSc	2	1	3	1	4	2	4	3	5	0	4	5	4	2	3	4
102	1	BSc (Human Nutrition)	2	2	3	3	3	1	4	3	3	4	2	2	2	2	3	3
103	2	B. Social Work	3	1	3	2	3	1	5	3	3	2	2	3	3	2	3	3
104	1	B. of Accountancy	2	2	3	3	3	1	3	2	1	5	4	4	3	2	4	4
105	1	B. of Arts, Politics and Social Anthropology	1	1	1	2	5	1	5	1	1	3	3	4	3	1	3	5
106	1	Phd	2	2	3	1	4	2	4	2	4	4	4	4	3	3	3	3
107	2	Phd	0	2	3	1	3	3	4	2	3	5	5	4	4	1	3	4
108	1	Phd	2	2	3	1	4	3	4	3	4	3	4	4	5	2	3	4
109	2	BSc Computer Science	2	1	3	2	4	2	3	2	2	4	5	4	3	2	4	4
110	2	PhD in IT	1	1	3	1	5	1	4	2	4	4	5	4	4	2	4	5
111	2	Graduate Diploma in CS	4	2	3	1	4	3	2	3	3	4	4	4	4	3	4	4
112	1	Graduate Diploma in CS	1	2	3	3	4	4	2	2	4	0	4	4	3	3	4	4
113	1	B. in IT and Project Management	4	0	3	3	5	1	4	5	3	5	4	4	4	2	5	4
114	1	B. of Information Science	2	1	3	2	4	2	3	2	3	3	4	5	3	2	4	5
115	2	B. of Info Science. PGDip	4	2	3	1	5	1	3	0	2	1	1	2	2	2	1	1
116	1	PhD. In Computer Engineering	2	2	3	1	4	3	3	5	5	3	4	5	3	1	3	4
343	2	PhD Animal Science	1	1	3	1	4	2	3	4	4	2	3	4	2	2	3	4
345	2	Phd	1	1	3	1	3	3	3	2	2	4	4	4	3	3	4	4
347	2	PhD Veterinary Epidemiology	3	1	3	2	2	4	2	3	2	4	2	2	2	3	2	2
348	1	phd in technology	1	2	3	3	4	2	4	4	3	3	4	4	4	2	4	3
349	2	PhD in History	1	1	3	1	3	5	3	4	4	1	2	2	2	4	2	2
354	2	PhD	1	1	3	1	1	5	1	3	3	3	2	2	2	4	2	2
355	2	PhD	2	2	3	2	4	4	4	4	4	4	4	4	4	4	4	4
356	2	PhD	1	2	3	2	3	2	3	3	3	3	2	2	2	4	3	3
358	2	Phd in Psychology	2	1	3	1	4	2	4	5	5	1	3	2	4	2	3	3
361	1	PhD in science	1	2	3	1	3	3	3	5	3	1	1	2	2	5	2	1

364	2	PhD in Statistics	1	1	3	1	2	3	3	4	3	3	3	3	3	3	3	3
367	2	PhD in Science	1	1	3	2	3	4	4	5	5	1	3	3	2	4	2	2
369	1	EdD	2	1	3	1	1	5	1	5	5	2	1	2	1	5	2	1
375	1	PhD in Public Health	4	1	3	2	4	1	2	5	4	2	4	4	1	3	3	3
380	2	PhD	1	2	1	2	2	2	3	3	2	2	3	3	4	4	4	4
381	2	PhD	2	2	3	1	4	2	4	2	2	4	2	5	5	4	3	3
382	1	PhD in Business	3	2	3	1	5	1	4	2	5	5	4	3	3	1	4	3
384	1	PhD in IS	2	2	3	2	1	5	1	2	2	2	2	2	2	2	1	1
386	1	PhD in Pyschology - volcanic hazards	1	1	3	3	3	4	2	2	2	4	4	3	3	3	3	4
388	1	PhD Public Health	1	1	3	1	2	4	2	4	4	2	3	2	2	2	3	3
391	1						2	2	2	1	1	4	3	3	2	2	4	3
393	2	PhD	2	2	3	2	5	1	5	1	4	5	5	5	5	4	4	5
394	1	PhD Sc	2	2		1	4	2	4	4	4	4	4	4	3	2	4	4
395	2	Ph.D in Education	1	2	3	1	2	4	1	4	4	3	5	5	3	2	3	4
396	1	MSc Mathematics	4	2	3	1	3	3	3	4	4	4	4	3	4	4	4	4
397	2	Doctorate in Education	1	2	3	1	4	2	4	4	4	2	3	3	2	2	4	4
398	1	B. of Accountancy	4	2	3	1	3	2	4	4	3	2	4	4	2	2	3	3
4115	2	PGD in Food Technology	1	2	3	1	3	2	4	2	2	4	4	5	4	2	4	4
4116	1	DClinPsych	2	1	3	2	4	2	3	4	4	2	2	2	2	5	2	2
4118	2	B. of Information Technology	4	2	3	1	4	1	3	4	3	1	4	4	3	1	3	4
4120	2	M.Sc IS	4	2	3	3	4	2	3	1	2	3	3	3	3	3	3	3
4122	2	B.of Information Technology	3	2	3	1	5	4	4	2	3	4	5	4	4	2	3	4
4130	1	B. of Technology Management	4	1	3	3	4	3	4	2	2	3	4	2	4	2	4	4
4133	2	Bachelor of Entrepreneur ship	4	2	3	2	4	1	4	2	3	4	4	4	4	2	5	5
4134	1	B. of human resources management	4	2	2	2	3	3	3	3	4	3	4	4	4	4	3	3
4136	2	B. of International Business Management	3	1	3	3	5	1	5	2	5	5	5	5	5	3	4	3
4140	2	B. of development management	4	2	2	1	5	2	5	5	5	5	5	5	5	1	5	5
4141	1	B. of International Bus.	4	2	3	3	4	2	4	3	3	3	4	4	3	3	3	3

		Management																
4143	2	B. of public management	2	2	3	3	3	4	2	4	3	3	4	4	4	3	4	3
4144	1	B. of Development Management	4	2	3	2	4	2	3	4	3	4	5	5	5	3	5	4
4149	1	B. of Education	2	2	3	2	2	3	5	5	4	2	4	5	5	1	4	4
4150	2	B. of Accounting	4	2	3	1	3	3	3	3	3	3	4	4	4	2	4	4
4151	2	certificate of it	4	2	3	3	5	1	1	1	1	1	1	5	1	5	1	1
4152	1	B. of agribusiness management sciences	4	2	2	2	5	1	4	1	4	3	4	2	4	1	4	4
4154	2	B. of tourism management	3	2	3	2	4	2	4	3	3	2	4	4	3	3	3	3
4158	1	B. of development	4	2	2	3	3	3	4	4	4	4	4	4	3	2	3	3
4159	2	B. of Multimedia	4	2	3	1	4	1	3	1	1	5	5	5	5	1	4	2
4162	2	No	1	2	3	2	4	4	4	4	4	4	4	4	4	4	4	4
4164	1	B. of Business Management	2	2	3	1	5	5	5	3	3	3	4	3	3	3	4	4
4168	2	B.of marketing	3	1	3	3	2	4	2	3	4	2	1	1	1	5	1	1
4176	1	B. of Business Administratio n	2	2	3	1	2	2	3	4	3	4	4	4	4	2	5	4
4177	2	PHD	1	2	3	2	5	1	5	4	4	3	4	4	4	2	4	4
4179	2	B. of Accounting	3	2	3	1	3	4	4	4	3	3	3	3	3	3	3	4
4180	1	B. of agribusiness management	3	2	2	3	3	3	3	2	2	2	4	4	4	1	4	5
4182	1	B. of Comm.	2	2	3	1	2	4	2	2	3	3	5	4	4	3	4	3
4186	2	B. of accountancy	4	2	3	1	5	2	3	4	3	5	3	2	3	2	4	4
4189	2	PhD in tourism and hospitality	1	2	3	3	2	4	3	1	4	4	5	4	4	1	5	5
4195	2	B. of Business Mathematics	4	1	3	3	4	3	4	4	2	2	4	4	3	3	2	1
4197	2	B. of Media Technology	4	2	3	3	4	2	4	3	4	4	4	2	4	3	3	4
4200	1	B. MUAMALAT ADMINISTRAT ION	4	2	3	1	5	1	5	5	1	5	5	5	5	1	5	5
4201	2	B..of Business Mathematics	2	2	3	3	3	3	3	4	2	3	2	2	3	4	2	4
4203	1	B. of IT	4	2	3	1	5	1	4	1	2	1	4	4	3	1	5	4

<u>Guideline for the columns in Table H-1</u>

1) Column 1 → Subjects' identification numbers
2) Colum 2→ Cat = Category
   1=DCSS, 2=Non-DCSS
3) Column 3→Programme= Programme of study

4) Column 4 →Year of study
1 = Less than a year, 2 = 2-3 years, 3 = More than 3 years, 4 = Never used the computer
5) Column 5 →English
1 = First language, 2= second language
6) Column 6 →Computer experience
1 = Less than a year, 2 = 2-3 years, 3 = more than three years, 4 = never used the computer
7) Column 7→E-learning experience
1= yes, 2= no, 3= not sure
8) Column 8→CO1 = Control dimension (item 1)
9) Column 9 →CO2 = Control dimension (item 2)
10) Column 10 →CO3 = Control dimension (item 3)
11) Column 11 →AF1 = Attention Focus (item 1)
12) Column 12 →AF2 = Attention Focus (item 2)
13) Column 13 →AF3 = Attention Focus (item 3)
14) Column 14 →CU1 = Curiosity (item 1)
15) Column 15 →CU2 = Curiosity (item 2)
16) Column 16 →CU3 = Curiosity (item 3)
17) Column 17 →II1 = Intrinsic Interest (item 1)
18) Column 18 →II2 = Intrinsic Interest (item 2)
19) Column 16 →II3 = Intrinsic Interest (item 3)

For column 8-19, 5-point Likert scale, 1(strongly disagree), 2 (strongly agree)

Pre-test and post-test results

Table H-2: Pre-test and post-test Results

ID	Category	Pre-test	Post-test
101	1	6	10
102	1	5	6
104	1	6	3
105	1	6	5
106	1	6	4
108	1	6	4
112	1	9	7
113	1	7	5
114	1	4	6
116	1	8	7
348	1	5	0
361	1	6	4
369	1	3	4
375	1	5	6
382	1	7	3
384	1	8	7
386	1	6	4
388	1	7	4
391	1	10	7
394	1	6	7
396	1	6	1
398	1	8	3
4116	1	6	4
4130	1	8	2
4134	1	6	2
4141	1	5	8

4144	1	7	0
4149	1	5	2
4152	1	4	1
4158	1	3	0
4164	1	9	3
4176	1	6	2
4180	1	7	4
4182	1	10	7
4200	1	5	0
4203	1	8	6
103	2	4	5
107	2	8	8
109	2	10	6
110	2	4	6
111	2	7	7
115	2	8	4
343	2	5	6
345	2	8	7
347	2	4	3
349	2	5	4
354	2	6	2
355	2	6	0
356	2	5	
358	2	5	5
364	2	9	6
367	2	4	5
380	2	5	0
381	2	4	0
393	2	5	1
395	2	9	7
397	2	6	6
4115	2	7	7
4118	2	7	6
4120	2	9	4
4122	2	10	4
4133	2	5	0
4136	2	4	0
4140	2	4	0
4143	2	4	0
4150	2	8	2
4151	2	5	0
4154	2	5	1
4159	2	9	7
4162	2	9	5
4168	2	7	5

4177	2	6	1
4179	2	6	0
4186	2	8	0
4189	2	6	0
4195	2	8	7
4197	2	7	3
4201	2	5	0

Experiment 2(Chapter 6)

Demographic Data

Table H-3: Demographic Data

ID	Cat	Programme	Background	Q2	Q3	Q4	Q5
5215	1	Bachelor of Multimedia	1	4	2	3	2
5217	1	Bachelor in Sociology	2	1	1	3	1
5222	2	multimedia	1	3	2	2	2
5225	1	phd in accounting	2	1	2	3	2
5229	2	Ph.D in Economics	2	4	2	3	3
5232	2	PhD in Information Technology	1	3	2	3	1
5236	2	Bachelor of International Affairs	2	1	2	3	2
5238	2	BIT	1	1	2	3	1
5240	2	Bachelor of operation management	2	2	2	3	1
5242	1	Bachelor of Science Management Agribusiness	2	4	2	3	2
5243	2	Bachelor Of Information Technology	1	1	2	3	1
5244	1	Bachelor of Information Technology	1	4	2	3	1
5246	1	bachelor management of technology	2	4	2	3	1
5250	2	Master of Information Technology	1	4	2	3	1
5251	1	Bachelor of Accountancy	2	2	2	3	1
5252	2	Bachelor of Technology Media	1	1	2	3	1
5253	2	Bachelor of Information Technology	1	2	2	3	3
5254	1	Bachelor of Information Technology	1	3	1	3	2
5255	1	Bachelor of technology	1	2	2	3	1
5256	2	Bachelor of Information Technology	1	4	2	3	1
5260	2	Bachelor of Information Technology	1	4	2	3	1
5262	1	bachelor of IT	1	3	2	3	1
5263	2	Bachelor of Information Technology	1	4	2	2	1
5264	1	Bachelor of Information Technology	1	3	2	3	3
5265	2	Bachelor of Information Technology	1	2	2	3	3
5266	1	Bachelor of Information Technology	1	3	1	3	2
5267	1	Bachelor of Information Technology	1	2	2	3	1
5268	2	BIT	1	4	2	3	1
5269	1	Bachelor of Information Technology	1	4	2	3	1
5276	2	Networking	1	4	2	3	3
5277	1	Bachelor of Information Technology	1	3	2	3	1

5279	1	Bachelor of Information Technology	1	4	2	3	1
5280	2	IT	1	4	2	2	1
5281	1	Bachelor of Information Technology	1	4	2	2	3
5283	1	bachelor tourism management	2	2	2	3	1
5284	2	bachelor of information technology	1	3	2	3	2
5286	2	MASTER OF INFORMATION TECHNOLOGY	1	1	1	3	1
5288	1	Bachelor of economic	2	1	2	3	2
5289	2	Bachelor of Information Technology	1	2	2	3	1
5290	1	Bachelor of Information Technology	1	2	2	3	1
5297	1	Bachelor of Information Technology	1	2	1	3	2

Guideline for the columns in Table H-3

1) Column 1 → Subjects' identification numbers
2) Colum 2→ Cat = Category
   1=DCSS, 2=Non-DCSS
3) Column 3→Programme= Programme of study
4) Column 4 → background knowledge
   1= IT background, 2 = non-IT background
5) Column 5 →Year of study
2 = Less than a year, 2 = 2-3 years, 3 = More than 3 years, 4 = Never used the computer
6) Column 6 →English
   1 = First language, 2= second language
7) Column 7 →Computer experience
   1 = Less than a year, 2 = 2-3 years, 3 = more than three years, 4 = never used the computer
8) Column 8→E-learning experience
   1= yes, 2= no, 3= not sure

Progressive Experience

Table H-4: Progressive Experience Data

ID	Cat	CO (1)	AF (1)	CU (1)	II (1)	CO (2)	AF (2)	CU (2)	II (2)	CO (3)	AF (3)	CU (3)	II (3)
5215	1	1	5	4	4	1	4	3	4	1	2	4	4
5217	1	4	3	4	3	4	3	3	3	3	3	3	2
5225	1	3	3	2	4	3	2	4	4	1	1	1	1
5242	1	3	4	3	5	5	5	5	5	5	5	5	5
5244	1	5	5	5	5	5	5	5	5	5	5	5	5
5246	1	4	4	3	3	2	3	3	2	3	3	3	3
5251	1	4	4	4	5	5	5	4	4	3	3	3	3
5254	1	4	4	3	4	4	4	3	3	4	4	3	3
5255	1	3	3	3	3	3	3	3	3	3	3	3	3
5262	1	5	4	4	5	4	4	4	4	4	4	4	4
5264	1	4	4	4	3	4	4	3	3	3	3	3	4
5266	1	3	3	4	3	3	3	4	3	3	3	4	3
5267	1	5	5	5	5	5	5	5	5	5	5	5	5
5269	1	5	5	5	5	5	5	5	5	5	5	5	5
5277	1	3	4	4	4	3	4	4	4	3	4	4	4
5279	1	4	4	4	4	4	4	4	4	4	4	4	4
5281	1	3	3	4	5	3	3	4	5	3	2	4	5

5283	1	3	4	3	4	4	5	4	5	5	5	5	5
5288	1	4	3	3	2	4	3	4	4	2	3	4	3
5290	1	5	3	5	5	5	3	3	3	3	3	3	3
5297	1	4	4	4	4	4	4	4	4	4	4	4	4
5222	2	4	5	4	1	4	3	4	5	5	4	5	4
5229	2	4	3	4	4	4	3	4	4	4	3	4	4
5232	2	4	5	5	5	4	5	5	5	4	5	5	5
5236	2	5	5	5	5	4	4	4	5	3	3	4	5
5238	2	4	3	4	2	4	3	4	2	3	4	3	2
5240	2	4	5	2	1	4	4	3	4	5	5	2	5
5243	2	4	4	4	4	4	4	4	4	4	4	5	4
5250	2	4	4	4	4	4	4	4	4	4	4	4	4
5252	2	3	3	3	4	3	3	3	4	3	3	3	4
5253	2	5	5	5	5	5	5	5	5	5	5	5	5
5256	2	4	4	5	5	5	5	5	5	4	4	4	5
5260	2	4	4	4	4	5	5	5	5	5	5	5	5
5263	2	3	4	3	3	3	4	3	5	3	4	4	3
5265	2	5	5	5	5	5	5	5	5	5	5	5	5
5268	2	5	4	4	4	4	4	4	4	4	4	4	4
5276	2	5	5	5	5	5	5	5	5	5	5	5	5
5280	2	4	4	4	5	4	4	4	5	4	4	4	5
5284	2	4	4	4	4	5	4	4	5	5	4	5	4
5286	2	5	4	5	5	4	4	4	4	4	5	5	4
5289	2	5	4	4	5	4	4	4	5	5	5	5	5

<u>Guideline for the columns in Table H-4</u>

1) Column 1 → Subjects' identification numbers
2) Colum 2 → Cat = Category
   1=DCSS, 2=Non-DCSS
3) Column 3 → CO(1) =Control dimension for Stage 1
4) Column 4 → AF(1) =Attention Focus dimension for Stage 1
5) Column 5 → CU(1)=Curiosity dimension for Stage 1
6) Column 6 → II(1) =Intrinsic interest dimension for Stage 1
   Column 7 → CO(2) =Control dimension for Stage 2
7) Column 8 → AF(2) =Attention Focus dimension for Stage 2
8) Column 9 → CU(2) =Curiosity dimension for Stage 2
9) Column 10 → II(2) =Intrinsic interest dimension for Stage 2
10) Column 11 → CO(3) =Control dimension for Stage 3
11) Column 12 → AF(3) =Attention Focus dimension for Stage 3
12) Column 13 → CU(3) =Curiosity dimension for Stage 3
13) Column 14 → II(3) =Intrinsic interest dimension for Stage 3

NASA-TLX

ID	C	Mental Demand	Physical Demand	Temporal Demand	Performance	Effort	Frustration	Overall Workload
5215	1	75	10	15	80	85	10	45.83
5217	1	71	18	10	76	15	15	34.17
5222	2	50	50	50	50	50	50	50.00
5225	1	60	55	70	88	36	90	66.50
5229	2	80	40	60	90	60	25	59.17

5232	2	20	1	1	80	1	0	17.17
5236	2	65	10	70	100	60	1	51.00
5238	2	90	73	69	40	83	65	70.00
5240	2	70	40	78	83	60	16	57.83
5242	1	85	50	50	80	85	15	60.83
5243	2	70	50	50	80	90	50	65.00
5244	1	96	98	97	99	99	99	98.00
5246	1	90	70	70	80	65	62	72.83
5250	2	65	40	55	64	70	40	55.67
5251	1	63	27	60	61	63	37	51.83
5252	2	57	74	45	75	80	37	61.33
5253	2	85	90	63	100	92	40	78.33
5254	1	60	55	71	53	57	74	61.67
5255	1	64	57	56	55	64	59	59.17
5256	2	82	81	80	88	73	78	80.33
5260	2	80	80	80	80	80	80	80.00
5262	1	66	59	69	82	95	90	76.83
5263	2	54	55	56	64	56	53	56.33
5264	1	56	52	55	60	68	85	62.67
5265	2	83	88	83	78	94	26	75.33
5266	1	52	54	55	54	68	89	62.00
5267	1	62	61	65	69	63	70	65.00
5268	2	54	63	65	67	57	55	60.17
5269	1	86	16	93	98	85	86	77.33
5276	2	80	42	60	85	55	21	57.17
5277	1	70	34	19	86	31	14	42.33
5279	1	80	78	20	88	20	10	49.33
5280	2	72	31	31	73	50	73	55.00
5281	1	70	70	75	95	60	50	70.00
5283	1	90	30	85	80	85	95	77.50
5284	2	56	54	59	61	59	91	63.33
5286	2	90	100	55	90	93	0	71.33
5288	1	58	57	43	70	66	65	59.83
5289	2	80	74	44	61	80	31	61.67
5290	1	73	50	49	53	50	51	54.33
5297	1	90	81	53	86	100	93	83.83

Experiment 3 (Chapter 7)

Questionnaire

Table H-6: Demographic data

ID	Programmes	Gen der	Year Of Birth	C a t	Year Of Study	Eng lish	Comp. Experienc e	E-learn ing	Prior Knowled ge
6332	PhD in Information Technology	F	3	1	2	2	3	2	2

6335	Doctor of Philosophy of Engineering	F	4	1	2	2	3	3	2
6336	Multimedia	F	4	1	3	2	3	1	2
6337	PhD in Management	M	5	1	3	2	3	2	1
6338	PhD (Technology)	F	3	1	2	2	3	1	1
6342	Bachelor of Information Technology	M	3	1	4	2	3	1	1
6343	PhD in Food Technology	F	3	1	1	2	3	1	1
6344	Postgraduate diploma of Information Technology	F	3	1	1	2	3	2	1
6345	PhD of Computer Science	M	3	1	4	2	3	2	2
6346	PhD	M	3	1	3	2	3	3	2
6347	PhD	F	4	1	4	2	3	1	1
6348	PhD of Computer Science	F	4	1	4	2	3	1	2
6350	PhD in Information Technology	M	3	1	2	2	3	1	2
6352	PhD in Information technology	M	5	1	2	2	3	1	2
6354	PhD	F	5	1	1	2	3	2	2
6356	Bachelor of Accounting	F	2	2	2	2	3	2	1
6360	Bachelor of accountancy	F	2	2	4	2	3	1	1
6361	bachelor of accounting	F	2	2	2	2	2	1	1
6362	Bachelor of Accounting Information System	F	2	2	2	2	3	1	1
6363	Bachelor of Business Studies	F	2	2	3	1	3	1	1
6364	Bachelor of Accounting	F	2	2	1	2	2	2	2
6366	bachelor of education in accounting	F	2	2	2	2	2	1	1
6367	bachelor of accounting (IS)	F	2	2	2	2	3	1	1
6396	Bachelor of Multimedia with Honours	M	2	2	1	2	3	2	2
6398	BSc	M	5	1	3	1	3	1	1
6405	Bachelor of International Business Management	M	2	2	3	2	2	1	1
6407	bachelor of banking	M	2	1	2	2	2	2	1
6408	bachelor of decision science	F	2	1	4	2	3	1	1
6409	entrepreneur	M	2	2	3	2	3	1	1
6410	Bachelor of Decision Science	F	1	2	2	2	2	2	1
6411	Bachelor Education	F	2	1	3	2	3	1	1

	of Accounting								
6412	Bachelor of Education (Guidance and Counselling)	F	2	2	2	2	3	1	2
6413	BIBM	F	2	1	4	2	3	3	1
6414	MSc(ICT)	F	2	2	1	2	3	1	1
6415	bachelor of statistical industries	F	1	1	1	2	3	2	2
6416	Bachelor of Multimedia	M	3	1	1	1	2	2	1
6417	Bachelor of Information Technology	F	6	2	2	1	3	1	1
6419	Bachelor of Banking	F	2	2	4	2	3	1	1
6422	Bachelor of Banking	F	2	1	4	2	2	1	2
6423	bachelor of decision science	F	2	2	2	2	3	1	2
6424	decision science	F	2	1	4	2	3	1	1
6425	bachelor education of accounting	F	2	2	3	2	2	1	1
6426	B. Ed. (Acct.)	F	2	1	3	2	3	2	1
6427	bachelor of decision science	F	2	2	1	2	3	2	1
6428	bachelor statistic industry	M	2	2	2	2	3	2	2
6430	management of technology	F	2	2	4	2	2	1	2
6432	Bachelor of Information Technology	M	2	1	4	2	3	1	2
6438	Bachelor of decision science	F	2	1	2	1	3	3	1
6439	BACHELOR IN DECISION SCIENCE	F	2	2	2	2	3	1	1
6441	bbs	M	4	1	2	1	3	1	1
6442	Bachelor of Decision Science	F	2	1	4	2	3	1	2
6443	Bachelor of Operations Management	F	2	2	3	2	3	3	1
6444	Bachelor of Production and Operation Management	F	2	1	4	1	3	1	1

Guideline for the columns in Table H-6

1) Column 1 → Subjects' identification numbers
2) Column 2→Programme= Programme of study
3) Column 3 → Year of Birth
   1= 17-20, 2=21-25, 3=26-30, 4=31-35, 5=36-40, 6=41-45, 7=46-50, 8=51-55, 9=56-60, 10=61 and above
4) Column 4 → Cat = Category
   1=DCSS, 2=Non-DCSS
5) Column 5→Year of study
6) = Less than a year, 2 = 2-3 years, 3 = More than 3 years, 4 = Never used the computer
7) Column 5 →English
   1 = First language, 2= second language
8) Column 6 →Computer experience
   1 = Less than a year, 2 = 2-3 years, 3 = more than three years, 4 = never used the computer

9) Column 7→E-learning experience
1= yes, 2= no, 3= not sure
10) Column 9→Prior knowledge
1=novice learners, 2= intermediate learners, 3= advanced learners

Table H-7: Learning Experience data

ID	CO 1	CO 2	CO 3	AF 1	AF 2	AF 3	CU 1	CU 2	CU 3	II 1	II 2	II 3	U 1	U 2	Cognitive Load
6332	4	2	4	1	2	5	4	5	5	1	4	5	4	4	2
6335	3	4	3	3	4	4	3	4	3	3	3	4	4	4	3
6336	4	1	4	1	2	4	4	4	4	2	4	4	4	4	3
6337	5	2	4	4	4	3	3	3	3	3	3	3	4	4	2
6338	4	2	5	3	4	4	4	4	5	2	4	4	4	4	2
6342	5	3	2	2	3	2	2	4	3	3	4	4	4	4	1
6343	4	2	3	4	4	3	5	4	3	2	3	4	4	4	2
6344	3	1	4	3	3	3	4	4	2	1	3	4	3	3	3
6345	4	1	4	2	2	4	4	5	5	1	5	5	4	4	5
6346	1	5	1	2	2	3	2	2	2	3	3	3	4	2	5
6347	5	2	5	5	5	5	5	5	5	1	5	5	5	5	1
6348	2	3	3	1	1	5	3	4	3	2	4	4	4	4	7
6350	4	1	4	2	2	5	4	3	4	2	4	4	3	4	7
6352	4	2	4	3	4	4	4	4	4	2	4	4	4	5	2
6354	4	3	2	2	2	4	3	3	2	3	4	2	2	2	5
6356	3	3	3	3	5	2	4	4	4	2	3	3	3	4	5
6360	3	3	3	3	3	3	5	5	3	1	5	5	4	3	4
6361	3	3	3	3	3	3	3	2	3	3	4	3	4	3	3
6362	3	2	2	2	2	4	4	3	4	2	3	3	4	3	3
6363	4	2	4	4	4	2	3	3	3	3	3	4	5	5	3
6364	4	3	3	4	4	2	4	4	4	1	1	4	3	4	5
6366	3	2	4	3	3	3	3	3	3	2	3	3	3	3	6
6367	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1
6396	5	1	4	2	2	5	4	4	4	1	5	5	5	5	2
6398	5	1	5	2	2	4	5	5	5	1	4	4	5	5	2
6405	5	3	4	5	5	4	2	2	3	2	3	4	5	4	3
6407	1	5	5	2	3	2	5	5	5	1	5	5	5	5	1
6408	3	2	4	4	3	4	3	3	4	2	4	4	4	3	5
6409	5	5	4	5	4	5	5	4	4	5	5	4	5	5	2
6410	4	4	3	3	4	5	4	4	4	1	3	4	4	3	2
6411	3	3	3	5	4	4	5	5	4	2	5	5	5	4	5
6412	4	3	3	4	4	3	4	4	4	2	4	4	4	4	3
6413	3	2	3	3	2	3	3	3	4	2	3	4	4	3	5
6414	2	2	1	5	3	1	2	2	2	4	3	3	2	2	7
6415	4	1	4	1	3	4	5	4	4	1	5	5	5	5	2
6416	3	1	4	1	1	5	4	2	4	1	5	4	4	2	1
6417	1	5	3	2	4	5	5	5	4	1	4	5	5	5	7
6419	4	2	2	3	2	2	3	3	3	2	4	4	4	3	2

6422	3	3	4	3	3	3	3	3	4	2	4	3	3	4	2
6423	3	3	3	4	4	4	4	4	4	2	3	3	3	2	5
6424	3	3	4	4	4	3	4	4	2	2	2	2	3	3	3
6425	3	3	4	4	4	4	4	4	4	2	4	4	5	4	3
6426	3	3	3	4	4	3	4	4	4	3	4	3	4	4	3
6427	4	2	3	2	3	4	3	3	4	1	4	4	3	3	3
6428	3	4	2	4	4	4	3	2	3	2	4	4	4	4	3
6430	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4
6432	3	3	3	4	4	4	4	4	4	2	4	4	4	4	4
6438	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1
6439	3	3	3	3	3	3	3	3	3	2	3	3	3	3	4
6441	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1
6442	3	4	3	3	4	4	4	4	3	2	3	4	5	4	3
6443	3	3	3	3	4	3	4	4	4	3	3	3	3	3	5
6444	3	2	3	3	3	3	3	3	3	3	3	3	4	3	5

Guideline for the columns in Table H-7

1) Column 1→ Subjects' identification numbers
2) Column 2→CO1 = Control dimension (item 1)
3) Column 3 →CO2 = Control dimension (item 2)
4) Column 4 →CO3 = Control dimension (item 3)
5) Column 5 →AF1 = Attention Focus (item 1)
6) Column 6 →AF2 = Attention Focus (item 2)
7) Column 7 →AF3 = Attention Focus (item 3)
8) Column 8 →CU1 = Curiosity (item 1)
9) Column 9 →CU2 = Curiosity (item 2)
10) Column 10 →CU3 = Curiosity (item 3)
11) Column 11 →II1 = Intrinsic Interest (item 1)
12) Column 12 →II2 = Intrinsic Interest (item 2)
13) Column 13 →II3 = Intrinsic Interest (item 3)
14) Column 14 →U1 Usability (item 1)
15) Column 15 →U2 = Usability (item 2)
16) Column 16 →Cognitive Load= Intrinsic Interest

    For column 1-15, 5-point Likert scale, 1(strongly disagree), 2 (strongly agree)

Appendix I: Ethics Document

This research has been peer-reviewed and classified as low-risk. The low-risk notification letter from the Research Ethics Office of Massey University is enclosed.

MASSEY UNIVERSITY

7 September 2010

Norliza Katuk
A1/71 Spencer Road
Oteha
NORTH SHORE CITY 0632

Dear Norliza

Re: Evaluation of Learners' Flow Experiences in Using Curriculum Sequencing Systems (CSS)

Thank you for your Low Risk Notification which was received on 7 September 2010.

Your project has been recorded on the Low Risk Database which is reported in the Annual Report of the Massey University Human Ethics Committees.

The low risk notification for this project is valid for a maximum of three years.

Please notify me if situations subsequently occur which cause you to reconsider your initial ethical analysis that it is safe to proceed without approval by one of the University's Human Ethics Committees.

Please note that travel undertaken by students must be approved by the supervisor and the relevant Pro Vice-Chancellor and be in accordance with the Policy and Procedures for Course-Related Student Travel Overseas. In addition, the supervisor must advise the University's Insurance Officer.

A reminder to include the following statement on all public documents:

> *"This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named above are responsible for the ethical conduct of this research.*
>
> *If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher(s), please contact Professor John O'Neill, Director (Research Ethics), telephone 06 350 5249, e-mail humanethics@massey.ac.nz".*

Please note that if a sponsoring organisation, funding authority or a journal in which you wish to publish requires evidence of committee approval (with an approval number), you will have to provide a full application to one of the University's Human Ethics Committees. You should also note that such an approval can only be provided prior to the commencement of the research.

Yours sincerely

J. O'Neill

John G O'Neill (Professor)
Chair, Human Ethics Chairs' Committee and
Director (Research Ethics)

cc Dr Hokyoung Ryu
Institute of Information and Mathematical Sciences
Albany

Prof Tony Norris, HoI
Institute of Information and Mathematical Sciences
Albany