Personality Effect in the Design of Adaptive E-learning Systems

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ABSTRACT

This PhD thesis is a theoretical and practical study concerning the user model for adaptive e-learning systems. The research activity is two-fold. It firstly explores the personality aspect in the user model which has been overlooked in the previous literature on the design of adaptive e-learning systems, in order to see whether learners with different types of personality would have different effects on their learning performance with adaptive e-learning systems. And secondly, it investigates how to embody the personality features in the current user model, proposing that the inclusion of the personality in the user model for adaptive e-learning systems would lead to better learning performance.

The thesis has considered the personality aspect in four parts. PART I reviews the theoretical and empirical literature on adaptive e-learning systems from which the main research questions are constructed. It explains how this study derives an overarching model for the inclusion of personality type in effective e-learning systems.

PART II consists of the experiments, which explore empirically the importance of identifying the personality in the user model for adaptive e-learning and its effect in individual learning. That is, the main theme of the thesis hypothesises that different personality type's influence performance with e-learning systems.

PART III shows the effects of personality type on groups of learners performing collaborative learning activities. It suggests practical implications of designing collaborative learning technologies in conjunction with the personality feature.

Finally, PART IV includes personality in the proposed user model and tests the primary hypothesis that "the personality may influence the learning performance of students using adaptive e-learning systems".

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PREFACE

This PhD is concerned with including the personality type in the user model which has been less thoroughly investigated in the previous studies of adaptive e-learning systems.

The thesis has considered and covered the personality effect in adaptive e-learning systems in four parts. PART I covered the theoretical and empirical literature on adaptive e-learning systems. PART II investigated and empirically showed the importance of identifying the personality in the user model for adaptive e-learning systems and its effect on individual learning. PART III considered and showed the effects of personality on the group of learners performing collaborative learning, and finally PART IV empirically included the personality in the proposed user model and assessed the assumption that the personality feature in the user model would influence the learning performance of students using adaptive e-learning system and conclusions are drawn regarding the thesis.

This study took place between 2002 and 2007 in the Institute of Information and Mathematical Science at Massey University. Both Prof. Scott Overmyer and Dr. Hokyoung Ryu supervised the thesis.

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me to finish this study. My special thanks to my brother Ali for his support and help when ever I needed it. This thesis dedicated to the memory of my mum and dearest brothers Saad and Sabah who died before it was completed. Special thanks go to Diana Hibbert, who read drafts of this thesis and greatly improved it by her valuable comments.

DECLARATION

I declare the research reported in this thesis to be my own, with the help of my supervisors both Prof. Scott Overmyer and Dr. Hokyoung Ryu. The research completed between July 2002 and 2007 in the Institute of Information and Mathematical Science, Massey University.

Chapter 3,4,5,6 and 7 of the thesis were presented and published at the International Conference on Advanced Learning Technologies (ICALT), in, 2005, 2006 and 2007, respectively. Also, a paper is in preparation for submission to the Journal of Technology Education (JTE).

Chapter 3 and 4 of the thesis were also presented and published in the doctoral consortium of Australian Computer Information Systems (ACIS), in 2005.

- Al-Dujaily, A., & Ryu, H. (2007). *Personality and collaborative learning experience*. Paper presented at the 7th IEEE International Conference on Advanced Learning Technologies (ICALT 2007). Niigata, Japan.

- Al-Dujaily, A., & Ryu, H. (2006). A relationship between e-learning performance and personality. In Kinshuk, R. Loper, P. Kommers, D. Kirschner & W. Didderen (Eds.), *The 6th IEEE International Conference on Advanced Learning Technologies (ICALT 2006)* (pp. 84-86). Kerkrade, Netherlands: IEEE Computer Society

- Al-Dujaily, A., & Ryu, H. (2006). An evaluation of adaptive educational information systems and its impact on university students' learning performance. In B. Unhelkar & Y. Chen lan (Eds.), *Proceeding of the 2nd International Conference on information Management and Business (IMB 2006)* (pp. 531-535). Sydney, Australia.

- Al-Dujaily, A., Ryu, H., & Kamal, J. (2005). Introversion and the implication of intelligent tutoring systems: A lesson from Arab students. In P. Goodyear, D. Sampson, D. Tan Yang, Kinshuk, T. Okamoto, R. Hartley & N. Chen (Eds.), *The 5th IEEE International Conference on: Advanced Learning Technologies* (pp. 993-995). Los Alamitos, CA: IEEE Computer Society.

- ACIS 2005 Doctoral Consortium: November 28-29, 2005. The Australasian Conference on Information Systems (ACIS). University of Technology, Sydney (UTS), Australia.

- I presented my work as an invited speaker at the Centre for University Preparation and English Language Studies (CUPELS) seminar, on the 26 April 2007.

CHAPTER 1. SUMMARY OF THESIS

The main motivation of this thesis is to study personality effect in the context of adaptive e-learning systems, exploring in particular the user model that might be enhanced along with the personality aspect. Through our investigation we found that early adaptive e-learning systems did not seem to consistently identify what features should be incorporated and how they can support students' learning activity effectively. This thesis argues that to some extent individual personality features might have effects on each knowledge acquisition strategy, which consequently might result in different use of adaptive e-learning systems. Therefore, the main contribution of this thesis is to propose how to embody the personality feature in the current user model, as this has been overlooked in the previous literature on the design of adaptive e-learning systems.

Overview of the research

The primary motivation of this research comes from the author's personal teaching commitments in one of the Gulf States universities where e-learning systems are employed as part of their learning process. Throughout that experience the author noticed that the design of learning technologies had mainly concentrated on the technological aspects, e.g., the structure of the contents, and the delivery medium of the content; however the question of how different individuals would benefit from the technologies has been less addressed. This experience has led the author to explore the literature on the personality aspect in the user model of adaptive e-learning systems and focussed on the effects of personality on the learning performance.

Overview of the thesis

The thesis enhances the theoretical and empirical understanding of the user model for adaptive e-learning systems. The research activity is thus two-fold. The study first examines the personality trait which has been less researched in the previous literature on the design of adaptive e-learning systems. Secondly, it proposes how to embody the personality feature in the current user model for better adaptation. The main aim of this thesis is thus to make some contributions to knowledge about the user model for adaptive e-learning systems. Figure 1.1 shows the overall structure of the thesis, and how this is interwoven.

Figure 1.1. Overall structure of the thesis and contents
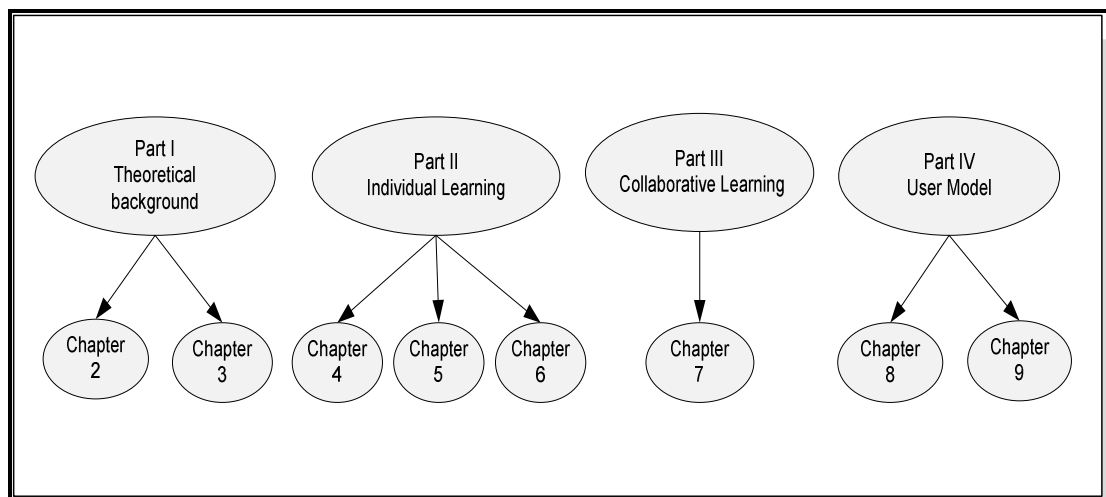
Figure 1.1 shows that the thesis explores the personality issue through the four parts. PART I consists of Chapters 2 and 3. It covers the theoretical approach to modelling the personality in the user model of adaptive e-learning systems. PART II consists of Chapters 4, 5 and 6, which shows empirically the role of the personality feature in the user model for adaptive e-learning systems and its effect on individual learning process. PART III describes and shows the effects of the personality on collaborative learning activity, which is widely thought to be another important learning activity. PART IV, i.e., Chapters 8 and 9, describes an experiment that includes the

personality feature in the user model proposed, as the last step to validate the process taken in this thesis. Finally, several conclusions and further discussion are drawn in Chapter 9 regarding the thesis.

PART I. Personality model and the literature review

Part I introduces the previous approaches to the user model for adaptive e-learning systems. It consists of Chapters 2 and 3.

Chapter 2. Research framework

This chapter describes the research framework of this thesis. The main purpose of this chapter is to show chronologically how this thesis has evolved from the literature or theoretical background. This chapter also raises the hypothesis that learners' personality features would have certain effects on uses of adaptive e-learning systems, and in turn it suggests that embodying this feature in the user model might be of great use for designing adaptive e-learning systems.

Chapter 3. Related literature and research question

This chapter provides a detailed overview of how e-learning systems have been advanced, with the underlying techniques and models. And it discusses a novel e-learning system, i.e., an adaptive e-learning system. The theoretical and practical basis of this thesis is constructed accordingly.

PART II. Experiments to understand the role of personality in the e-learning systems

This part involves three studies to explore empirically the personality effect in the individual learning with e-learning systems. Four experiments are conducted to see if the personality type could actually have effects on the use of adaptive e-learning systems. The first two experiments were carried out in Oman, one of the Gulf States universities. The second two were conducted in New Zealand. The first one was to

investigate whether different learning styles would have any consequence for the learning performance of Western students, and subsequently, to validate the effect of personality in the same experimental setting.

Chapter 4. A comparative study of personality effect on traditional e-learning and adaptive e-learning systems

This chapter discusses and covers the work concerning the experiments and the findings from the empirical study that has been done to see whether the personality type of each learner would affect their performance when using e-learning systems. This chapter thus reports firstly on the comparison of two different types of e-learning system: traditional e-learning and adaptive e-learning system. Secondly, it explores the personality effect on adaptive e-learning systems in more detail.

Chapter 5. Other personality traits and learning performance

This chapter revisits the work concerning the experiment and findings from Chapter 4, in order to re-confirm whether the results from Chapter 4 can be generalised to other tertiary education contexts.

Chapter 6. Personality and learning material design

In this chapter we intend to validate the effect of different personality type (from the previous findings of Chapters 4 and 5). It describes an experiment to test whether or not the learner's personality may dictate their preferences for a particular style of learning material

PART III. To understand collaborative learning and personality types

This part describes and shows possible effects of personality in groups of learners performing collaborative learning. It suggests practical implications of designing collaborative learning technologies in conjunction with the personality feature.

PART IV. Personality type in the proposed user model

This part consists of two chapters**.** Chapter 8 describes how personality is incorporated in the proposed user model and finally conclusions are drawn regarding the thesis in Chapter 9.

Chapter 8. Encompassing the personality effect in adaptive e-learning systems design

This chapter shows empirically whether the personality consideration in the user model can improve the learning performance of adaptive e-learning systems.

Chapter 9. Conclusions and discussion

This chapter summarises the contribution of this thesis to the current research on the user model of adaptive e-learning systems.

PART I. PERSONALITY MODEL AND THE LITERATURE REVIEW

PART I of the thesis considers the early literature of adaptive e-learning systems, covered in two chapters. Chapter two explains how this study derives an overarching model for the inclusion of personality type in effective e-learning systems. And Chapter three details the early studies in this domain, relating to the research questions raised in Chapter 2.

CHAPTER 2. RESEARCH FRAMEWORK

The main purpose of this chapter is to explain how this study offers an overarching approach to the inclusion of the personality type in designing e-learning systems. Firstly, this chapter presents a brief history of the evolution of e-learning systems to date, and further how we can establish the research framework throughout this thesis to this end.

Overview of the Chapter

Section 2.1 briefly describes the history of the evolution of e-learning systems to date, which implies the main research question raised in this thesis, giving an insight into how the current user models have been designed and how they would support students' learning process. Following on this understanding, section 2.2 depicts the research framework and methodology employed in this thesis.

2.1 The main research question

In traditional e-learning systems, the major usability issues came from their inability to accommodate the individual differences of learners, since they provide all students with the same information regardless of their individual differences (e.g., Papasalouros & Retalis, 2002; Vasilecas, 2005). Whilst web-based e-learning systems have increased the effectiveness of educational applications with a certain extent of freedom to explore in the information space (e.g., Chen & Magoulas, 2004), they are still primitive in terms of students' needs (Abramowicz, Kowalkiewicz, & Zawadzki, 2002; Kaicheng & Kekang, 1997). These criticisms have been significantly overcome by the advent of adaptive e-learning systems in higher educational applications, such as AHA (De Bra & Calvi, 1998a), ELM-ART (Brusilovsky, Schwarz, & Weber, 1996a; Weber & Brusilovsky, 2001) and Interbook (Brusilovsky, Schwarz, & Weber, 1996b; Eklund &

Brusilovsky, 1999). Adaptive e-learning systems are thought to effectively support each user's learning process, adapting to the current level of their own knowledge, allowing a more directive tutor style, and providing a flexible student-centred approach in computer-assisted instructions (Virvou & Tsiriga, 2001).

These contributions proved useful in more advanced adaptive tutoring systems (Jones, Scanlon, Tosunoglu *et al.*, 1999; Virvou & Tsiriga, 2001; Woolf & Hall, 1995), but there has been little agreement as to what features of adaptive e-learning systems should be kept. In consequence, research on identifying the most significant features is required (Brusilovsky & Weber, 1996; Cristea, Stewart, Brailsford *et al.*, 2005).

The research interest raised from the state-of-the-art is thus how adaptive e-learning systems can address this adaptation issue more effectively. Many of these systems first established an appropriate model of a user's knowledge. In turn, ***the learner's user model*** specifies what to adapt and how to support the user's learning process for obtaining knowledge of the application domain, and then suggests the most relevant contents from the application domain for the learners to enhance their learning in an effective way. Figure 2.1 depicts this process that was proposed by Brusilovsky (2002).

Figure 2.1. The user model, extended from Brusilovsky (2002)
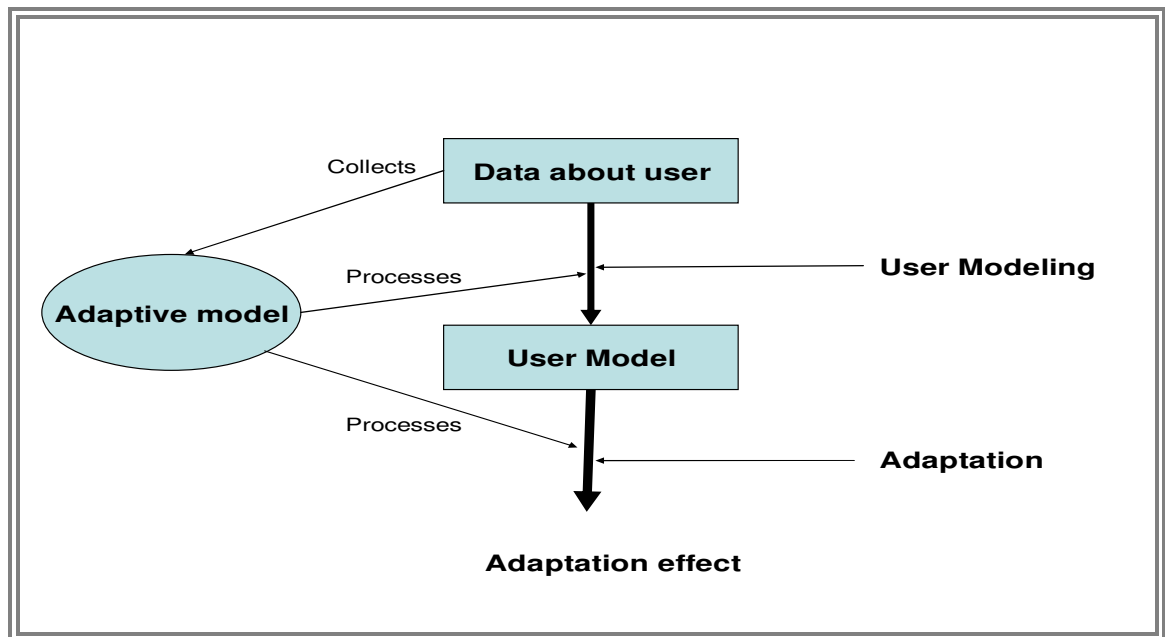
Figure 2.1 depicts the essential procedure of collecting the relevant information of each individual, and manipulating the user profiles to generate an appropriate user model for an individual. Also, this personalised user model monitors consequent adaptive effects to tune itself up for the finer adaptation later. Yet, the user models employed in most of the adaptive e-learning systems do not seem to consistently embrace what is to be included and how it can support the students' learning activities in terms of their different knowledge acquisition strategy. For instance, in order to accommodate different learners, ELM-ART (Brusilovsky *et al*., 1996a) provides adaptive navigation support, and course sequencing that represents the student's individual learning history as a series of episodes, whereas Interbook (Eklund & Brusilovsky, 1999) provides individual guidance that integrates the student's individual learning history, prerequisites and knowledge, to achieve the student's learning goals. The details of both systems are discussed in Chapter 3.

The main research question addressed in this thesis is thus to identify the problems arising from the user model briefly described above, in particular,

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investigating whether learners' personality features might have effects on their use of adaptive e-learning systems, now that this issue has been paid much attention in the modern intelligent tutoring systems (Felder & Brent, 2005; Ford, Miller, & Moss, 2001; Holodnaya, 2002; Humanmetrics, 2006; Stash & De Bra, 2004; Zhang, 2006).

2.2 Research framework

Figure 2.2 shows the research path taken throughout this thesis. Based on this plan, we organised the thesis structure in order.

Figure 2.2. The research plan
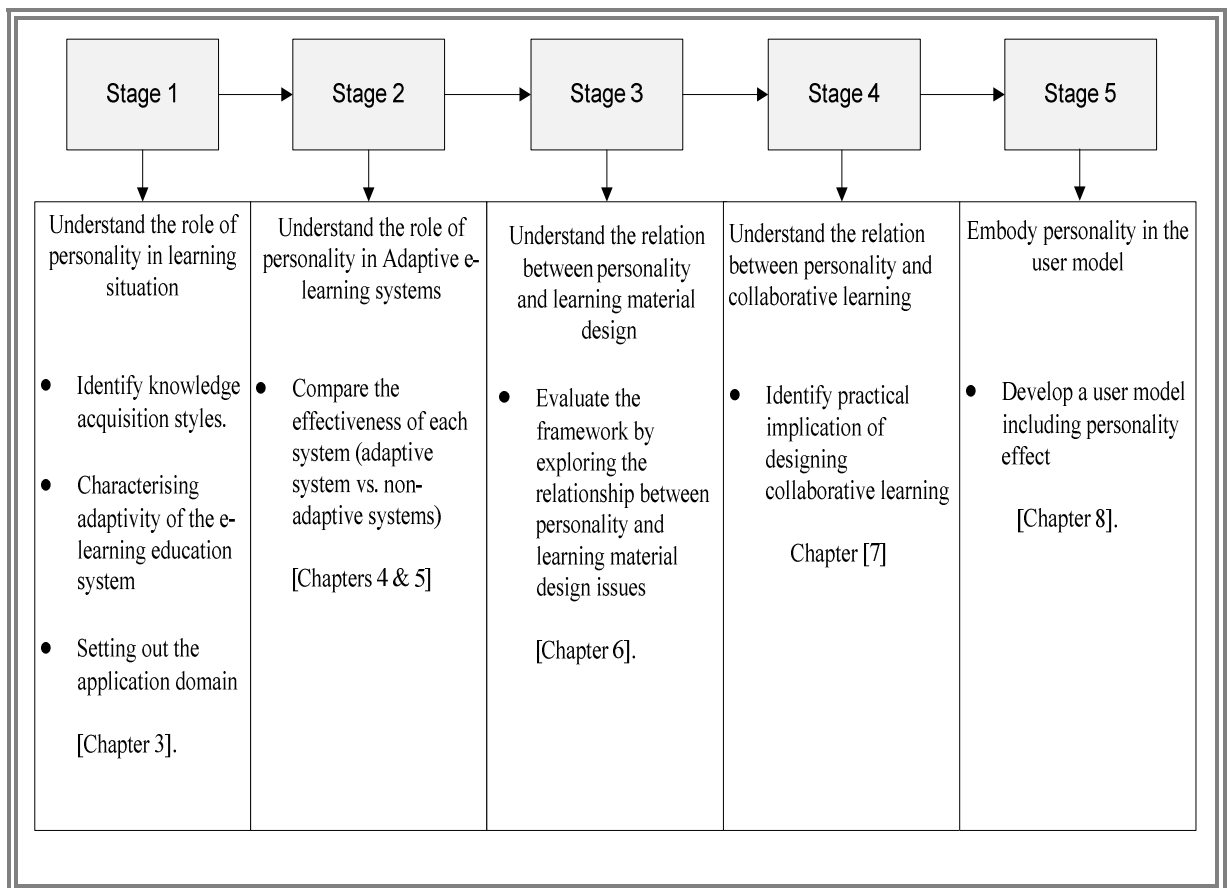
2.2.1. Stage 1: Understand the role of personality in the learning situation

In the early stages of the research, we intended to generate a structure to understand how we could review the effectiveness of the adaptive e-learning systems. Three aspects were included as follows: (i) identifying each student's knowledge acquisition style,

using psychological theories, (ii) characterising adaptivity of e-learning systems, comparing different e-learning systems, and (iii) setting out the application domain for the case studies. We suspected that personality type may be relevant to the knowledge acquisition style of each learner, which corresponds to the first aspect above. In particular, we assumed that the non-adaptive e-learning systems would be less affected than adaptive e-learning systems by the personality type, because of non-inclusion of the user model. Finally, we only considered the Computer Science discipline for the convenience of the author to enable collecting empirical data. The three aspects were fully described in Chapter 4 and 5.

Also, this stage reviewed the current adaptive e-learning systems, identifying that they possess the same basic components of the domain model, the user model, and the techniques to adapt both contents and links with respect to the user model (Brusilovsky & Peylo, 2003; Cannataro, Cuzzocrea, & Pugliese, 2001; De Bra, Stash, & Smits, 2004), which was fully described in Chapter 3.

2.2.2. Stage 2: Understand the role of personality in adaptive e-learning systems

Based on the understanding of Stage 1, the main objective of this stage was to extend the accounts from the previous stage with an empirical study. To this end, we carried out a set of experiments to see if the personality type could indeed have effects on the use of adaptive education systems. The first half of the experiment was carried out in one of the Gulf States universities, and then the same experiment was performed in a Western University, for external validity checking. This will be further explored in Chapters 4 and 5.

2.2.3. Stage 3: Understand the relation between personality and learning material

In order to further validate the results from Stage 2, the main purpose of this stage is to consider the personality trait as a tool for structuring the learning materials. One experiment was conducted to examine the relationship between the learner's personality type and the learning material design. This will be further discussed in Chapter 6.

2.2.4. Stage 4: Understand the relation between personality and collaborative learning

The main point of this stage is to explore the personality effect in collaborative learning activities. An experiment was performed to see whether collaboration between different personality-typed learners would facilitate a better collaborative learning experience. This will be further discussed in Chapter 7.

2.2.5. Stage 5: Embody Personality in the user model

The purpose of this stage is to show empirically whether the personality factor in the user model can dictate the learning performance of adaptive e-learning systems. An experiment is carried out in Chapter 8 to empirically validate the hypothesis.

2.3 Summary

This chapter outlined the research path chosen in this thesis. In the following chapter, the early studies of this research domain are discussed in detail and in turn the research questions are rigorously specified along with the literature review.

CHAPTER 3. RELATED LITERATURE

E-learning applications are becoming increasingly advanced, having been supported by newly evolved learning technologies for effective and efficient learning experience, e.g., Intelligent Tutoring Systems (ITSs) and Adaptive Hypermedia Systems (AHSs). They have provided greater opportunities for teachers to address the different needs of each student. This chapter provides an overview of how e-learning applications have evolved with advanced techniques, establishing a theoretical and practical basis of this thesis accordingly.

Overview of the Chapter

The first section (Section 3.1) investigates the traditional hypermedia systems to give an insight into how they were designed and supported students' learning processes. Section 3.2 describes a relatively new approach to the design of the traditional hypermedia systems, which offers more personalised contents and, as a consequence, ensures a customised learning process for each learner. The following two sections (Section 3.3 and 3.4) further discuss this process as to how the adaptation process has been implemented in practice, so that they can illustrate the critical features of the design of AHSs. Section 3.5 describes the significant features of the user models employed in the newly developing AHSs. Section 3.6 explores the relationship between personality and the user model, which is central to the research question throughout this thesis. Finally, in Section 3.7, this chapter is summarised.

3.1. Introduction

This thesis introduces a new approach to a user model that may be used in the practical design of future Electronic-Learning (E-Learning) systems. In this chapter, we present the early studies in order to discuss user models. It will establish a general context of the range and the purpose of the thesis.

Although we have used the term "e-learning systems" in the previous two chapters, in this chapter the term "hypermedia systems" is used, which can narrow down the scope of the thesis. Indeed, the two terms "e-learning systems" and "hypermedia systems" may be interchangeable in this thesis, because most e-learning systems are now based on web technologies.

E-learning is a general term referring to learning enhanced by computer. It is networked, which makes it being capable of instant update, storage, retrieval and sharing of instructions or information. However the term has been used interchangeably in many different contexts so that it is critical to be clearer what one means when one speaks of 'E-learning'. In many respects, it is commonly associated with the field of Advanced Learning Technology (ALT), which deals with both the technologies and associate methodologies in learning. Further, now it includes games-based applications and web2.0 technology such as social networking.

Although it covers a wide set of applications and processes, such as web-based learning, computer-based learning, virtual classrooms, and augmented learning environments, our focus is 0n web-based learning systems.

Hypermedia Systems (HSs) have long been considered as effective e-learning tools to deliver volumes of teaching materials to learners via computers or the Internet (Lennon & Maurer, 1994), so the learner can do their learning activities beyond the traditional classroom environment, for example, using Learning Management Systems

(LMS) such as Moodle, and WebCT. WebCT, i.e. Web Course Tools is a web-based course management system that allows teachers, professors, and staff developers to create or enhance instructions with on-line courses.

Advantages of HSs have thus been widely acknowledged by many early studies, guiding finer approaches to development of educational application (Brusilovsky, 1998, 2001; Hammond, 1989; Höök, 1996; Höök, Karlgren, Waern *et al*., 1996). However, Ford and Chen (1997; 2000a) pointed out that HSs would be of most use for highly motivated learners to willingly organise their own independent learning, whilst less motivated learners would benefit less.

Apart from this, there have been more pivotal criticisms of this learning experience with HSs, mostly because face-to-face interaction with teachers has been significantly removed from the whole learning process. To overcome this limitation various methods have been proposed to strengthen the interaction between the learner and the teacher in many ways, such as audio and video-based web-conferencing applications and so forth. However, this inevitably leads to a high development cost of HSs (Baltasar & Sancho, 2002; Pilgrim, Leung, & Grant, 1997).

Recently, to compensate for these limitations of HSs, a novel approach to the design of HSs – Adaptive Hypermedia Systems (AHSs) – has been introduced. Thus, it is worth reviewing this line of the development to understand the benefits and limitations of HSs, and further to see the critical characteristics of AHSs.

3.2. Traditional E-learning systems: Hypermedia Systems (HS)

The main concept of HSs is to employ hyperlinks (or hypertexts), allowing the proactive use of learning materials via the Internet beyond geographical constraints. Whilst many studies (e.g., Chen & Ford, 1997; Jonassen, 1991) showed the effectiveness and usefulness of HSs, practical problems are often associated with '*the*

lost in hyperspace' phenomenon where learners tend to get confused about orientation or where they are now and where they should go while navigating in a complex learning space (Chen & Macredie, 2002; Daniels & Moore, 2000; Eklund, 1995; Hammond & Allinson, 1989, 1990; Manathunga, 2002; Meyer, 1994). Often, this phenomenon results in unnecessary cognitive loads (Jonassen & Grabinger, 1992), demanding more time for choosing and navigating their learning space. Indeed, in face-to-face learning situations, this would not be a major issue in the sense that the teacher would be aware of what treatment is best for each student, adopting different pedagogical approaches. To minimise this problem, many HSs employ a structured guidance system (e.g., document maps) for learners to find their learning paths more easily or at least avoid forgetting where they are and where they have been in the learning space. Yet, it still seems to be very hard to ensure an effective learning process for each individual without the teacher's support (Brusilovsky, 2001; Cannataro *et al*., 2001; Kavcic, 2000; Papasalouros & Retalis, 2002). In fact, there is a wide consensus on the fact that teachers know the best way to educate their students, using their understanding of each student in terms of backgrounds, interests, goals, learning style and knowledge level. However, this is not possible in the traditional design of HSs, so the subsequent development, Intelligent Tutoring Systems (ITSs), was intended to simulate this interaction style between the learner and the teacher.

Table 3.1. Some examples of ITSs

Name	Developers	Focus	Adaptation
LISP tutor	Anderson & Reiser (1985b)	Acquire user knowledge	Expert model based production rules
Advanced Geometry Tutor	Matsuda & VanLehn (2005)	Problem solving	Step-by-step demonstrations of the construction procedure
LISPITS	Corbett & Anderson (1992)	Knowledge tracing	Model tracing
SQLT-Web	Mitrovic & Hausler (2003)	Knowledge and Constraint- based	Constraint-based modelling

Table 3.1 summarises several ITSs that have proven successful in actual learning practice. For example, *"LISP tutor"* (Anderson & Reiser, 1985a) encodes experts' problem solving techniques as production rules, in order to teach LISP language in a more efficient and effective manner. It allows comparing the production rules with what the learner has done to determine the most relevant contents to be delivered next, to the learner. Likewise, the *"Advance Geometry Tutor (AGT)"* (Matsuda & VanLehn, 2005) employs natural language processing to deliver the most relevant geometry materials to each student, based on her or his initial queries. This interactive style using AGT helps students learn the reasons behind their problem-solving actions. *"LISPITS"* (Corbett & Anderson, 1992) applies a knowledge tracing technique for monitoring the learner's process, comparing the actual steps that the student takes with the expert's model that is necessary to develop a LISP programme in an effective way.

In this way, most ITSs present each student with appropriate content based on their knowledge level, so they generally force the student not to miss some essential concepts. However, these systems seem to be too instructive (system-driven learning process), so that students have little control over their own learning process, which accordingly results in less-motivated learning experience. Several studies (e.g., Kavcic,

2000; Sack, Soloway, & Weingrad, 1994) claimed that since student's learning

motivation varies over time, the design of an ITS should consider if the system-driven

learning process keeps up with the changes in learner's attitude.

Whilst many ITSs' adaptation processes have been mainly based on the

knowledge level of each student, AHSs attempt to overcome the problems specified

above by encompassing other characteristics, such as preferences, skills, and learning

goals, as well as prior knowledge of the subject. Many studies (e.g., Brusilovsky,

Karagiannidis, & Sampson, 2001, 2004; Chin, 2001; Mitrovic & Hausler, 2003)

demonstrated that AHSs are of practical use for individuals with different goals and

knowledge levels, which can simulate the way a teacher effectively interacts with

students. For instance, in practice, AVANTI (Fink, Kobsa, & Nill, 1996) serves a

variety of users with different needs (e.g., tourists, residents, elderly people, and

disabled people), adapting the contents and the presentation of web pages to each

individual based on a user model (Fink, Kobsa, & Schreck, 1997) This helps learners

(or users) organise their own learning process with the support of adaptive guidance and

controlled delivery of the learning contents. In the following section, some prevalent

adaptive hypermedia systems are discussed, focussing on how they manage adaptation

to each individual.

3.3. AHSs: An advance on HSs

Early studies (e.g., Cannataro *et al*., 2001; Eklund & Brusilovsky, 1999; Kavcic, 2000)

defined the five common features of AHSs. The first three features, i.e., *hypertext,*

domain model and *flexibility*, are exactly the same as those of HSs or ITSs, but the

following two items, *user model* and *adaptivity,* distinguish AHSs from the traditional

HSs and ITSs.

Some examples of AHSs, e.g., ISIS-TUTOR (Brusilovsky & Pesin, 1994), MetaDoc (Boyle & Encarnacion, 1994), HyperTutor (Prez, Gutirrez, & Lopistguy, 1995) and C-Book (Kay & Kummerfeld, 1994), seem to be very successful in delivering specialised materials in an adaptive way, even though they were limited to a particular application domain. Recently, with the widespread uptake of the Internet in educational sectors, more attention has been paid to web-based AHSs. For instance, ELM-ART I (Brusilovsky *et al.,* 1996a), its successors ELM-ART II (Weber & Specht, 1997), and III (Weber & Brusilovsky, 2001), and AHA (De Bra & Calvi, 1997, 1998a) provided a general framework and engines to implement adaptive learning materials for other learning domains on the World Wide Web (WWW). One benefit the web-based AHSs employ is its platform independence, so that learners with different computing environments could easily access the systems without extra effort to set up their computers. Also, the platform independence motivates teachers' uptake and matches their demands for web-course design in a more effective way. This thesis is mostly concerned about this type of web-based AHSs for this reason.

Table 3.2. Several AHSs

Name	Developers	Focus	Adaptation
ELM-ART I	(Brusilovsky *et al*., 1996a)	Knowledge-based	Adaptive navigation support, link annotation, presentation
ELM-ART II	(Weber & Specht, 1997)	Knowledge-based and goal	Adaptive navigation support, link annotation and direct guidance
ELM-ART III	(Weber & Brusilovsky, 2001)	Knowledge-based and preferences	Adaptive navigation support, link annotation and direct guidance
AHA	(De Bra & Calvi, 1997, 1998b)	Knowledge-based, gaol and interest	Adaptive navigation support, link hiding, sorting, presentation and map adaptation
KBS HyberBook	(Henze & Nejdl, 1999b)	Knowledge, goal and preferences	Adaptive annotation, guidance and presentation

Table 3.2 describes some examples of web-based AHSs. ELM-ART I (Episodic Learner Model Adaptive Remote Tutor) integrated the concept of electronic textbook with ITSs, which was firstly developed to adapt to the student's knowledge state. It explicitly collects the knowledge states of each learner to deliver content appropriate to their level of understanding, with comprehensive questions on the content that has been taught. Two empirical studies of ELM-ART I (Brusilovsky & Pesin, 1998; Schwarz, Brusilovsky, & Weber, 1996) showed that learners with ELM-ART I gained more benefits than those who were trained by a traditional HS.

Yet, a limitation of ELM-ART I was discussed by several researchers, e.g., Brusilovsky and Eklund (1998) and Brusilovsky and Pesin (1998), which was that its adaptation technique – hierarchical structured approach – has some serious drawbacks for determining a student's states on the different concepts, and as a consequence, inappropriately inferring the knowledge state of each student. This limitation has been

much reduced in ELM-ART II (Weber & Specht, 1997), providing personalised feedback which refers students to adaptively selected examples and supports their problem solving based on their learning path. The most recent development – ELM-ART III (Weber & Brusilovsky, 2001) – makes the adaptation more effectively and efficiently using the multi-layered overlay model, storing all information on the user's knowledge state in a portfolio to enable users to view and navigate their personal knowledge states at any time. Each of the techniques employed in the ELM-ART systems are beyond the scope of this thesis.

A further advance in the evolution of AHSs was Adaptive Hypermedia Architecture (AHA; De Bra & Calvi, 1997, 1998a). As De Bra puts it, "It is an open source software which offers adaptive content through variants and adaptive link presentation through link annotation, link hiding and /or link removal" (De Bra, 2002, p. 60), it can be used for all kinds of applications, not necessarily limited to a particular application domain. Several empirical studies also confirmed the advantages of AHA (e.g., Brusilovsky, 2001; De Bra, Aerts, Berden *et al*., 2003; De Bra, Aerts, Smits et al., 2002; De Bra, Aroyo, & Chepegin, 2004).

In sum, it can be seen that adaptive hypermedia systems advanced the functionality of the conventional hypermedia systems, reducing users' cognitive overload and disorientation by combining the freedom to navigate with personalised contents that make the learning with hypermedia more goal-oriented.

3.4. Applications of AHSs: Authoring tools

For educators to design their own course more easily building upon AHSs, some authoring tools have also been developed as shown in Table 3.3.

Table 3.3. Authoring systems for AHSs

Authoring tool	Systems	Focus	Adaptation
InterBook	ELM-ART I	Same approach as ELM-ART domain independent	Adaptive annotation, direct guidance and adaptive help
AHAM	AHA	Knowledge, goal and preference	Content and link structure
KBS HyperBook	KBS HyperBook	Knowledge, preferences and goals	Adaptive annotation, guidance and presentation

For instance, InterBook has been developed on ELM-ART architecture. Whilst ELM-ART is only delivering a LISP course for the Computer Science discipline, InterBook can be used to create other courses, using *adaptive annotation* and *direct guidance* (Brusilovsky *et al.*, 2001; De Bra & Calvi, 1998a). Figure 3.1 depicts the InterBook system.

Figure 3.1 InterBook, Reprinted from Brusilovsky and Eklund (1998)
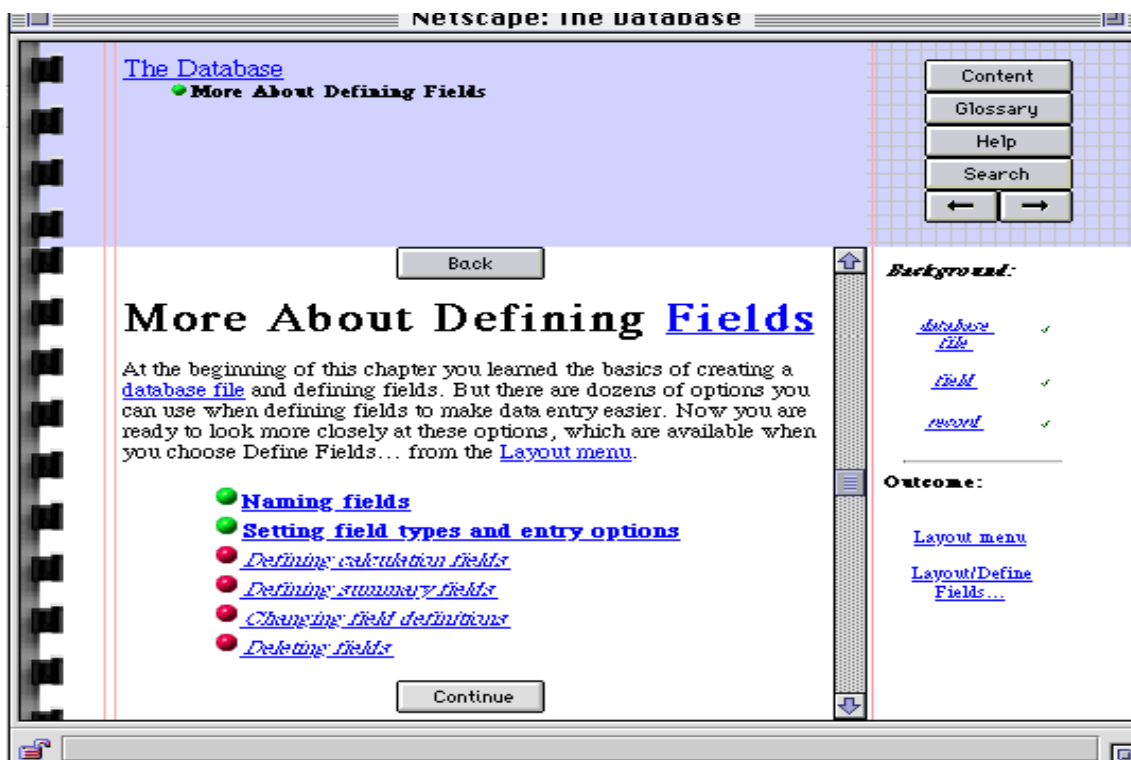
Recently, other authoring tools based on the latest version of ELM-ART, e.g.,

WHURLE (Brailsford, Stewart, Zakaria *et al*., 2002) and NetCoach (Weber, Kuhl, &

Weibelzahl, 2001) have been introduced. Figure 3.2 shows these two authoring tools.

Several empirical studies with InterBook and its authoring tools on ELM-ART

(Brusilovsky, Eklund, & Schwarz, 1998) demonstrated the benefits of AHSs from

educator's perspective.Figure 3.2 (a) The transistor lesson in WHURLE, Reprinted from

Min *et al.* (2005)
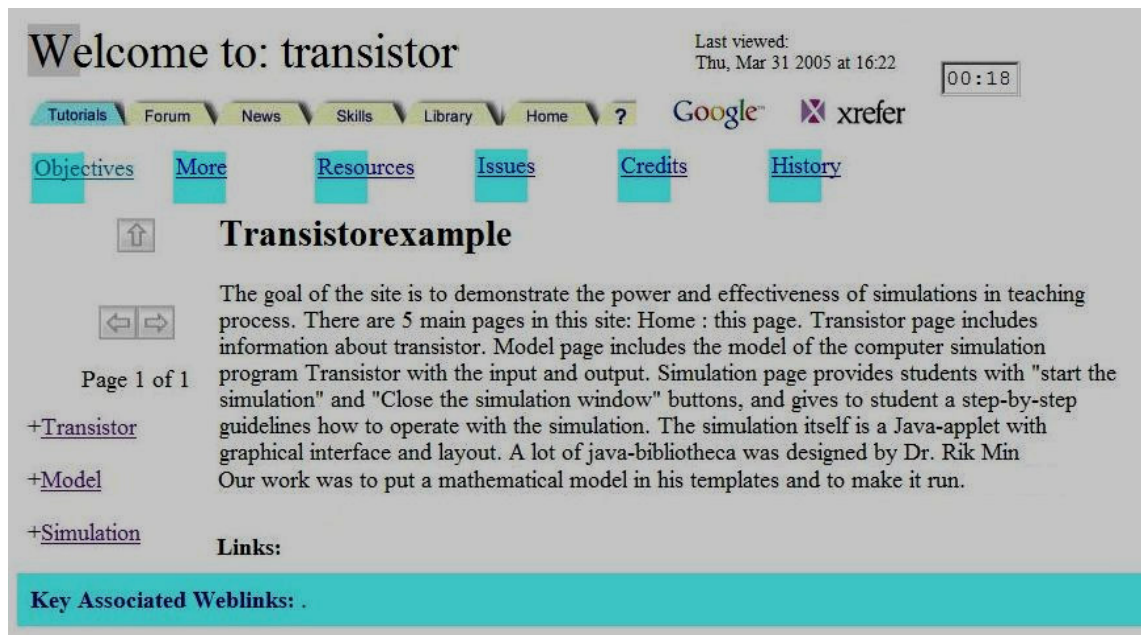
Figure 3.2 (b) NetCoach, Reprinted from Lippitsch *et al.* (2002)
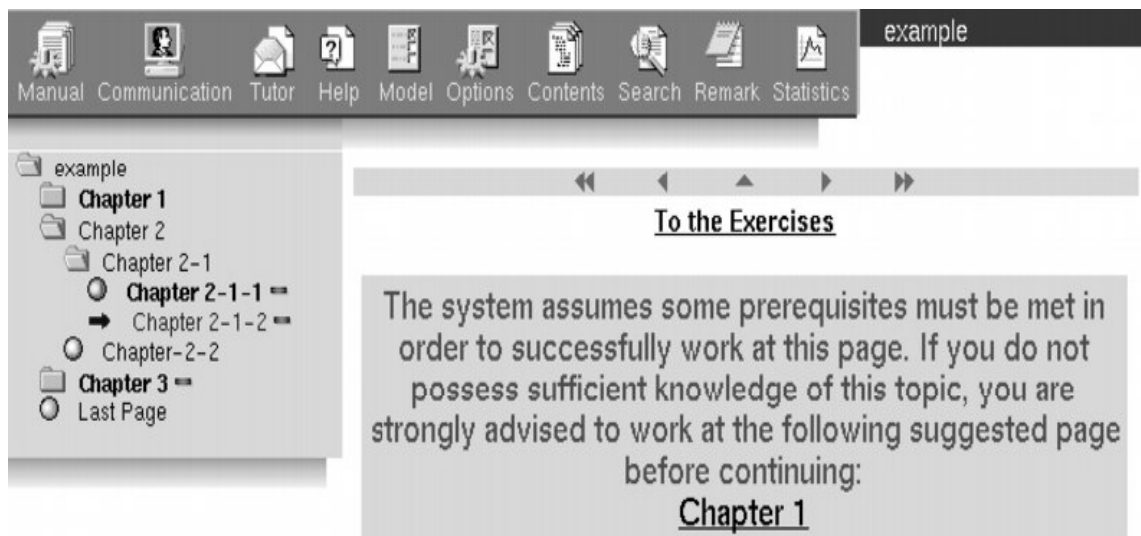
AHAM (Adaptive Hypermedia Application Model) was developed as an authoring tool, based on AHA framework (Wu, Houben, & De Bra, 1998). It offers a rich user model, based on condition-action rules of AHA. The key elements in AHAM are the teaching model, which recognises the importance of pedagogical rules in courses using AHSs, the domain model, and user model. The latter is constructed not only from the user's reading and navigation, but also from external sources (e.g., tests) which are useful for exchanging parts of a user model between different AHSs (De Bra & Stash,

2002; De Bra, Stash *et al.*, 2004*).* The latest version – AHA! (De Bra & Ruiter, 2001) -

has turned AHA into a more versatile adaptive hypermedia platform, which was

designed for more general-purpose uses such as developments of on-line courses,

museum sites, encyclopaedia, and so forth. Its most important feature is the use of

XHTML (eXtended HTML).

Figure 3.3. KBS Hyperbook, Reprinted from Henze, NejdI and Wolpers (1999)
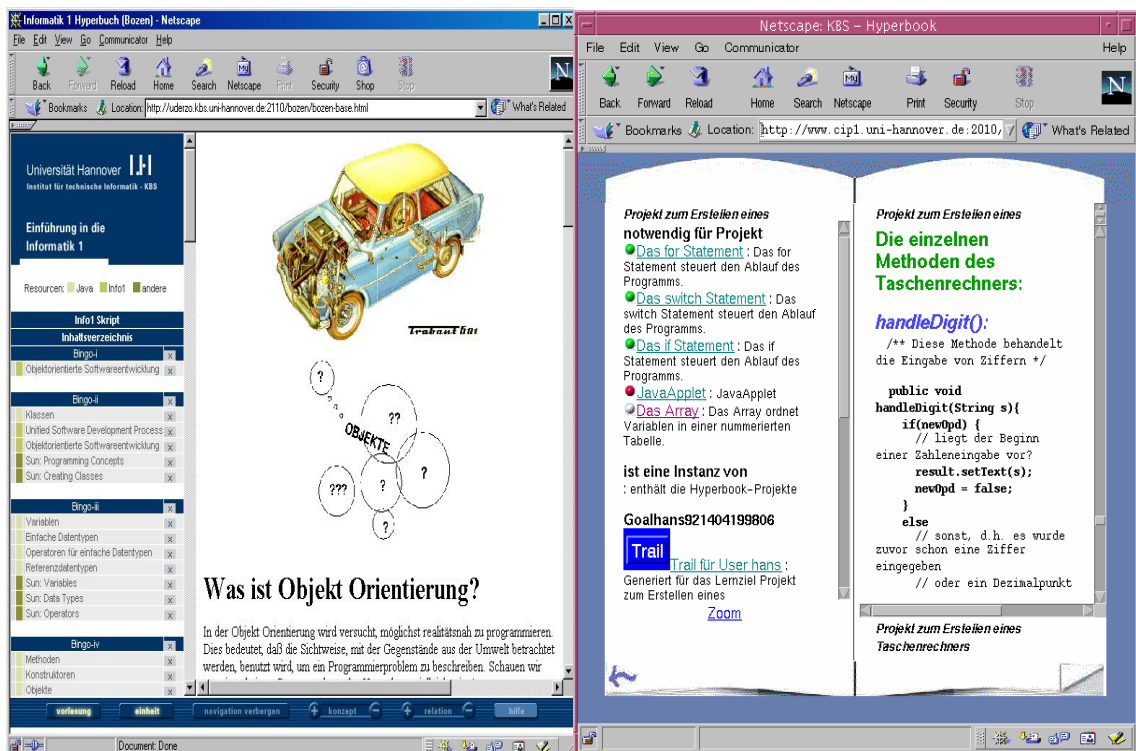
Another authoring tool – KBS HyperBook system (Henze & Nejdl, 2001) -

employs the *Bayesian Networks* approach (Yearling & Hand, 1996) which is believed

to be the most effective technique for designing course contents. It gives learners the

ability to define their own learning goals, and then proposes the next reasonable

learning steps to take. Figure 3.3 gives an insight into this system.

As discussed above, AHSs provided a complete framework and authoring tools

for developing courses on the web. Demand for AHSs has increased particularly in

higher education (more in distance learning activities) where each student is

individually guided into their own learning process without interaction with teachers.

An AHS can be of critical use when students vary in their characteristics (e.g., background, knowledge, personality, and so forth), helping them with the presentation of the page (content level adaptation) and with the navigation (link level adaptation). The most important part to be considered in the design of AHSs is thus to identify how these different individual characteristics can be accommodated in the adaptation process. The following section discusses this aspect of AHSs.

3.5. User models and AHSs

A user model is a standard data model of a user. For AHSs, it ensures a wide range of adaptive processes for each individual, especially in the learning process, accommodating each individual's characteristics, e.g., their goals, interests, and knowledge level. Indeed, this wide consideration in the user model is a key feature to distinguish AHSs from ITSs.

Generally speaking, all the AHSs discussed above build a user profile for each learner, collecting the relevant information, and then they make decisions about what content would match the user's needs according to the features of that profile. One of the initial proposals for the user profile introduced by Wegner (1987) includes all the features (i.e., goals, interests and the knowledge level) of the user's behaviour and knowledge that may affect her/his learning and performance. Yet, in reality, it is not economically feasible to collect such a great deal of personal data, partly because it is too time-consuming and mostly because it is not clear how the collected data would be used in the adaptation process. The biggest concern of the user model for AHSs is thus to identify which features should be included in the user model and how they can be justified. This constructs the main research question of this thesis, which proposes that the inclusion of personality is a key to the user model. It will be further discussed later in Section 3.6.

Figure 3.4. The user model of an AHS, extended from Brusilovsky (2002)
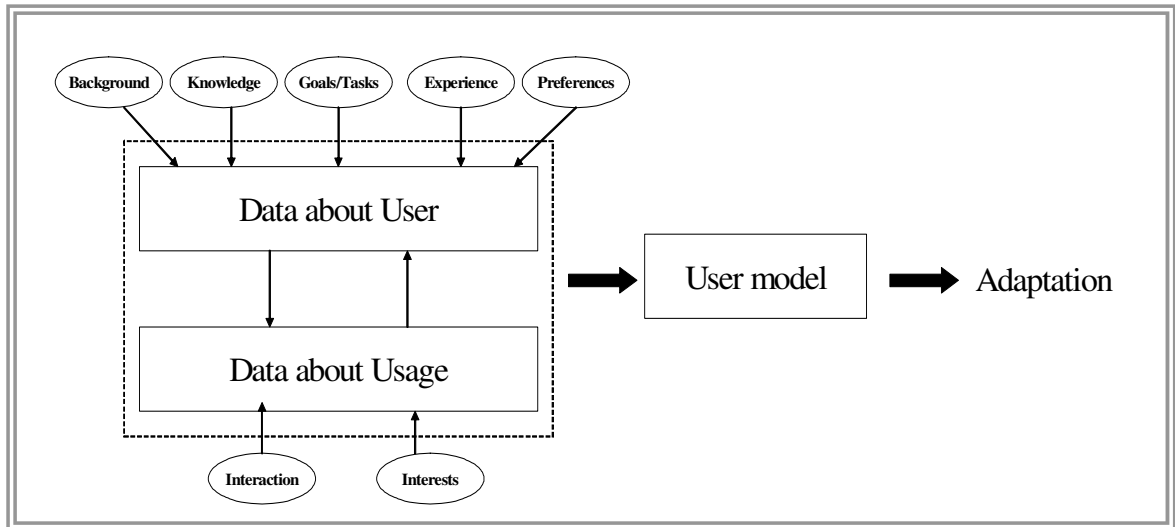
Some studies (e.g., Carver, Howard, & Lane, 1999; Kinshuk & Lin, 2004; Vincent & Ross, 2001b) identified attitudes, goals, interests and their knowledge level as critical attributes in defining different users. They thought that these four items are strongly associated with each learner's cognitive style (Kogan, 1971a; Messick, 1970, 1976b), which can accordingly determine the different learning style for each learner. Therefore, a systematic way of determining the cognitive style in advance using the relevant attributes was of the greatest interest in the design of early AHSs. More comprehensively, Brusilovsky (2002) proposed seven attributes that might be of wide use in any user models for AHSs, as shown in Figure 3.4: *learners' backgrounds, knowledge, goals/tasks, previous learning experience, preferences, interests,* and *interaction style* to match their learning styles. This has a significant impact on the subsequent user modelling activities in the design of AHSs.

Table 3.4. Characteristics being used in the AHSs

Systems	Background	Knowledge	Goal	Experience	Preferences	Interaction	Interest
ELM-ART	✔	✔	✕	✕	✔	✕	✔
AST	✔	✕	✔	✕	✔	✔	✕
InterBook	✔	✔	✔	✕	✕	✕	✕
AHA	✕	✔	✕	✕	✔	✕	✔
KBS	✕	✔	✔	✕	✕	✕	✕
AHAM	✔	✔	✔	✔	✕	✕	✕
AHA!	✕	✔	✕	✔	✔	✕	✕

Much of the choice out of the seven items depends on how easily the features would be modelled. For example, in DCG (Dynamic Courseware Generation), which allows dynamic planning of the contents of an instructional course with a given goal, Vassileva (1998) modelled learners' goals and previous knowledge to generate individual dynamic courses. In contrast, Brusilovsky (2000) considered learners' interests and preferences to explore LISP material. AHA (De Bra & Calvi, 1997) used learner knowledge and interests to provide adaptation to the personal features of a user, including preferences, e.g., colour preferences, text or video/audio for representation. In contrast, KBS HyperBook (Henze & Nejdl, 1999a) allows a user to define learning goals, and then it suggests relevant information, and presents appropriate projects. INSPIRE (Kyparisia, Papanikolaou, Grigoriadou *et al.,* 2001) models learners' goals and previous knowledge.

Consider the details of each item. The learner's *background* formulates all the information related to a learner's context, mostly demographic data, i.e., ages, gender, and educational background. Even though it appears to be quite evident that the learner's background would have an effect on the learning style to some extent, there are no consistent results as to what data should be collected under the learner's

background. For instance, on the one hand, Ford, Miller, and Moss (2001) and Sabine *et al.* (1994) focussed on the gender difference, demonstrating that men were more likely to prefer the abstract conceptualisation mode of learning than women. On the other hand, Heffler (2001) identified no significant gender differences in some learning modes. Some researchers (e.g., Heffler, 2001; Sabine & Bekele, 2006) hypothesised the age of the learner as part of the learner's background, but they consistently concluded that there is no significant correlation between learning styles and age. In contrast, a learner's educational background has long been recognised as a factor influencing his or her educational achievement (Cano, 1999; Ruzic, 2000). In effect, even though it is not easy to generalise what data should be collected for the specification of the background, the first column of Table 3.4 showed several AHSs are explicitly employing the background for their adaptation process. For instance, AST (Specht *et al.,* 1997) collects both gender and educational background in an introductory screening questionnaire for establishing a user profile.

Second, the learner's *knowledge* state is measured by different techniques. The simplest way to represent a learner's knowledge state is by means of measuring how much (or little) the learner knows about the concepts being taught. For instance, InterBook traces student actions (page visits, problem-solving, quizzes answering) and uses them to adapt their knowledge levels for the concepts being taught. It classifies the student's knowledge state in three types: learnt, ready to learn, and not learnt; as a consequence, the system can offer the best contents to follow. By comparison, AHA classifies the knowledge level into two: known or not known, either by acknowledging if a student had read a particular page, or by taking a test. Indeed, the knowledge state, as described in the second column of Table 3.4, is deemed to be of architectural importance in the user model and must be collected for the adaptation process of AHSs.

Thirdly, each student may have individually assigned or created learning *goals*. Adaptive guidance will ensure that the student achieves the learning goals in a sequence. InterBook, for example, models the individual learning goals as a sequence of sets. To exemplify this, imagine a HTML (Hyper Text Markup Language) course design. Arguably, most of this course would be specified in a sequence as follows: 'Definition of HTML', 'Basic HTML tags', 'Advanced HTML tags', 'How to create a web page', and 'How to publish web pages'. InterBook helps a course coordinator formulate these learning goals as a set of predefined achievement goals (Vassileva & Deters, 1998) so eventually each learner should follow this sequence to accomplish the goals specified by the course coordinator. Yet, some learners may have their own learning goals for this HTML course; for example, those who are very keen to publish the web pages do not need to learn HTML tags or the way to create a web page. In this case, the students should be given opportunities to select their learning goals or at least the system could support a way for a student to notify the system about their own learning goals (Henze, Naceur, Nejdl *et al.*, 1999). In particular, when specifying their user profile, Interbook allows learners to select their own learning goals.

Fourthly, some user models for AHSs (e.g., AHA!) also consider all the comparable knowledge that may be employed in the learning process. *Previous experience* has been regarded as an important determinant to specify the possible learning outcomes of each student. For instance, the previous experience of programming languages that a student has may be a pivotal indicator of each learner's intellectual capability to learn the other programming languages. Likewise, adaptive guidance based on previous experiences with an e-learning system itself would help a student organise their learning process effectively (Hothi & Hall, 1998). Therefore, in its deepest sense, the *experience* collected for defining the user model is different from 'background' and 'knowledge state' discussed above, in that *knowledge* state usually

intends to take measures of the level of understanding of the course contents themselves being taught. Indeed, ELM-ART is using the term '*background*' for the term '*experience*'. However, this thesis considers that *experience* differs from both *background* and *knowledge* state in the sense that experience is a more indirect indicator of intellectual capability of each student. In ELM-ART, for instance, learners should specify their relevant experiences for the creation of each user profile.

Finally, learners can explicitly state their own preferences (i.e., presentation or learning styles) through an input form as an AHS initialises a user model or user profile. Mostly, the information on the preferences is being collected by a learner's input, rather than automatically gathered by the system. The preferences chosen by the learner can dictate the adaptive guidance in both presentation and learning styles. For instance, in AST, learners can specify both preferred learning materials and preferred learning strategy like learning-by-example, reading texts and then examples, or learning-by-doing. By comparison, other AHSs, as shown in Table 3.4, only adapt to the presentation style preferred by the learner. Presentation style adaptation has been regarded as a marginal enhancement of the student's learning performance (Jonassen & Grabowski, 1993).

It can be seen that all the features described above are data about the user which are relatively static rather than dynamic, which will be discussed below. Mostly, these types of information are manually given by the users, normally at the beginning of the learning process or implicitly through the user's browsing actions (e.g., number of pages visited, time spent on page, selection of links, searching for further information, and looking for help). By comparison the other two items, i.e., *interests* and *interactions*, which are more dynamic and may be changing all the time, are also considered in the user models for AHSs. The data of the actual usage can thus provide the other side of the user model. Firstly, learners interact with the system in different ways, thus "the

kind of data and the way it is recorded and collected" mostly depend on individual interests (Brinkman, Gray, & Renaud, 2006). For instance, in an HTML course, as we exemplified above, inexperienced learners might be interested in learning simple tags that are the more essential topics of HTML. By comparison, more experienced ones might have more interests in learning 'control structures' to build a graphical user interface. Taking into account the interests of a learner, the system can adapt different aspects of the instructional process. Of course, the detection of the interest would not be so straightforward, because interest could change over time. However, dynamically building hypotheses about the learner's interests would be possible based on characteristics of episodes with certain assumptions about the learner's interests (Snow, Corno, & Jackson, 1996). Secondly, all the interactions of the learner with the objects can be a major input to the user model. They include a time stamp, the units or modules involved, the material presented, material-specific extensions, and the modality in which a material was presented to the learner. However, these data have been little explored in the current AHSs.

The previous studies of the features for different user models conclude that building a user model depends on information provided by the users through their preferences and actions directly, or in most cases, indirectly, when the system observes the choices made by users and tries to infer their underlying goals or preferences (Shneiderman, 1987). Yet, the user models that were employed in most of the AHSs do not seem to consistently incorporate what is to be included and how it can support the student's learning in terms of their differences. Most of them have mainly concentrated on several features that can be easily modelled with the current techniques, e.g., the structure of the contents, and delivery medium of the contents. In particular, how different individuals would benefit from the adaptive process has not been greatly considered. Therefore the next section investigates whether learner's personality

features might have effects on the use of web-based hypermedia systems, which is central to this thesis.

3.6. **Personality and User Models**

Early studies (e.g., Piombo, Batatia, & Ayache, 2003; Riding & Rayner, 1999) on user models have identified that a student's individual features can also be modelled by: (i) *Personality features* that represent the student's identity, (ii) *Overlay features* that denote the student's domain knowledge, and (iii) *Cognitive features* that represent student's individual characteristics. The last two features have been considerably discussed above, following Brusilovsky's account. In contrast, even though it is quite true that the personality difference would be an important issue in traditional e-learning system development (e.g., Felder, Felder, & Dietz, 2002; Soles & Moller, 2001a), less attention has been paid to adaptive e-learning systems, except for several researchers (Gilbert & Han, 1999; Grigoriadou, Papanikolaou, Kornilakis *et al.*, 2001; Kwok & Jones, 1985; Moallem, 2003) who tried to integrate the learning style into the adaptive application. This section thus intends to explore how the inclusions of this personality feature in the user model, which has been overlooked in the early studies of adaptive e-learning systems.

Jungian-based educational psychologists (e.g., Bayne, 2004; Corno & Snow, 1986; Keirsey, 1998; Kwok & Jones, 1985; Soles & Moller, 2001) have claimed that people's personal interests and personality influence the way learners may or may not want to become more actively involved in their learning processes. These seem to be significant variables for determining the learning performance. They thought that personality is also closely tied to their learning styles and preferences, in the sense that a particular outcome would reflect the person's preferences for taking in information and making decisions. Yet, few AHSs had considered these features in their user model,

because there is no easy way to model the personality, except AHA! (Stash, Cristea, & De Bra, 2004) which specifies attributes which reflect the learner's style as "Activist/Reflector". Based on self-rated personality types, AHA! can adaptively guide the subsequent learning process.

There are many different schema of personality types, e.g., Kersey's temperament theory (Keirsey, 1998; 1985), Big-five theory (Buss, 1996) and MBTI (Myers, 1993). Of them, MBTI has been widely used and validated extensively in the education domain (DiTiberio, 1996; 1998) and has long been noted as an important instrument by educational psychologists (Blaylock & Rees, 1984; Stewart, 2006), even though it is a questionnaire-based identification process that is very time-consuming. In particular, the outcomes of MBTI are said to be easy to connect to learning styles of each individual learner from the theory of psychological types described by Jung (Myers, 1993; Myers & McCaulley, 1985). The MBTI reports a person's preferences on four scales, as shown in Table 3.5.

Table 3.5. The four MBTI preferences and the basic definition of the preference

Personality types	Basic definition and the preference	Possible examples of technology in use
Extraverted vs. Introverted	Where they prefer to focus their attention	Videoconferencing in e-learning systems may be of interest for the extraverted learners, which provides face-to-face personal interaction
Sensing vs. Intuitive	The way they prefer to take information	Sensing learners may need the structured framework of the course with specific guidelines and directions.
Thinking vs. Feeling	The way they prefer to make decisions	Thinking learners want to see precise, action-oriented cognitive, affective and psychomotor objective, so they may enjoy an e-learning situation if it follows a more traditional course style, i.e. with case studies and solving logical, planned interactive activities and tests to measure progress.
Judging or Perceiving	How they orient themselves to the external world	Judgers expect an organised routine and will push for decisions to be made and then carry them out. Perceivers, on the other hand, usually need to gather more information and will postpone decisions.

Firstly, the *Extravert-Introvert* dimension refers to where people get their interests. Extraverts are focused on the outer world of people, things and actions, whilst introverts are focused on the inner world of ideas and feelings. Because of these differences, extraverts tend to express emotions freely, and to be energised by interacting with people and seek out feedback from others. They also have a tendency to act first and then reflect. Introverts, on the other hand, will think things through first before acting, store up their emotions, and are sometimes exhausted by interacting with large groups of people. Therefore, newer technology such as videoconferencing may provide face-to-face interaction that the extraverted prefers whereas the introverted learner may prefer

asynchronous communication which enables him/her to see ideas from others, take time to reflect on their ideas, think through a reply, and then communicate with one another.

The *Sensing-Intuitive* dimension refers to how to gather information. Sensing type persons gather information through their five senses and by focusing on facts, data, and observable phenomena. Intuitive type learners gather information by the so-called "sixth sense", by focusing on the big picture and searching for connections, patterns, relationships and meaning. Sensing types rarely make errors about factual things and details, by comparison, the intuitive frequently misses the details while searching for the grand design behind something. In an e-learning situation, sensing learners may need the structured framework of the course with specific guidelines and directions. They may need to see the course objectives and may want to know what is expected and when. They, therefore, may appreciate establishing a learning contract where they set their learning goals (Soles & Moller, 2001), whereas intuitive may prefer the abstract contents, learn by seeing connections, and deal with theory more than experience. E-learning may provide the sensing learner with practical work (using a structured framework with specific guidelines and directions). They may prefer asynchronous communication to collaborate on their group work, whereas the intuitive learners deal with theory more than experience which enables them to create designs.

The *Thinking-Feeling* dimension refers to how to make decisions. Feeling type learners' base decisions on subjective values while thinking types based their decisions on logic, facts, and objectivity. Thinking types see things relatively objectively from outside a situation and are concerned with ideas and principles. They may respond to analyses, case studies and logical problem solving, which may increase their motivation. They also tend to question the conclusions of other people, while feeling-type persons agree with those around them, thinking them to be right. In the e-learning situation, thinking learners want to see precise, action-oriented, cognitive, affective objectives, so

they may enjoy an e-learning situation if it follows a more traditional course style, i.e., case studies, planned interactive activities and tests to measure progress. The feeling-type learners may prefer group exercises and working with small groups (open-end constructivist format).

The *Judging-Perceiving* dimension looks at our drive for closure and organisation. Perceivers like an open-ended, free-flowing, almost structureless environment, while judgers like things definite, settled and organised. Judgers like to have life under control while perceivers prefer to experience life as it happens. Judgers expect an organised routine and will push for decisions to be made and then carry them out. Perceivers, on the other hand, usually need to gather more information and tend to postpone decisions. E-learning may provide judging learners with well structured instruction with clearly defined goals to motivate self-improvement, while perceivers may be provided with more flexible course design (Felder *et al.*, 2002).

As discussed above, it can be concluded that learners with different types of personality tend to have different learning styles, and that; in particular, these might be more significant in the use of e-learning systems. Therefore, to enhance e-learning experience the designer should consider embodying the personality feature into the design of AHS. Knowing the personality of each learner helps to identify those learning preferences and strengths and utilise instructional designs which maximise a learner's potential. Identifying learners' preferences will help the designer create customised educational material tailored to each individual. Although personality is relatively stable to hint each learner preferences (Biggs, 1970; Entwistle & Entwistle, 1970), it is also claimed that personality traits, such as introverted/extraverted can change over time (Heckmann, 2006). However, it is commonly used by several researchers (e.g., Moallem, 2003, Stash, 2004) to integrate personality into their adaptive learning applications.

This thesis proposes that the designer of the user model for AHSs consider the four MBTI preferences as they design educational materials in an attempt to meet the learning needs for each preference.

3.7. Conclusions and Discussion

We have discussed the constituents of the current user models for AHSs, and how they are aiming at the delivery of adaptive guidance. The contribution of the thesis will be two-fold.

It first makes provision for the personality feature as an extension to Brusilovsky's user model (Brusilovsky & Maybury, 2002). Generally, learners having different types of personality tend to respond differently to the learning material and that would have different effects on their performance. Hence, identifying learners' preferences will help the designer create customised educational material tailored for each individual to strengthen and utilise instructional designs which maximise a learner's potential. Therefore, the designer should consider embodying the personality feature into the design of AHS to enhance the e-learning experience. The second contribution of the thesis would be that it provides empirical accounts of the personality feature in e-learning systems. For instance, Chapter 4 discusses whether the personality type of each learner would affect their learning performance with traditional e-learning systems. In the next chapter, we will describe the empirical approach to one of the main elements in the user model. We also intend to provide some theoretical accounts of the user model design that can lead to a more practical e-learning systems design, along with the empirical data we obtained from several experiments. Later, we can see whether our user model framework fits into adaptive e-learning system design.

PART II. EXPERIMENTS TO UNDERSTAND THE ROLE OF PERSONALITY IN THE E-LEARNING SYSTEMS

This part involves three studies to explore empirically the personality effect in individual learning with e-learning systems. Four experiments are conducted to see if the personality type could actually have effects on the use of adaptive e-learning systems. The first two experiments were carried out in Oman, one of the Gulf States Universities in which most of the students were thought to have different learning styles from those of the students in Western Universities. The second two were conducted in a Western University. The first one was to investigate whether different learning styles would have any consequence for the learning performance of Western students, and the second one, to validate the effect of personality.

CHAPTER 4. A COMPARATIVE STUDY OF PERSONALITY EFFECT ON TRADITIONAL E-LEARNING AND ADAPTIVE E-LEARNING SYSTEMS

This chapter explores the use of both traditional and adaptive e-learning systems by learners who have different personality types. The main purpose of this chapter is to see whether the personality feature discussed in Chapter 3 would realistically affect the learning performance with e-learning systems. This chapter thus contrasts two different types of e-learning systems: traditional e-learning systems and adaptive e-learning systems, against the learner's personality types. It is hypothesised that the different personality types of the users would have different effects on their performance of both traditional e-learning and adaptive e-learning. If this is the case, our research would imply the personality feature should be encapsulated in the user model. To do this, two controlled experiments were performed, revealing that the learner's personality type has certain effects on performance in both traditional e-learning and adaptive e-learning systems. These results signalled the importance of personality factor in designing e-learning systems. As a consequence, they indicated the appropriate adaptation in the development of adaptive e-learning systems, taking the personality effect into consideration.

Overview of the Chapter

Section 4.1 questions the personality effect on a traditional e-learning system, exploring its potential effects on learner's performance, in conjunction with the literature on the learning style that is believed to be associated with personality. Section 4.2 empirically shows the impact of individual personality on learning performance with a traditional e-learning system. Compared to this, section 4.3 investigates the personality effect with an

adaptive e-learning system (especially, ELM-ART). These two sections are intended to reveal the effect of personality on the two different types of e-learning systems. The lessons learnt from these empirical studies and some conclusions are drawn in the final section.

4.1. Personality effect on traditional e-learning systems.

Some of the early studies on e-learning (e.g., Mehlenbacher, Miller, Covington *et al.*, 2000), which are mainly about distance learning systems, showed that e-learning systems (e.g., WebCT™, Blackboard™) usually provide various types of learners with the same self-paced learning materials. Whilst the benefits of e-learning systems are generally acknowledged in many cases, more recent research (Brusilovsky, 1998, 2003; De Bra, 2002; Gordon & Bull, 2004; Kobsa, 1994; Weibelzahl, 2001) has criticised the lack of adaptivity of the conventional e-learning systems. In particular, a general classroom learning environment allows both the teacher and the student to interact more conveniently, so they can adapt the contents being taught, or most likely the way of delivering them in response to the student's instant feedback. However, this type of interactivity is not guaranteed in e-learning system use, even though they normally present various ways to be in contact with the teacher. In a self-controlled e-learning environment, learners would inevitably have different paths to learn, depending on their own learning styles. This suggests the importance of considering of learning styles in the design of e-learning systems.

Recently, the consideration of various learning styles in using e-learning systems has been of great interest to educational psychologists who have long thought that there may be explicit relationships between personality types and learning styles. In particular, Jungian educational psychologists (e.g., Bayne, 2004; Corno & Snow, 1986; Keirsey, 1998; Kwok & Jones, 1985; Pask, 1988; Soles & Moller, 2001) have claimed that

people's personality influences the way learners may or may not want to become more actively involved in their learning process, as well as their personal interests in and preferences for the learning materials. In their vast empirical studies, Keirsey (1998), for instance, demonstrated that the personality type of the learner is highly relevant to the learning style, i.e., *Rational type* (NT – **in**tuitive **t**hinking, strategic intellect), *Idealist type* (NF – **in**tuitive **f**eeling, diplomatic intellect), *Artisan type* (SP – **s**ensory **p**erception, tactical intellect), and *Guardian type* (SJ – **s**ensory **j**udgment, logical intellect). Personality type would thus reflect the learner's preferences for taking in information and making decisions, which may be defined by one's learning style. For instance, science students would like to be the rational type; in contrast, those from humanities are often the idealistic personality type.

Hence, this chapter intends to empirically show the personality effect on the use of e-learning system when students use either a traditional or an adaptive e-learning system. It has been noted that the traditional e-learning system does not adapt to individual characteristics of learners to help and guide them during the learning process (Brusilovsky, 2001; Cannataro *et al*., 2001; Kavcic, 2000; Papasalouros & Retalis, 2002; Younis, Salman, & Ashrafi, 2004), so we assumed that the performance data with the traditional e-learning system would represent the baseline figures of the learners who have different personality types. The following experiment with an adaptive e-learning system is expected to produce a comparative analysis against the traditional e-learning system. The personality type of each learner served as the critical variable to contrast the two types of e-learning systems. Also, the interpretation of the learning style of each learner was associated with his or her personality type.

A note on personality type is needed here. Throughout this thesis, we employed the Myer-Briggs Type Indicator (MBTI) to identify the personality type of each learner. There are many different instruments to classify personality types. For instance, one of

the first indicators developed was *Group Embedded Figures Test* (GEFT; Witiken, 1971) was originally to identify two types of cognitive styles: Field Dependent (FD) and Field Independent (FI). FI students appear to be more adept at well-organised and structured learning than their FD counterparts, because FI is more autonomous in cognitive restructuring skills than the FD type. Whilst GEFT firstly proposed a guideline to identify different types of cognitive styles by displaying the norm, and measuring either general intelligence or some specific ability, GEFT learning style only assesses mental traits, so it seems to be imperfect and incomplete (Bonham, 1987).

To address the issues arising from GEFT, the Learning Style Inventory (LSI; Kolb, Boyatzis, & Mainemelis, 2000) classified personality types according to practical learning styles in four groups: conversing, accommodating, diverging and assimilating. People with the conversing type prefer solving problems and finding practical uses for ideas and theories rather than simply understanding the concepts. The second type (i.e., accommodating) specifies people who prefer to use their instincts rather than logical analysis to understand ideas and theories, so their learning style seems to be much more intuitive rather than analytic. This type of learners is often identified as having an artistic talent (Holtzman, 1988). The diverging personality denotes imaginative and sensitive persons who prefer learning by observing, and are good at viewing concrete situations. In particular, this type of learners tends to give up learning activities, so that it is necessary for the teacher to develop a way to encourage this type of learners with adequate support and spontaneity in the learning process (Bonham, 1987). Finally, the last personality – assimilating – prefers to learn by organising information into a concise logical order, so it is generally believed that this type of learner might not go well with the top-down delivery-mode (Sewall, 1988). This type of personality will be further discussed in Chapter 5. Whilst LSI is highly effective to determine the learning style of each student in the educational sector, so it is of great use in the development of

appropriate lesson preparation, the four classifications of LSI have not been widely used. In an empirical sense it is not easy to take measures of the personality of each individual in such an exclusive manner. Several studies (e.g., Danchack, 2004) showed that many students have both conversing and assimilating personality, which implies that we need a more integrated way of discussing personality type.

MBTI ensures this approach. In this vein, there are three reasons to favour MBTI in this thesis. Firstly, it was originally developed to identify people's personality type (Myers & McCaulley, 1985), particularly for the education domain. Second, MBTI personality type is widely recognised as a determining factor for how people learn and has been used to develop a better understanding of the influences on on-line learners' performance and success (Felder *et al.*, 2002; Horikoshi, 1998; Kilmann, 1998; Meisgeier, Murphy, & Meisgeier, 1989; Whittington & Dewar, 2000; Whitworth, 2005). Finally, it has been used for developing different teaching methods for meeting different students' learning styles, and providing some guiding principles to improve learners' performance in the learning process (Soles & Moller, 2001). Therefore, MBTI has been used throughout this thesis.

4.2. Experiment 1: Personality and traditional e-learning system

As discussed above, the relationship between personality and performance on traditional e-learning systems has been much investigated. Several studies (Daughenbaugh, Ensminger, Frederick *et al.*, 2002) clearly indicated the extraverted students outperformed the introverted, but many experimental results also found the opposite or no significant outcomes (e.g., Calvi & DeBra, 1997; De Bra, 2002; Höök, 1996; Younis *et al.*, 2004). The experiment in this chapter does not intend to reinvent the wheel, but to present comparative data for the following experiment described in Section 4.3. This experiment aimed to understand the impact of personality on learning performance with

a traditional e-learning system. Indeed, the main concern of this chapter is to identify the difference between a traditional e-learning system and an adaptive e-learning system in terms of the MBTI personality type, in particular, extraverted vs. introverted.

To do this we implemented a traditional e-learning system. In fact, it had the same learning contents as the adaptive e-learning system used later in Section 4.3, except for the adaptive mechanism. That is, the two systems used in the chapter were exactly the same except that the traditional e-learning system did not have any adaptation process for each individual difference that the adaptive e-learning system actually has. To see a particular personality effect in this experiment we recruited relatively homogeneous participants from an Omani University, at which the author has worked.

4.2.1. Method

4.2.1.1. Participants

20 males (19-25 years old) and 20 females (19-25 years old) from an Omani University took part voluntarily in this experiment. They received no reward for their participation. They had some degree of homogeneity in that they were all undergraduates taking Computer Sciences (CS) courses at the University. The homogeneity of the participants was evident from their previous learning outcomes in the other CS courses (all of them are more than B+ grade average) and their knowledge level of programming skills (e.g., C, C++, and Pascal) are within average. These courses are compulsory for their learning progress in the undergraduate degree of computer science.

Demographic data about participants was gathered to categorise the learners according to their background experiences. To interpret data correctly, learners were asked to answer a questionnaire (see Appendix 1.1 and 1.2), that was provided by the system at the beginning of their learning experiment, as shown in Table 4.1.

Table 4.1. Background experience of Omani learners (Experiment 1)

	Background Experiences						
	Working with WWW			Programming languages		Using Computers	
	Little	Sometime	Frequently	Pascal, C, C++	Others	Up to 100 Hours	More than 100 Hours
Oman (n=40)	34	6	0	40	0	32	8

Table 4.1 summarises the data on the background experience of the Omani learners. It clearly showed that all these Omani learners have little experience in using the computer and the Internet and that because of the lack of university facility.

All the students were guided to have very similar levels of self-motivation and self-regulation, in other words, they were all autonomous, competent, able to generate access, evaluate and apply knowledge to address the problems, in the sense that this experiment was considered as part of their tutorial session of the artificial intelligence (AI) course. Based on the MBTI test, 28 introverted and 12 extraverted types were identified. In each group 50% of the participants were females and 50% males which indicates there was no gender difference in the personality type.

4.2.1.2 Apparatus

A traditional e-learning system for teaching LISP, as shown in Figure 4.1, was developed (based on the contents of ELM-ART). This system only included the course contents of declaration, functions, and lists, comprising ten web pages. Also, it presented some quizzes on the contents at the end of every page, but our participants were not actually forced to answer them. Instead, at the end of the learning session, a paper-based test having 40 questions was administered, in order to measure their overall learning performance with the e-learning system. Appendix 1.3 shows the paper-based

test. Figure 4.1 represents the interface of the designed system. See Appendix 1.4 for some other diagrams of the apparatus.

Figure 4.1. A web-based e-learning system for teaching LISP
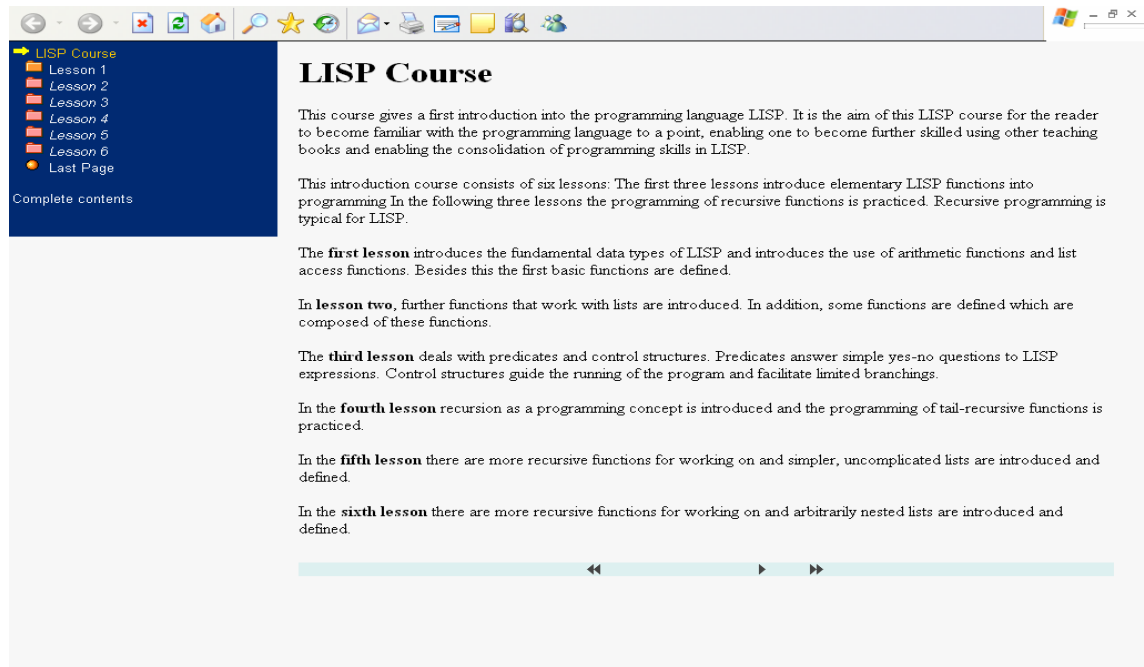
4.2.1.3. Experiment design

A one-way experimental design was implemented, where personality is an independent variable. Time taken (to complete all the lessons), correct answer (out of 40 quizzes), number of navigations (to check all the navigational movements) and number of repetitions (to measure how many times learners returned to see the pages visited) served as dependent variables.

4.2.1.4. Procedure

Firstly, participants were provided with the instructions regarding the experiment. These gave information about the experimental procedure, the purpose of the study, and the data protection policy. All the participants then performed MBTI tests, and then they were all seated in a laboratory where an e-learning system for LISP (see Figure 4.1) was installed on each computer. They were given sufficient time to learn all the materials

with the system. At the end of the learning session, they were administered 40 questions about the contents that they had learned from the system. See Appendix 1.3 for the questions used in the experiment.

4.2.2. Results and Discussion

Figure 4.2 gives an insight into how different personality types can be depicted using their overall learning patterns. Interestingly, the introverted were taking more time in the early stage of learning, whilst the extraverted spent less time at the beginning and more time at the end of the learning. This pattern of learning seems to be consistent with the previous findings (e.g., Felder & Brent, 2005) of the personality effect on learning performance.

Figure 4.2. Time taken in the traditional e-learning use situation
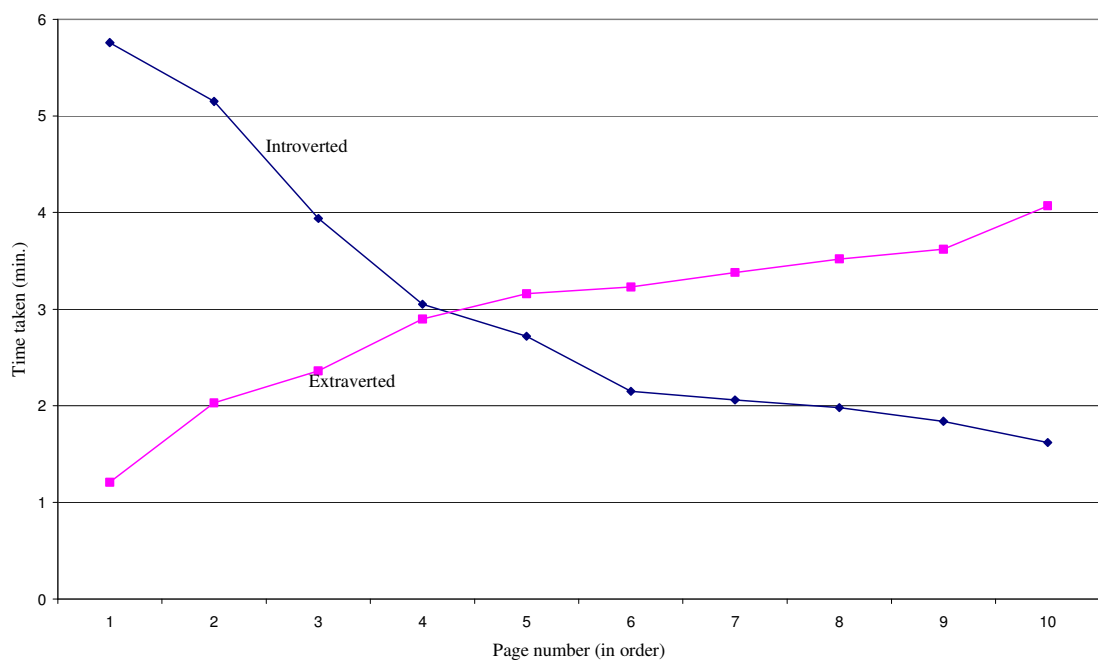
Table 4.2. Time taken (mean/s.d) unit: Mins.

Personality type	Page1, 2 and 3	Page 4, 5, 6 and 7	Page 8, 9, and 10	Total
Introverted (n=28)	14.85 (2.62)	9.99 (1.75)	5.45 (.96)	30.27
Extraverted (n=12)	5.64 (.68)	12.65 (1.56)	11.20 (1.46)	29.47
Sig.	p<0.01	p<0.01	p<0.01	n.s

This pattern of the learning process can be also identified in Table 4.2, which summarises the time taken in the three stages, for the reader to understand the learning pattern more easily: beginning stage (page 1, 2 and 3), middle stage (page 4, 5, 6 and 7), and last stage (page 8, 9 and 10).

Looking at the figures in Table 4.2 it appears that the introverted learners were spending more time at the beginning of their learning process; however the extraverted spent more time at the end of the learning process. T-tests described in the bottom row of Table 4.2 were also supportive of this account. Nevertheless, the total time spent has no significant difference.

Table 4.3. Other task performance (mean/s.d)

	Introverted (n=28)	Extraverted (n =12)	sig.
Correct answers (%)	55.29 (14.11)	57.67 (10.23)	n.s.
No. of navigations	55.64 (7.08)	55.00 (5.86)	n.s.
No. of repetitions	12.89 (3.50)	12.75 (3.14)	n.s.

Table 4.3 summarises the other performance measured in this experiment. Unlike the results above, both introverted and extroverted seemed to have no significant difference in the terms of the three measures. This was confirmed by multi-variate one-way between-subject analysis of variance, revealing that no significant personality effect was found.

These experimental results briefly show that the personality type itself may not have significant effects on learning performance itself when the learners were being

taught by a traditional e-learning system, even though there is a certain relationship between the personality and the learning style.

To some extent, this result parallels with early studies of the relationship between e-learning systems and learning styles (Felder *et al.*, 2002; Kwok & Jones, 1985; Monthienvichienchai, Owen Conlan, & Seyedarabi, 2005; Soles & Moller, 2001), which revealed that the traditional e-learning systems only allow students to see the same learning path, so there were fewer significant differences. However, the other studies (Daughenbaugh *et al.*, 2002; Soles & Moller, 2001) demonstrated against the findings from our experiment, claiming that the extraverted would have more benefits from e-learning systems than the introverted. Our experiment only identified that there is some difference in their learning process, i.e., the introverted took more time in the beginning rather than the extraverted, as they learnt LISP with the traditional e-learning system.

This can be explained in three ways. Firstly, the previous studies have not considered the other characteristics (e.g., backgrounds or knowledge levels), so it is very difficult to separate the personality effect from them; however our experiment was set up with relatively more homogeneous learners, so it may take only the personality effect under a more realistic consideration. Secondly, both the learning domain (i.e., computer science discipline) and learning materials (LISP) used in Experiment 1 are different from the early studies. Therefore, the direct comparison with the previous studies would not be reasonable. Thirdly, Experiment 1 was completed in the computing lab supervised by the experimenter, so this overt monitoring may change their performance.

Notwithstanding the constraints described above, it seems to be very clear that Experiment 1 was to empirically represent that traditional e-learning systems were not designed to support personality difference so it was a neutral learning system to help

and guide the learners. In the following experiment, we intended to re-use the same experimental setting, except using an adaptive e-learning system, which may reveal the effects of the personality feature against the two different types of e-learning systems.

4.3. Experiment 2: Personality and an adaptive e-learning system

Experiment 1 revealed that personality type could not make a significant difference to the learning performance with a traditional e-learning system, probably since it was not designed to support adaptation to individual characteristics to help and guide them during the learning process. In particular, it identified that the way time is being spent seems to be a critical issue to be reviewed. Experiment 2 aims to understand the impact of individual personality on learning performance, implementation and the use of an adaptive e-learning system.

4.3.1. Method

4.3.1.1. Participants

20 participants (12 males and 8 females), who had not participated in Experiment 1 took part in this experiment. None of them had any experience of LISP before. The MBTI tests classified them into two groups: 12 introverted and 8 extraverted. They were believed to have a certain level of homogeneity in the sense that they all had very similar learning outcomes in other computer science courses and similar knowledge level of computer science programming skills. The demographical data were also collected as shown in Table 4.4. See Appendix 2.1 for the detail of the experiment.

Table 4.4. Background experience of Omani learners (Experiment 2)

	Background Experiences						
	Working with WWW			Programming languages		Using Computers	
	Little	Sometime	Frequently	Pascal, C, C++	Others	Up to 100 Hours	More than 100 Hours
Oman (n=20)	18	2	0	20	0	16	4

Figure 4.3. ELM-ART used in Experiment 2
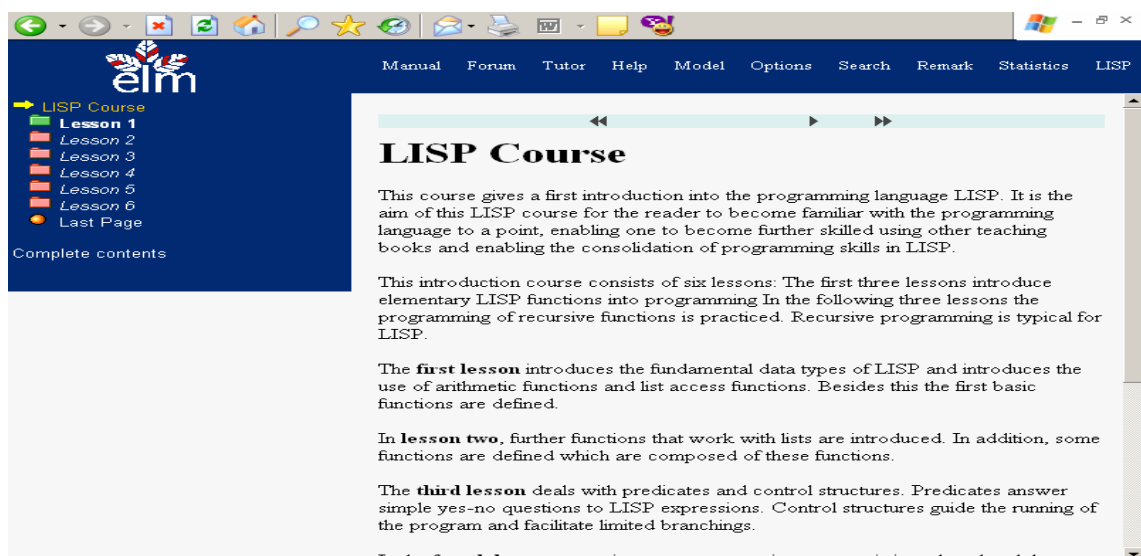
4.3.1.2. Apparatus/Design/Procedure

An adaptive e-learning system for teaching LISP was designed based on ELM-ART (Brusilovsky *et al.*, 1996a) with the permission of the developers. That is, the same adaptive logic and interfaces in ELM-ART were used, but some contents were modified to be the same as those of Experiment 1. The same procedures and experimental design as Experiment 1 were followed. Figure 4.3 gives an insight into the experimental apparatus. See Appendix 2.2 for the detailed apparatus of the experiment.

4.3.2. Results and Discussion

Table 4.5. Overall task performance in Experiment 2

Task performance (mean/s.d)			
Time taken (unit: Mins.)	Correct. Answers (%)	No. of navigations	No. of repetitions
30.08 (8.28)	80.55 (14.04)	41.70 (15.30)	10.15 (8.43)

Table 4.5 shows the overall performance of Experiment 2. Comparing these figures with Table 4.3, we see that our participants in Experiment 2 generally had benefits from the adaptive e-learning system in terms of correct answers (mean 56.64 vs. 80.55), numbers of navigations (mean 55.32 vs. 41.70) and numbers of repetitions (mean 12.82 vs. 10.15). These results clearly show the adaptive e-learning system could present advantages over the traditional e-learning system, which is consonant with early studies (Boyle & Encarnacion, 1994; Brusilovsky, 1998; Calvi & De Bra, 1997; Höök, 1998). This was confirmed by T-test, revealing that there was no difference between Experiment 1 and 2 in terms of time taken, but significant difference on other variables, i.e., correct answers, navigation and repetition.

Table 4.6 Personality effects on the traditional and adaptive e-learning systems

Systems	Personality	Time taken (unit: Min.)	Correct answers (%)	No. of navigation	No. of repetition
Non-adaptive e-learning	Introverted (n=28)	30.27 (5.29)	55.29 (14.11)	55.64 (7.08)	12.89 (3.50)
	Extroverted (n=12)	29.47 (3.71)	57.67 (10.23)	55.00 (5.86)	12.75 (3.14)
Adaptive e-learning	Introverted (n=12)	32.54 (8.58)	76.75 (15.83)	46.58 (15.51)	13.17 (9.57)
	Extroverted (n=8)	26.40 (6.69)	86.25 (8.89)	34.38 (12.47)	5.31 (3.16)

Table 4.6 contrasts the results of Experiment 1 with Experiment 2. It shows that extraverted learners using the adaptive e-learning system outperformed the extraverted learners using the traditional e-learning system except in the time taken. In terms of the

correct answers (mean 86.25 vs. 57.67), the adaptive e-learning system significantly enhanced their understanding of LISP. Also it facilitated more efficient navigation (mean 34.38 vs. 55.00) and less repetition of the pages (mean 5.31 vs. 12.75) which they had already seen Also it showed that the introverted using adaptive e-learning outperformed the introverted using traditional e-learning in terms of correct answers (mean 76.75 vs. 55.29) and number of navigations (46.58 vs. 55.64) but not in the number of repetition.

This was further analysed by T-tests, indicating that there were no significant differences between extraverted and introverted learners in the traditional e-learning systems, whereas there were significant differences between extraverted and introverted in all measures with adaptive e-learning. This was also presented in Table 4.7.

Table 4.7. Other measures of task performance in Experiment 2

	Introverted (n=12)	Extraverted (n =8)	Sig.
Correct answers (%)	76.75 (15.83	86.25 (8.89)	p<0.05
No. of navigation	46.58 (15.51)	34.38 (12.47)	p<0.05
No. of repetition	13.17 (9.57)	5.31 (3.16)	p<0.01

Table 4.7 summarises the task performance by the two different personality groups (introverted and extraverted). It shows that extraverted students considerably outperformed introverted on the three measures (mean 86.25 vs. 76.75 in correct answer; mean 34.38 vs. 46.58 in number of navigations; mean 5.31 vs. 13.17 in number of repetitions). As these figures seem to reveal the benefits of adaptive e-learning systems, the effect of the adaptation can be seen as more pivotal in the adaptive e-learning systems.

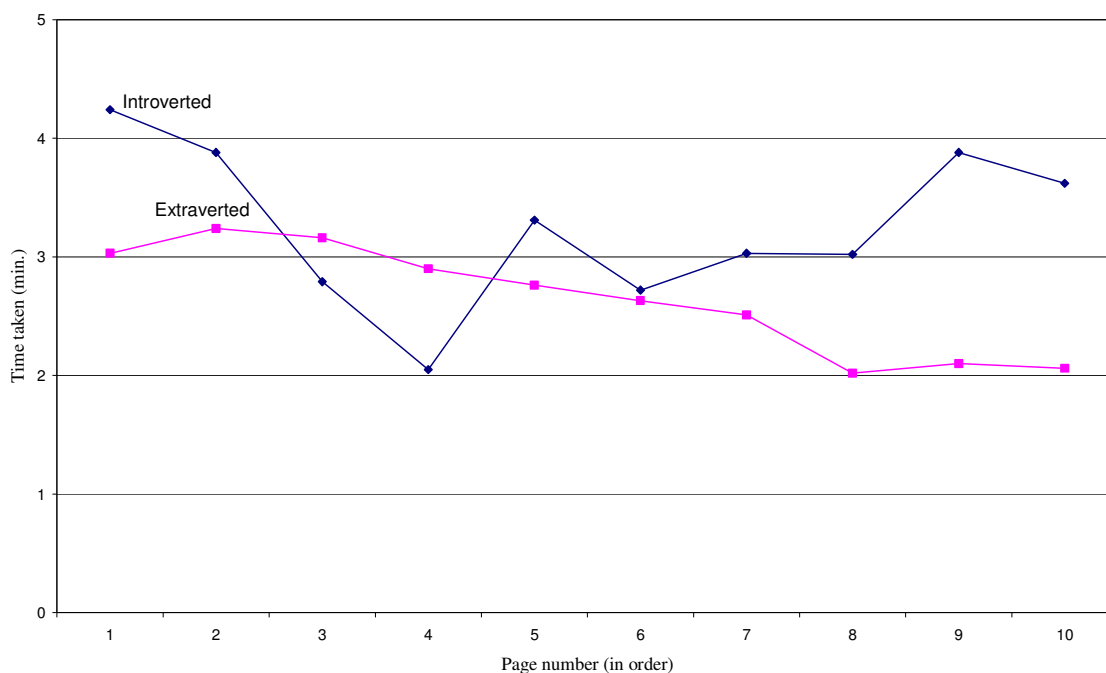**Figure 4.4. Time taken using the adaptive e-learning (unit: Mins.)**

Figure 4.4 shows the learning pattern in terms of the time taken; it can be seen that the extraverted seem to be spending their time more evenly than the introverted in the learning course, i.e. progressing more steadily. Secondly, comparing this with Figure 4.2 (using the traditional e-learning system) the extraverted seem to become faster when using the adaptive system while the introverted become slower, possibly less efficient. This suggests that the personality effect could be more significant in adaptive e-learning systems than the traditional e-learning system. This was also presented in Table 4.8.

Table 4.8. Time taken (mean/s.d) unit: Mins.

Personality type	Page1, 2 and 3	Page 4, 5, 6 and 7	Page 8, 9, and 10	Total
Introverted(n=12)	10.93 (2.96)	11.38 (3.09))	10.22 (2.55)	32.54
Extraverted(n=8)	9.42 (2.23)	10.79 (3.02)	6.18 (1.52)	26.40
Sig.	n.s	n.s	p<0.01	p<0.01

However, it can be also understood that the ELM-ART course has a high degree of linear structure, and programming skills with a practical utility that extraverted learners may prefer. Therefore, more experiments with more participants and other

learning situations will be needed to be done to reconfirm and generalise the results; this is considered in Chapter 7.

4.4. General Discussion

The main questions raised in the introduction of this chapter were how personality difference works in the process of learning, and what benefits the different types of learners could get from both the traditional e-learning system and the adaptive e-learning system.

The first conclusion to be drawn was that performance resulting from the traditional e-learning systems might be less related to individual personality type. The second conclusion, which resulted from Experiment 2, was that adaptive e-learning systems seemed to be more dependent on individual differences. That is, adaptive e-learning systems are more vulnerable to the personality effect, so it paradoxically raises awareness of the importance of the personality in the design of adaptive e-learning system. Other studies (Chen & Macredie, 2002; Moallem, 2003; Papanikolaou, Grigoriadou, Kornilakis *et al.*, 2003) had a similar approach to this study, emphasising the same fact that learners perceive and process information in very different ways depending on personality. Lauridsen (2001) further claimed that adaptive e-learning systems should focus not only on technologies but also on the learners' learning styles and personal approach. In this respect, guidance in the e-learning experience is a key so that the individual learner with different personality can get some suitable material and some support according to his/her need for how to interact with the system functionality, which is the main empirical contribution of this chapter.

Yet, it should be noted that on the one hand, the size of the experiments was small, and on the other hand, there were other factors that might affect the learning performance of our participants, for example, their lack of experience (background) in

using the technology, and computer skill (Holscher & Strube, 2000). It indicates that more thorough experiments need to be carried out before generalising the finding from these two experiments, which will be fully addressed in the next chapter, given the limitations discussed above.

CHAPTER 5. OTHER PERSONALITY TRAITS AND LEARNING PERFORMANCE

This chapter describes another experiment that was intended to review the outcomes from the previous chapter, which was performed in a Western University. The main concern of this chapter was to see whether the results from the previous chapter, particularly Experiment 2, could be generalised in the other tertiary education context, and further, whether the other personality types can affect student's learning performance with adaptive e-learning systems. To do this we considered the other types of MBTI (i.e., Sensing - Intuitive, Thinking - Feeling, and Judging - Perceiving), which were not considered in Chapter 4. We found consistent results between Experiment 2 (Chapter 4) and the experiment in this chapter; however, there were less significant differences in the other personality traits.

Overview of the Chapter

The main purpose of this chapter is to repeat Experiment 2 (Chapter 4) at a Western University in order to generalise the findings from Chapter 4. Section 5.1 describes the personality types newly considered in this chapter. Section 5.2 illustrates whether the other personality types would help us empirically understand the learning performance with adaptive e-learning systems. Finally, Section 5.3 discusses the lessons learnt and draws some conclusions from this case study.

5. 1. Other Personality Types and Their Potential Effects

A subsequent question raised from Chapter 4 was that learning performance on adaptive e-learning systems might be affected by other personality types. Indeed, we only considered the "Extravertedness and Introvertedness" in Chapter 4, so this chapter

further investigates whether the other personality types of MBTI (Sensing - Intuitive, Thinking - Feeling and Judging - Perceiving) would be of use to understand learning performance on adaptive e-learning systems.

According to the literature on personality theory (e.g., Felder *et al.*, 2002; Rao, 2002; Shuck, 1999; Sloan & Jens, 1982), it is generally thought that sensing type learners tend to be practical and detail-oriented, so they are more keen to focus on facts and procedures. It implies that systematic instruction or step-by-step learning material would suit the sensing type learner. By comparison, intuitive learners prefer abstract and concept-oriented approaches, so they more easily attain complex concepts and ideas than the sensing type learner (Soles & Moller, 200). Another personality type – thinking vs. feeling – has been considered as an important characteristic to predict a learner's general learning style. The thinking personality facilitates decisions based on logic and rules, so those who have this trait lean toward practical values in their learning process. In contrast, the feeling type learners tend to make decisions based on personal accounts rather than on a logical basis, so they enjoy more capturing the values of their learning experience from interacting with both teachers and friends rather than learning materials (Leanmont, 1997; Myers, 1993; Vincent & Ross, 2001). This collaborative issue will be further discussed in Chapter 7. Regarding the final personality type, Judging and Perceiving, Myers *et al.* (1998) states that these preferences are the ways people interact with their environment. According to several studies (Felder *et al.*, 2002; Myers *et al.*, 1998; Vincent & Ross, 2001a) judgers like well-structured instruction with clearly defined assignments, goals, and milestones, so the system needs to structure the instruction clearly, perhaps providing a written outline, to point out what is going to be covered. On the other hand, perceivers like to have choice and flexibility in their assignments and dislike rigid timelines (Lawrence, 1984, 1997), so they need a structure decomposed into tasks, with more opportunities for feedback.

Table 5.1. The relationship between learning style and preferred learning material design, extended from Soles and Moller (2001)

Personality from MBTI	Preferred learning materials	References
Sensing	Systematic instructions or step-by-step learning materials (e.g., structured lectures and practical examples)	Soles & Moller (2001a)
Intuitive	Conceptual instructions (e.g., concept maps)	Soles & Moller. (2001a)
Thinking	Instructions that include logical and practical accounts (e.g., case studies, examples of applications)	Myers (1993)
Feeling	Interactive learning materials or equipment that can explicitly represent meanings	Myers (1993)
Judging	Planned learning materials (e.g., course materials that tightly follow the syllabus of the course), Qualitative and quantitative analysis (e.g., statistics and research methods)	Leanmont (1997)
Perceiving	Exploring ideas to solve problems and find solutions creatively (e.g., artistic students)	Lawrence (1984)

Table 5.1 summarises the differences of the preferred learning materials between personality types. This understanding between personality types and learning preferences has long been considered in developing effective learning environments. For instance, Wicklein and Rojewski (1995) showed that a better understanding of personality can lead to more satisfaction of individual learning needs, and also create an opportunity for educators to ensure the optimal learning environment. Therefore, this additional consideration will help us develop adaptive e-learning systems, achieving the primary purpose, which is to adapt to learners' needs.

Considering these personality types that were not investigated in the previous chapter, we performed the same experiment as in Chapter 4 in New Zealand. Indeed, we realised that the participants from Oman were not appropriate for this experiment, because there were many obstacles which made it too difficult to investigate the other personality types. For instance, we found that there were not sufficient numbers of feeling-type students in the Omani university. Therefore, the New Zealand case study

described here is to address these issues, in which the learners are expected to have different learning styles from the Omani students and this may give a contrasting result.

5.2. Experiment 3

This experiment was performed to see whether the understanding of the other MBTI personality types would help to account for learning performance on adaptive e-learning systems, and to see if the findings from Experiment 2 (Chapter 4) can be generalised, by replicating the same experiment with New Zealand students. The reasons for choosing New Zealand for the investigation are firstly that the author is studying at a university in New Zealand, and secondly, the student population is generally expected to have more diverse cultural backgrounds than Omani students. Both Table 5.2 and 5.3 show the contrast between Omani and New Zealand students, those who were recruited for Experiment 2 (Chapter 4) and the experiment in this chapter.

Table 5.2. Comparison of background experience of both Omani participants and New Zealand participants

	Working with WWW			Programming languages		Using Computers	
	Little	Sometime	Frequently	Pascal, C, C++	Others experience	Upto100 Hours	More than 100 Hours
Oman* (n=20)	18	2	0	20	0	16	4
NZ (n=39)	4	3	32	20	19	0	39

*The data of Omani participants were reused from Experiment 2.

Table 5.3. The participants in Experiment 3

Ethnicity	Number of participants
Chinese	14
Arabic	5
Indian	7
New Zealander	13
Total	39

Table 5.2 compares the background experience of New Zealand participants in this experiment and Omani ones. It clearly showed that New Zealand learners generally have more experience in using the computer and the Internet than the Omani students. Also, Table 5.3 indicates that the New Zealand participants are multi-cultural learners (Howles, 2007), which may help us to explore different personality traits in this experiment.

5.2.1. Method

5.2.1.1. Participants/Apparatus/Design/Procedure

39 students were to voluntarily participate in the experiment. They had some degree of homogeneity in that they were all undergraduates taking Computer Sciences (CS) courses at the University. The homogeneity of the participants was evident from their previous learning outcomes in the other CS courses (all of them are more than B+ grade average) and their knowledge level of programming skills (e.g., C, C++, and Pascal) are within average. Their ethnic background/experience data were shown in Table 5.3. The details of each personality are described in the results section. The apparatus, procedure and experimental design were exactly the same as Experiment 2 of Chapter 4. See also Appendix 2.2 for some figures of the apparatus. For taking part in the experiment, they received a five-dollar voucher.

5.2.2. Results

Table 5.4. Personality effects on an adaptive e-learning system in both Oman and New Zealand. (mean/s.d)

		Time taken (unit: Mins.)	Correct answers (unit: %)	No. of Navigations	No. of Repetitions
Oman*	**Extravert (n=8)**	26.40 (6.69)	86.25 (8.89)	34.38 (12.47)	5.31 (3.16)
	Introvert (n=12)	32.54 (8.58)	76.75 (15.83)	46.58 (15.51)	13.17 (9.57)
	Overall	29.47 (7.64)	81.50 (12.36)	40.48 (13.99)	9.24 (6.36)
New Zealand	**Extravert (n=28)**	18.05 (2.44)	82.49 (5.47)	53.32 (12.42)	15.68 (8.95)
	Introvert (n=11)	22.28 (4.59)	75.77 (8.07)	66.45 (9.62)	20.36 (8.52)
	Overall	20.16 (3.52)	79.13 (6.77)	59.88 (11.02)	18.02 (8.73)

*Oman data from Chapter 4, for the reader to compare the results easily.

Table 5.4 summarised the overall results from both Experiment 2 of Chapter 4 and this experiment, to help the reader see the difference between Oman data and New Zealand data. It appeared that New Zealand learners (mean=20.16) outperformed Omani students (29.47) in terms of the time taken. New Zealand participants completed the entire lesson in two-thirds of the time taken by Omani students. This can be explained by the fact that Omani learners are less experienced in computer technology as depicted in Table 5.2. Similar patterns can be observed in both numbers of navigations and repetitions. That is, New Zealand learners took more navigations and repetitions on the course materials to learn, which may emphasise that they are more experienced and confident in using the system (Howles, 2007); therefore experience level must be included in the user model.

Indeed, it is very hard to compare this finding with the results from Omani-only group because our participants in this experiment were from different ethnicities, i.e., Chinese, Arabic, Indian, and native New Zealanders. However, the comparisons among the different ethnic groups were not significant by multi-variate ANOVA, so we analysed these data in an aggregate way in the following sections. Also, the participants

for this experiment were carefully chosen; all the participants have been educated for a long time (i.e., five years and over) in the New Zealand education curriculum, so the comparison between the Oman and New Zealand data sets does not seem to be problematic.

Firstly, we found that there seems to be no considerable difference in "correct answers" which implies both Omani and New Zealand students have the same level of comprehension of LISP using the adaptive e-learning system. However, the other general performance (i.e., number of repetition and navigation) showed that New Zealand learners had more exploratory behaviour with the adaptive e-learning system. This can be explained by Martinez's finding (2002), which identified that the lack of confidence in using a particular system makes the users very reluctant to explore the system; instead they are more careful using the system.

Looking closely at the personality data in Table 5.4, the results indicate that the extraverted learners in both Oman and New Zealand significantly outperformed their counterpart (i.e., the introverted learner) in all four measures. That is, the extraverted learners took less time ($F_{1,18}=3.20$; $p<.05$ in Oman, $F_{1,37}= 14.08$; $p<.05$ in New Zealand), and gave more correct answers ($F_{1,18}=2.89$; $p<.05$ in Oman, $F_{1,37}=9.04$; $p<.05$ in New Zealand), along with more self-organising learning experience ($F_{1,18}=3.70$; $p<.05$ in Oman, $F_{1,37}=9.90$; $p<.05$ in New Zealand). Therefore, the pattern of findings in Experiments 2 and 3 can be generalised that personality type (Extraverted vs. Introverted) does influence the learning performance when learners are being taught by adaptive e-learning systems.

Table 5.5. The task performance of other personality types

	Dimension 1		Dimension 2		Dimension 3		Dimension 4	
	Extravert (n=28)	Introvert (n=11)	Sensing (n=29)	Intuitive (n=10)	Thinking (n=26)	Feeling (n=13)	Judging (n=29)	Perceiving (n=10)
Time taken (unit: Mins.)	18.05 (2.44)	22.28 (4.59)	19.69 (3.97)	17.95 (2.35)	18.40 (2.26)	20.92 (5.25)	18.20 (3.27)	22.27 (3.17)
	p<.01		**p<.05**		**p<.05**		**p<.01**	
Correct ans (unit: %)	82.49 (5.47)	75.77 (8.07)	79.65 (6.40)	83.34 (7.95)	81.51 (4.78)	78.78 (9.91)	80.83 (5.57)	79.92 (10.23)
	p<.01		**n.s.**		**n.s.**		**n.s.**	
No. of navigations	53.32 (12.42)	66.45 (9.62)	59.48 (13.56)	49.90 (8.29)	56.08 (10.91)	58.92 (14.91)	54.10 (10.91)	65.50 (15.47)
	p<.01		**p<.01**		**n.s.**		**p<.05**	
No. of repetitions	15.68 (8.95)	20.36 (8.52)	19.38 (8.67)	10.10 (5.95)	17.15 (8. 50)	16.69 (10.23)	15.55 (5.55)	21.20 (4.78)
	p<.05		**p<.05**		**n.s.**		**p<.05**	

Table 5.5 summarises the performance comparison in terms of other personality types. One can see that the first dimension of MBTI (Extraverted vs. Introverted) reveals the salient difference. In terms of the four measures used in this experiment, the extraverted outperformed their counterpart. However, the other dimensions (i.e., Sensing - Intuitive, Thinking - Feeling, and Judging - Perceiving) do not provide consistent results over the four measures. That is, in dimension 2 (sensing – intuitive), 3 (thinking – feeling) and 4 (judging – perceiving), there seemed to be no considerable differences in terms of correct answer, which was the most important variable (measure). Neither the number of navigations nor the number of repetitions provided any consistent difference in Dimension 3, especially. Therefore, it could be thought that the personality types other than "Introverted/ Extraverted" are less influential, at least with the CS students in New Zealand using the LISP course on ELM-ART.

5.3. Conclusions and Discussion

The main concern of this chapter was to see whether the results from Experiment 2 could be generalised to another cultural context (which is likely to affects the individual personality). Secondly, it intended to show whether the other personality types could affect the performance in learning using adaptive e-learning. The first conclusion to be drawn was that the New Zealand experiment confirmed the findings from the Omani experiment, revealing that the level of extravertedness (i.e., the first dimension of MBTI) appeared to be a significant personality trait to be considered in designing the user model. Both experiments (i.e., Experiment 2 and 3) concluded that extraverted type would lead to more effective and efficient learning experience, so it implies that the introverted needs to be more carefully treated to enhance their learning experience in adaptive e-learning systems (Felder & Brent, 2005). Secondly, of course, the other personality traits from MBTI would have effects on the learning performance, but they were not as salient as the level of extraversion. Therefore only this one aspect will be considered in the design of the user model in the experiments that follow (Al-Dujaily & Ryu, 2006; Al-Dujaily, Ryu, & Kamal, 2005).

However, we should note that there are several limitations in this experiment. The sample sizes were relatively too small (in particular, some of the personality traits had only 10 subjects), so it would not be so straightforward to generalise the findings from this experiment to the other context. Also, the participants from these experiments were only from the computer science discipline, so the implications for the other learning domain might be limited. Furthermore, the material or learning contents (LISP) used in both Experiment 2 and Experiment 3 might suit only the extraverted students so that we need a thorough external validity test for this reason, which will be partially discussed

in the next two chapters; for instance, Chapter 6 employs new learning materials rather than the LISP course used in both Chapter 4 and 5.

CHAPTER 6. PERSONALITY AND THE LEARNING MATERIAL DESIGN

In both Chapter 4 and 5, we identified that a personality trait, in particular, the level of extravertedness, would be a critical feature to be considered in the design of adaptive e-learning system. However, we were not sure of how this personality trait would be associated with developing adaptive e-learning systems. This chapter aims to deal with this issue. Understanding how differently the extraverted and introverted respond to the same e-learning material design, helps to build an instance of personality traits used to design effective adaptive e-learning systems. An experiment performed in this chapter implied that different personality types (i.e., extraverted vs. introverted) have a significantly different responses to a particular learning material structure. It shed light on the future design of adaptive e-learning systems.

Overview of the Chapter

The first section 6.1 describes the relationship between personality and learning material design issues from early literature. Section 6.2 shows empirically the relationship between learner's personality type and the learning material structure. Finally, section 6.3 discusses the lessons learnt from the experiment and draws some conclusions.

6. 1. Personality types and learning material structures

One important understanding from both Chapter 4 and 5 was that to successfully enhance adaptive e-learning systems, we should consider the personality trait (or type) of each individual learner.

Yet, to understand how and what to be included in designing the adaptive e-learning system is not so straightforward. As a first attempt in this line of study, we considered the personality traits as structuring the learning material.

The assumption of this study is that learners' cognitive style (which comes from personal trait) significantly influences their preferences for a particular learning material structure (Blaylock & Rees, 1984; Hough & Ogilvie, 2005; Moallem, 2003). For instance, Experiment 3 showed that ISFP (**I**ntrovert, **S**ensing, **F**eeling, **P**erceiving) learners performed poorly as they were being taught by ELM-ART, arguably because they tend to seek freedom to learn at their own pace (Keirsey, 1998; Myers & McCaulley, 1985), while those who are ENTJ (**E**xtravert, **I**ntuitive, **T**hinking, **J**udging) type learners performed well with the adaptive system because they appreciate planning and prefer sequential learning, which means they fitted well with ELM-ART. Therefore, the designers of an adaptive e-learning system may need to consider this aspect in order to make an effective learning system design for diverse learner groups. This is what we are seeking in this chapter, to see how to incorporate the personality trait in designing the structure of learning materials.

Previous studies (e.g., Riding & Fanning, 1998; Riding & Rayner, 1999; Zang, 2002; 2006) suggested that different personality types cause preferences for different learning material structure. This is probably because different personality traits would generate different cognitive styles to process the information given (Blaylock & Rees, 1984). For example, the extraverted learner tends to benefit from general ideas, then moving toward more detail. This style helps them pay attention to the whole learning experience first (Soles & Moller, 2001). In contrast, the introverted seem to be more self-reliant, and they may benefit more from the conceptual information that emphasises fundamental understanding first to generate a big picture of their learning process

(Myers, 1993; Myers *et al.*, 1998). Therefore, perhaps, different learners would have different preferences for the structure or flow of the contents delivered.

In e-learning material design, there have been two major strategies: Breadth-first and depth-first (Ford & Chen, 2001). The breadth-first strategy concentrates on establishing on an overview of learning outcomes before moving to further details. Hypothetically, it may be well suited to the extraverted learner due to its overall picture given prior to every detail of the course. By comparison, the depth-first strategy employs a bottom-up approach, starting from low-level details first (basic principles) and then moving toward more global perspectives, which may meet the preference of the introverted. For example, consider the course material of HTML (HyperText Markup Language), simply consisting of three lessons, i.e., the concept of HTML (lesson 1), working with HTML (lesson 2), and publishing HTML (lesson 3). Lesson 1 would generally have several sub-sections such as definition, background, structure of HTML, which introduces the basics of HTML. The "Working with HTML" lesson would then provide information on practical coding in HTML, such as webpage formatting, and style tags for designing web pages in its subsection. Finally, it follows a lesson on how to upload and maintain web pages for publishing. If the course structure is designed in the breadth-first strategy, it firstly presents all the top levels, and then describes the detailed subsections. This structure is very likely to help the learners capture what they should learn firstly, in the sense that they can hold the overall course structure in advance so they can find what contents would be more important than the others. In contrast, the depth-first strategy takes a different way to deliver the same contents. It explains all the details under each lesson. That is, it firstly introduces the definition, background, and structure of HTML under lesson 1 and then moves to lesson 2 for the full exploration and finally delivers lesson 3 in full details. That means the learner does not have any opportunity to capture what is to be followed, so that it is very

unlikely that the learner can organise all the learning contents before they learnt all the relevant lessons, but they are certain to have acknowledged every detail before obtaining the global outline of the course. This approach is believed to be particularly useful for learners who are more inductive (Trochim, 2006); we suggested that it would be introverted learners.

Several studies (e.g., Felder & Brent, 2005; Ford & Chen, 2001; 2000b; Hayes, 1996) concluded that these two strategies (depth-first and breadth-first) would be subject to learners' personality styles if given the opportunity to use their preferred methods of learning. That is, introverted learners who are usually inductive learners are likely to have benefits from the depth-first strategy, the extraverted from the breadth-first strategy.

Yet, a number of other studies identified that the personality type itself has nothing to do with preference for learning material structure (e.g., Stash & De Bra, 2004). Felder *et al.* (2002) showed that the learners who have learning materials mismatching their personality type may perform better in their learning session, because in the long term, it can encourage them to develop their own learning strategies that cope with wider range of materials and experiences in the future. That is to say, extraverted learners are aware of the need to develop the organised skills that introverted learners generally have, while introverted learners can have opportunities to enhance the multidisciplinary combination of skills that the extraverted learners generally have (e.g., Entwistle, 1990; Honey & Mumford, 1992), by using learning material structures that mismatch their personality type. Hence, this chapter explores this issue empirically with an adaptive e-learning system, an example of using personality traits in designing effective adaptive e-learning systems.

6. 2. Experiment 4

An experiment was conducted to examine the relationship between learner's personality

type and the learning material structure. Two learning material structures, i.e., Depth-

first and Breadth-first structures, were considered in this study. Haskell 1 was designed

with the Depth-first strategy, which is hypothesised to be good for the introverted and

Haskell 2 with a Breadth-first structure, which seems to be better for the extraverted.

The two systems only differ in the order of content presented. Both systems were

designed to teach Haskell, which is a declarative programming language, in the

Computer Science course.

Figure 6.1. Haskell 1. It is designed with depth-first strategy.
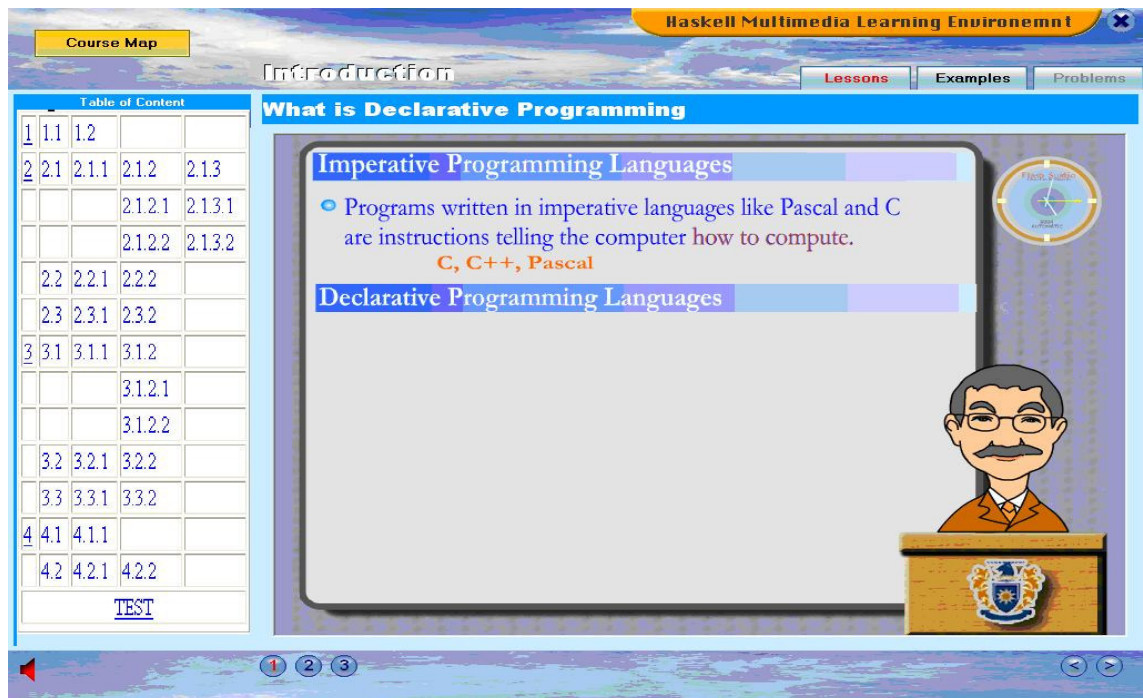
Figure 6.1 depicts Haskell 1. The left hand side of the interface are the links of

chapters and subsections consisting of 4 chapters, and relevant subsections of Haskell.

Chapter 1 is about the introduction of Haskell. Chapter 2 is for 'Types', Chapter 3 is

about 'Functions' and finally Chapter 4 is about 'Lists'.

Figure 6.2. The structure of Haskell 1. (Exp. means examples and Ex. for exercises).
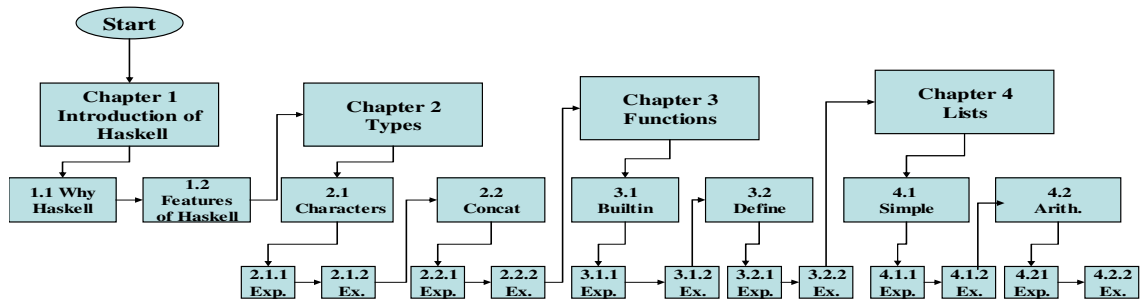
The sequence of delivering content is shown in Figure 6.2, following the depth-first strategy. It starts from Chapter 1, followed by all the subsections (i.e., 1.1 and 1.2). When Chapter 1 was fully explained, then it moved to Chapter 2. As shown in Figure 6.2, Section 2.1 was firstly fully described along with sub-section 2.1.1 and 2.1.2, and then moved to Section 2.2.

Figure 6.3. Haskell 2

Figure 6. 4 The structure of Haskell 2. (Exp. means examples, and Ex for exercises)
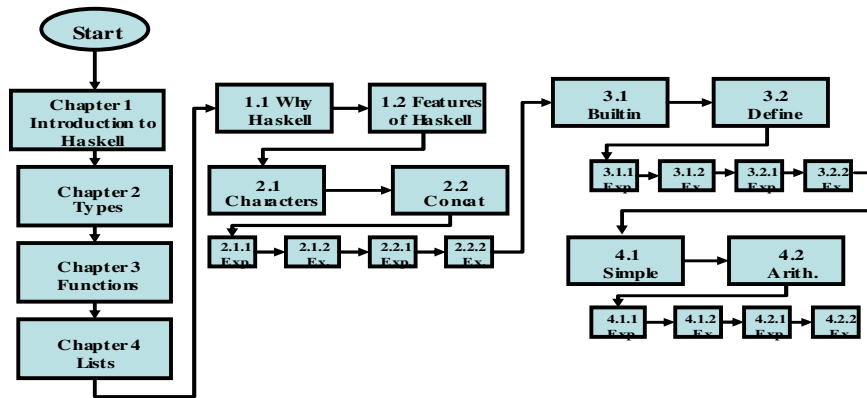
By comparison, as shown in Figure 6.3 and 6.4, the structure of Haskell 2 follows the breadth-first strategy, providing the learners with the overall picture of what contents would be taught, so it may help them organise or associate their learning activities with a broad view.

6.2.1. Participants

33 participants, as shown in Table 6.1, took part in this experiment. They were all homogeneous in terms of their previous learning outcomes in other computer science coursework and their knowledge levels of computer science programming skills which would considerably affect their comprehension of Haskell language. Also all the participants worked through the MBTI test to identify their personality types, revealing 14 were introverted and 19 were extraverted. All the participants were Massey University students (aged 18-25), who enrolled in the CS course. This experiment was treated as a part of tutorial, so all the participants received 5% course-credit.

Table 6.1. The participants of Experiment 4

System	Introvert	Extravert	Total
Haskell 1	7	9	16
Haskell 2	7	10	17
Total	14	19	33

6.2.2. Apparatus

Two versions of adaptive e-learning structures were designed for teaching Haskell. Haskell 1 was designed with a depth-first strategy, whereas Haskell 2 followed in a breadth-first strategy, as described above. These two systems have the same course structure, but only differ in the navigational paths that the learners must follow. See Appendix 3.1 and 3.2 for the introductory part. Also see Appendix 3.3 for some figure of the apparatus.

Two types of questions were administered for learners at the end of the experiment; multiple-choice questions which more likely demand a declarative knowledge and open-ended ones which require conceptual and procedural knowledge. They were also asked to draw the course structure on blank paper to reveal their understanding of the whole course structure.

6.2.3. Experiment design

2 (Haskell 1 / Haskell 2) by 2 (Introverted / Extraverted) between-subject design was proposed. Both personality type and systems used were independent variables. The dependent variables were time taken, correct answers, and the number of revisited pages. Also, their drawings of the course structure were qualitatively analysed to see their comprehension of the course structure.

6.2.4. Procedure

As the participants sat in the laboratory, they were told the objectives of this experiment and how it would proceed. Every participant was randomly assigned to either Haskell 1 (Depth-first) or Haskell 2 (Breadth-first). It took around 25 minutes to complete.

Both Haskell 1 and 2 only equip the learners with the "previous" and "next" button at the bottom of each page to navigate the contents, so they cannot directly move to a particular page by clicking to different pages from the left-hand-side linking interface (see figure 6.1 and 6.3). They were asked to answer 20 questions about Haskell language. Those questions were comprised of 10 multiple choice and 10 open-end questions about what they had learnt from the system. See Appendix 3.4 for the test questions. An additional test followed, which involved drawing the structure of the course on blank paper.

6.2.5. Results

Table 6.2. Task performance in Haskell 1

Task performance			
Personality type	**Reading time (unit: Mins.)**	**Answering question time (unit: Mins.)**	**Number of Correct answer**
Introvert (n=7)	8.56.(.80)	14.89.(3.05)	13.57 (1.72)
Extravert (n=9)	2.94 (1.64)	16.48.(2.01)	10.89 (1.01)
Sig.	**p<.05**	**n.s.**	**p<.05**

Table 6.2 summarises the task performance of Haskell 1. Comparing the performance between the introverted and the extraverted learners, it seems that the extraverted learners (mean=2.94 mins.) read all the contents very quickly, but they took slightly more time to answer the questions. It probably led to a fewer number of correct answers (mean=10.89). In contrast, the introverted learners spent considerably more time on reading materials, so it would result in more correct answers than the extraverted.

These accounts were confirmed by two-way ANOVA, revealing significant differences in the time taken for reading and number of correct answers. That is, the first measure (time taken to read the content) showed that the extraverted were quicker than the introverted. However, the last measure, i.e., number of correct answers, was better in the introverted group. This can be interpreted as implying that, in general, the introverted benefit from the depth-first strategy, which Haskell 1 follows.

In particular, the correct answers out of twenty questions can be separated, as shown in Table 6.3. One can see that there seems to be considerable difference in the correct answers of the open-end questions. These questions require more conceptual understanding of the contents, so they need more in-depth understanding. The results clearly showed that the introverted gained more benefits from Haskell 1 than the extraverted.

Table 6.3. Task performance in Haskell 1 (Depth-first)

Task performance (mean/s.d)		
Personality type	**No. of multi choice questions (out of 10)**	**No. of open-end questions (out of 10)**
Introvert (n=7)	6.14 (1.06)	7.43 (.97)
Extravert (n=9)	6.78 (.83)	4.11 (.78)
Sig.	n.s.	p<.01

It seems that conceptual knowledge may be enhanced for introverted participants when the learning material structure matched their personality type. This result can be found in other studies (e.g., Ford & Chen, 2001; Moallem, 2003), which identified the relation between the learning process and recall of conceptual knowledge.

Table 6.4. Task performance in Haskell 2

	Task performance		
Personality type	**Reading time (unit: Mins.)**	**Answering question time (unit: Mins.)**	**Number of Correct answer**
Introvert (n=7)	11.34 (.59)	22.17 (8.02)	10.57 (1.92)
Extravert (n=10)	6.74 (2.25)	13.93 (6.15)	14.00 (1.04)
Sig.	p<.01	p<.01	p<.01

We also analysed the performance of Haskell 2 in the same way as shown in Table 6.4. In this case on all the three measures, it appeared that the extraverted outperformed the introverted. It seems to represent the opposite pattern from Haskell 1.

This was analysed by two-way ANOVA, revealing significant differences in all the three measures. This implies that when the extraverted learners were being taught by the breadth-first structure, this matches their personality type, with tend to adopt a holistic approach to the learning process.

Table 6.5. Task performance in Haskell 2 (Breadth-first)

	Task performance (mean/s.d)	
Personality type	**No. of multi choice questions**	**No. of open-end questions**
Introvert (n=7)	6 00 (1.29)	4.57 (1.39)
Extravert (n=9)	7.80 (0.72)	6.40 (0.72)
Sig.	p<.01	p<.01

Likewise, we examined the correct answers using two categories: multiple-choice vs. open-ended questions, as shown in Table 6.5. It showed that the extraverted outperformed in both categories, implying that the extraverted can easily establish conceptual knowledge to answer the open-ended questions, and declarative knowledge to answer the multiple-choice questions. ANOVA results confirmed these accounts.

Also, the experiment only allowed the participants to go back to the previous pages, so the numbers of revisits may provide an indication of how they organise their

learning experiences. Hypothetically, the user group that has a well-matched learning material structure would have less navigation movement. These self-organising learning activities may show the mismatch between their personality trait and the structure of their learning material.

**Table 6.6. Number of participants who revisited
the previous pages in Haskell 1 use**

System	Personality type	Number of participants revisited pages	Sig.
	Introvert	2 out of 7	
Haskell 1	Extravert	7 out of 9	p<.05

Table 6.6 showed that in using Haskell 1, only 2 introverted participants out of 7 revisited the pages that they had already learned, whereas 7 extraverted learners out of 9 revisited the pages for more reading. We applied Fisher's exact test ($\chi2_{(1)} = 3.87$), because of the small sample size, and found that significant difference. It can be seen that the introverted learned better with Haskell 1, which was thoroughly understood with one attempt.

In contrast, the extraverted learner needs to revisit pages more often. This could imply that when the extraverted spend less time on average in reading the materials, they may not fully understand the complexity of the learning material.

**Table 6.7. Number of participants who revisited the previous pages
In Haskell 2 use**

System	Personality type	Number of participants revisited pages	Sig.
	Introvert	4 out of 7	
Haskell 2	Extravert	3 out of 10	p<.01

In contrast, Table 6.7 showed that in using Haskell 2, only 3 extraverted participants out of 10 revisited the pages that they had already learned, whereas 4 introverted learners out of 7 revisited the pages for more reading. A Fisher's exact test

($\chi 2_{(1)} = 1.25$) showed the significant personality difference. It suggests that as the extraverted learners tend to be global learners; they may benefit more from the structure of Haskell 2 materials.

We have identified that matching learner's personality with the learning material designs might be important in terms of the task performance. One of the important aspects we should also consider is their learning experiences, i.e., how easily they remember what they have learnt. This can be examined by constructing a knowledge structure map (Smith & Riding, 1999), which can represent a deeper insight into participants' comprehension of the learning materials. At the end of the experiment the participants were asked to draw the structure of what they had learnt from both Haskell 1 and Haskell 2. They made this as detailed as they could. The marking strategy was based on the Group Embedded Figures Test (GEFT; Oh & Lim, 2005). The criterion used to measure the drawings was how many levels they used to draw the course structure. Simply, the more levels descriptions they drew, the more likely they have global understanding of the contents. Thus, if the participants only manage to describe one level of the structure, they are classified as weak performers. If they described two levels, they are thought of as on-average performers; otherwise they are good performers.

Figure 6.5. Knowledge structure map: An example of weak performance (a) and good performance (b)

(a) a weak performer example   (b) a good performer example
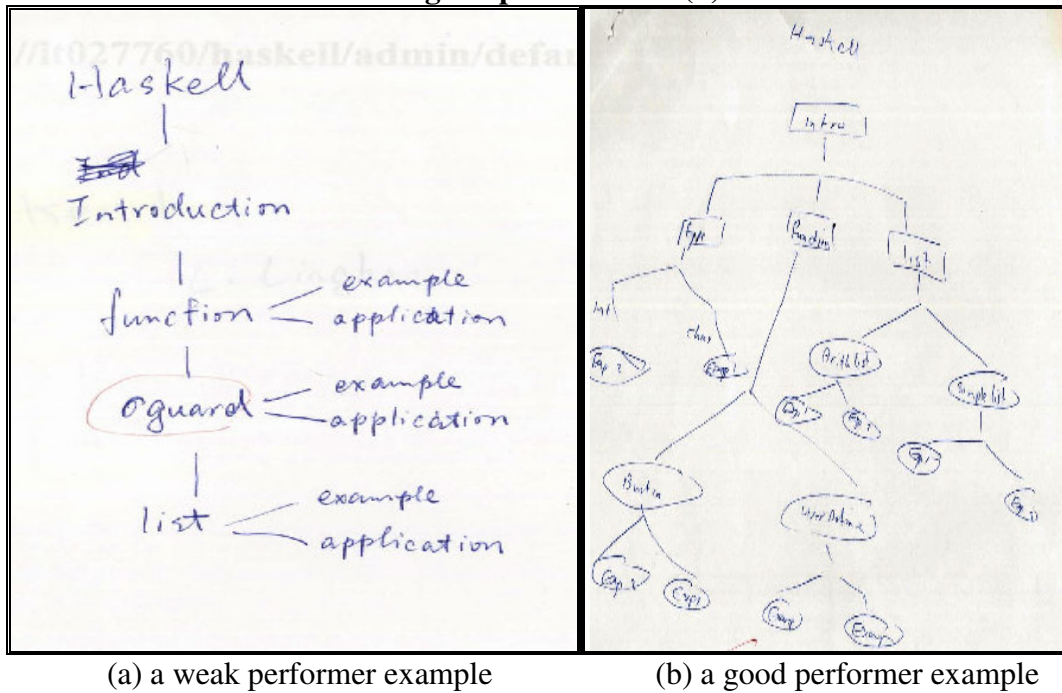
Table 6.8. Cognitive map for Haskell 1/Haskell 2

System	Personality type	Number of participants		Sig.
		Weak performance	Good performance	
Haskell 1	Introvert	2	5	p<.05
	Extravert	7	2	
Haskell 2	Introvert	5	2	p<.05
	Extravert	2	8	

Table 6.8 showed clearly that the introverted outperformed the extraverted in Haskell 1. Two out of seven introverted participants were weak performers, whereas, seven out of nine extraverted were weak performers. In contrast, Haskell 2 is for the extraverted. Fisher's exact tests supported these accounts.

These results also supported our assumption that the learners may perform better if they can employ the learning material matched to their own personality type in the learning process.

6.3. General Conclusions and Discussion

The assumption of this study was that the learner's cognitive style may significantly influence their preferences for a particular learning material design. The findings from this study indicated that the task performances by the two different personality groups (introverted and extraverted) were significantly affected by the two different material designs. That is, the introverted with Haskell 1 outperformed the extraverted with Haskell 1. As opposed to this, the extraverted with Haskell 2 outperformed the introverted. These findings strongly indicated that the personality type could be an influential indicator of learning performance when learners were being taught by different learning strategies.

Both the Haskell 1 and Haskell 2 use cases revealed that introverted were interested in detailed understanding, concentrating on separate topics, which leads to taking a longer time to read materials. In contrast, the extraverted, according to their personality, tended to adopt a global approach to learning, concentrating on building a conceptual overview and fitting in the detail subsequently.

This understanding of the relationship between the personality type and the learning material structure is not new (e.g., Riding & Fanning, 1998; Riding & Rayner, 1999). However, the contribution of this chapter is to empirically identify this relationship for the design of adaptive e-learning systems, which has not been shown before. The approach to encompassing personality in the design of structuring the contents is new, in these experiments, which clearly demonstrated that different learners may process the learning material using different strategies.

This study thus implies that the user model in adaptive e-learning system should accommodate learners' different learning styles. For instance, for the introverted, it may be of great use to present more in-depth knowledge before global or associative

knowledge. This would ensure that any adaptive e-learning experience had a spread of activities that would appeal to a range of personalities.

Even though this empirical study showed that the personality type affected the learning process, there are some limitations to generalising these results to the design materials. Firstly, the number of participants was small, so they may not be representative of a whole population. Secondly, the contents used in this experiment were personal and individual learning with computers rather than collaborative understanding, which has been paid more attention in recent e-learning systems design. The next chapter addresses this collaborative learning experience in order to see the relationship between personality and collaborative work in designing adaptive e-learning systems. Also the sample size issue will be discussed in Chapter 9 which conservatively limits the interpretation of the thesis.

PART III. TO UNDERSTAND COLLABORATIVE LEARNING AND PERSONALITY TYPES

This part describes and shows the effects of personality in groups of learners performing

collaborative learning. It suggests practical implications of designing collaborative

learning technologies in conjunction with the personality feature.

CHAPTER 7. COLLABORATIVE LEARNING AND PERSONALITY

Previous chapters in this thesis demonstrated the potential effects of the personality type of each learner on the learning performance with adaptive e-learning systems, which was closely associated with learning styles. Yet, the learning experiences we have considered so far have been limited to individual learning instances. That is, all the experimental treatments in the previous chapters intentionally overlooked one of the learning activities that is now widely taking place at the university level – *collaborative learning*. Although the individual learning process has been considered the essential learning experience, it is generally thought that collaborative learning activities further enable learners to take more responsibility for their learning activities, help them to learn how to make joint decisions, and promote concerted efforts on their collaborative learning activities (Corich, Kinshuk, & Hunt, 2004). This issue is central to this chapter.

Previously, we found that the introverted and the extraverted learners have different learning strategies, such that the introverted would be better off understanding theoretical contents and the extraverted would be more comfortable with practical examples. Therefore, hypothetically, a mixture of these two different personalities in the collaborative learning activities may make a difference in their collaborative learning experience. An experiment was thus conducted to examine the combination of personalities in collaborative learning. The findings from this study indicated that the task performances of a heterogeneous group of learners with different types of personality were better than those of homogenous groups of learners that have the same type of personality. Also, the learning materials (either the theoretical or the practical content) should be matched with their preferred material type, i.e., the introverted with the theoretical and the extraverted with the practical ones, which was in line with the

findings from the previous three chapters (Chapter 4, 5, and 6). This chapter intimated that the personality feature in the user model might be one of the important resources in designing adaptive e-learning systems to support collaborative learning activities. It also presented an explicit example of the use of the personality feature in designing effective learning experiences.

Overview of the Chapter

The first section reviews the literature on collaborative learning activities and personality type. Section 7.2 describes the experiment that was conducted to examine the combination of personalities in collaborative learning. Finally, section 7.3 discusses the lessons learnt from the experiment findings and draws some practical conclusions.

7. 1. Personality and collaborative learning

In the previous chapters, it was understood that learners with different personality traits have their own preferred learning styles, approaching their learning tasks in different ways. For example, the introverted tend to be more self-reliant and reflective, so they may benefit more from the conceptual information and materials that emphasise fundamental or theoretical understanding (Corno, 2001; Oh & Lim, 2005). Unlike the introverted, the extraverted seem to prefer interacting with others, being more action-oriented (Hough & Ogilvie, 2005; Soles & Moller, 2001a). Several studies (Oswald, 1995; Russell, 2002; Santo, 2006) showed that learners who have different personality types tend to approach the same learning material in different ways according to their preferences. Thus introverted learners seem to understand conceptual and complex knowledge more eagerly and thoroughly, whereas extraverted learners are more interested in applying their understanding to practical problem solving. However, it seems that the interaction between these two types of learners in their collaborative

learning activity has been less considered. It is generally thought that, in many cases, learning arose from opportunities for the group members to monitor each other's thinking, opinions, and beliefs. In particular, it may challenge the learners' understanding, and can further motivate their subsequent learning(Glaser & Bassok, 1989).

Indeed, Vygotsky (1926; 1978) claimed that collaborative and social learning activity should be further understood in conjunction with individual learning, proposing that learning activity itself should be more connected to the environment where it takes place, such as communities, cultural norms, and collaborative work. Following on Vygotsky's approach, Lave and Wenger (1991) also emphasised that unintentional learning from the collaborative and social learning activity would be more effective than deliberate individual learning in the traditional face-to-face classroom environment. They saw collaborative and social learning activity as one of the core opportunities that should be available in educational sectors. Anuradha and Gokhale's findings (1995) empirically demonstrated the benefits of the collaborative learning activity, such as the opportunities to analyse, synthesise, and evaluate what they learnt to reinforce further learning outcomes. In the same vein, Gweon *et al.* (2006) showed that collaborative learning activity would give learners a significant opportunity to coordinate their communication, and encourage deeper thinking in which they can share their ideas with each other or one another. In effect, it can be thought that collaborative learning activity can significantly support learners to restructure their learning experiences, relating their understanding to that of other learners (Kinshuk & Lin, 2003).

In accordance with learning styles, Lawrence (1993) and Biggs (2003) stated that learners with different preferences might benefit more from collaborative work, since it allows them to follow different paths through the same learning material. Syed and Adkin's study (2005) also demonstrated this phenomenon with adaptive e-learning

systems, collecting each individual's preferences before the collaborative learning

activity, in order to organise collaborative learning groups for the experimental

treatments. Indeed, Fay *et al.* (2006) recently demonstrated how collaborative work

among different personalities would enhance their work performance, sharing their

experiences more easily and effectively and exploring diverse viewpoints from the

others.

Relating the review of the collaborative learning activity discussed above to our

own findings from previous chapters, we can hypothetically argue that organising

collaborative learning activity built on each learner's different personality traits would

enhance students' performance together and help them have a more efficient learning

experience. For example, in organising collaborative learning, it would be of great

benefit to organise collaboration between the extraverted learners who prefer the global

overview of course material before the details are presented (i.e., practical approach)

and introverted learners who enjoy sequentially exploring the course material in detail

(i.e., theoretical approach). This would arguably help the learners develop effective

thinking skills to consolidate the desired outcomes from this collaborative learning

experience (Jacobs, 1988; Sabine & Bekele, 2002). Therefore, we hypothesised that

adaptive e-learning systems along with the personality feature in their user models

could support the better collaborative learning activities.

To empirically examine this potential in adaptive e-learning systems with the

personality feature, we firstly identified each individual's personality type with MBTI

as we did in the previous chapters, and then various personality combinations for a

collaborative learning activity were investigated in this chapter. We assumed that

practical learning materials such as practical examples would suit the extraverted; by

contrast, theoretical contents would be more easily handled by the introverted learners.

If this is the case, it can be claimed that the collaborative learning activity in adaptive e-

learning systems should thoroughly consider the personality type of each individual. This will also support the research question of this thesis – the relationship between the personality and the user models of adaptive e-learning systems.

7.2. Experiment 5

An experiment was conducted to examine effective group formation regarding their collaborative learning experience. A web based hypermedia system was developed for the Human-Computer Interaction (HCI) course. It consists of two parts, theory and practical one, and provides a text-chatting facility for collaborating between the students. The "theory" part delivers " Nielson's 10 golden rules for interface design" (Nielsen, 2006), and the "practical" part shows "20 examples for the 10 golden rules". For both the theory part and the practical part, see Appendix 4.1 and 4.2 for more details. Two practical examples were used to explain each golden rule. The hypothesis of this study is that matching the theory part for the introverted learner and the practical for the extraverted may outperform the other group formations (Soles & Moller, 2001). We considered the four group formations: two groups were homogeneous (i.e., extraverted – theory learning/extraverted – practice learning; introverted – theory learning/introverted – practice learning), whereas the other two had heterogeneous personalities (i.e., extraverted – theory/introverted – practice; introverted -theory/ extraverted - practice). Based on the findings from the previous chapters, it was hypothesised that the last group, i.e., the introverted who studied the theory part and the extroverted who studied the practical examples would have a significant opportunity to enhance their collaborative learning performance.

7.2.1 Participants

<div align="center">

Table 7.1. Participants in this experiment

Groups	N (pairs)	Type of personality	Learning material	Match with personality
Group 1	6	Introvert Extravert	Theory Practice	Full
Group 2	5	Extravert Introvert	Theory Practice	None
Group 3	4	Introvert Introvert	Theory Practice	Half
Group 4	5	Extravert Extravert	Theory Practice	Half

</div>

40 participants consisting of 20 pairs took part in this experiment who had never attended the previous experiments. Initially all the participants completed the Myers-Briggs Type Indicator (MBTI) to identify their personality types.

Table 7.1 shows the details. Group 1 consists of the introverted learner who was learning the theory part, and the extraverted with the practical part, which is hypothetically considered as the best matched group since the learning materials are designed to be matched with their personality types. Group 2 is the opposite. Each of the Groups 3 and 4 has only one personality type. The final column in Table 7.1 explains the match of material to personality.

7.2.2 Apparatus

A web based e-learning system was designed as part of the HCI course as shown in both Figure 7.1 and 7.2. One part of the system is to deliver the theory part and the other for the practical part. It was equipped with a text-chatting facility for the participants to collaborate or explain to each other in separate places. They were allowed to study only

one part, and they had to explain their understanding to each other, which simulated a

collaborative learning experience.

Figure 7.1. Theory part of the system
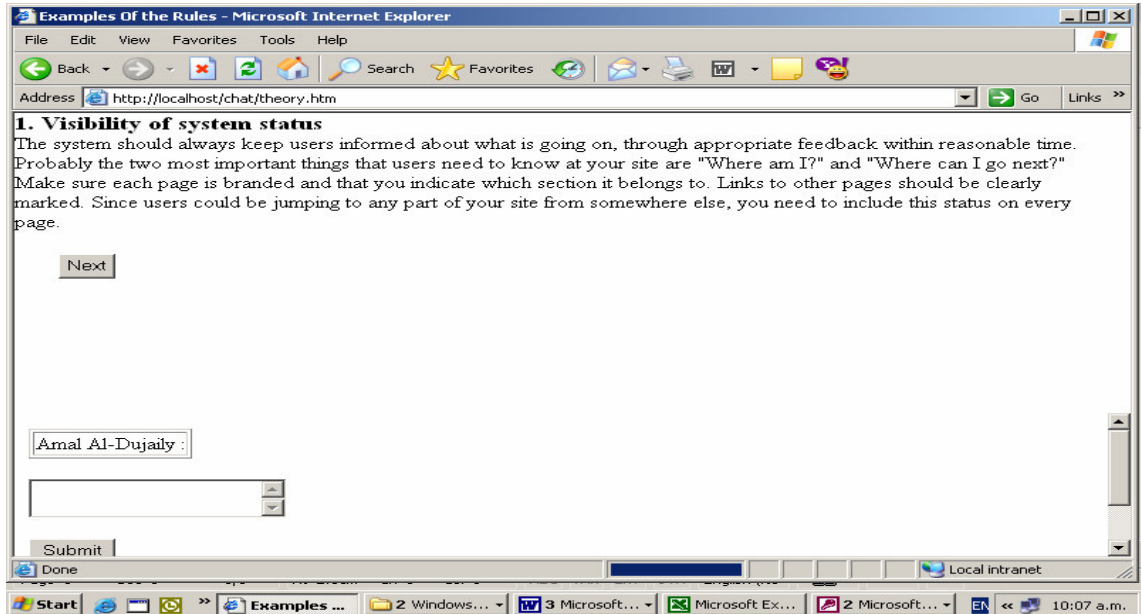
Figure 7.2. Practical part of the system
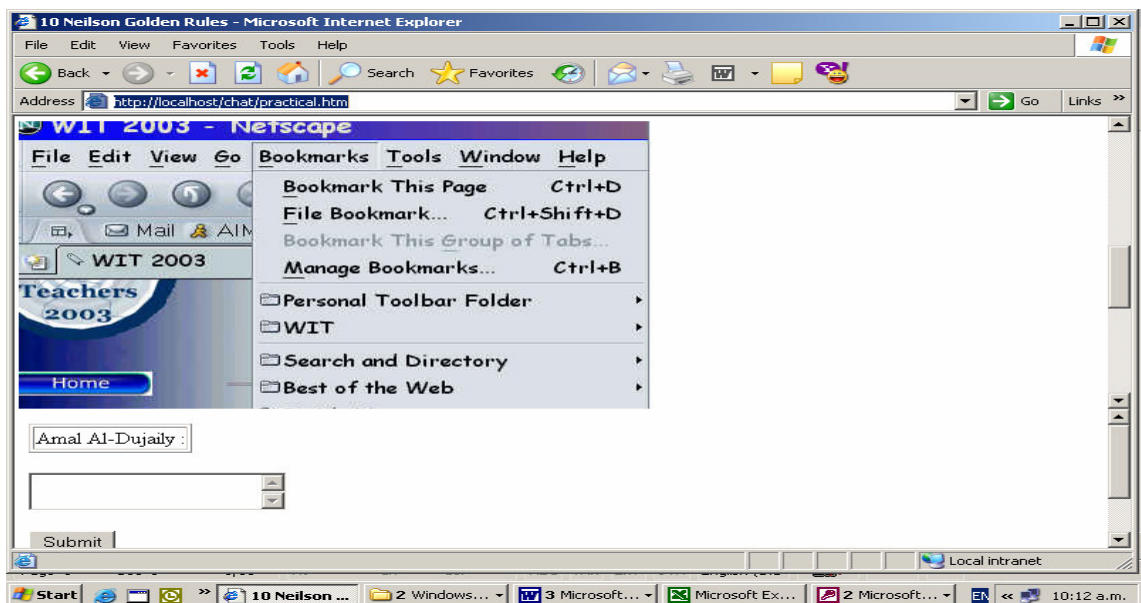
7.2.3 Experiment design

A one-way between subjects experimental design was used. The independent variable

was the personality match for the course contents: Full-match (Group1), Half-match

(Group3 and 4), and no-match (Group2). The dependent variables were time taken, and

learning performance by pairs of learners of collaborative matching.

7.2.4 Procedure

As participants came in, they were told the objective of this experiment. Each participant went through the MBTI test which took approximately 25 minutes. This would be used in the analysis phase to classify every participant according to their style. Participants were randomly assigned to one of the four groups, as shown in Table 7.1. In this experiment the theory learner was in the leading position for the collaborative learning activity, so that firstly he or she had to explain the meaning of each rule via the text-chatting facility, and then the counterparts searched the relevant examples from his/her own end. The pair of students was only allowed to use the text-chatting facility to communicate and explain what they had to do. As they agreed on matching between the examples and the rules, they were asked to write their answers on blank paper. In total, the experiment took around 60 minutes for each pair of students to complete the collaborative problem solving session and to agree on results based on what they have learned from each version.

7.2.5. Results

Figure 7.3. Task performances time taken (unit: Mins.)

92
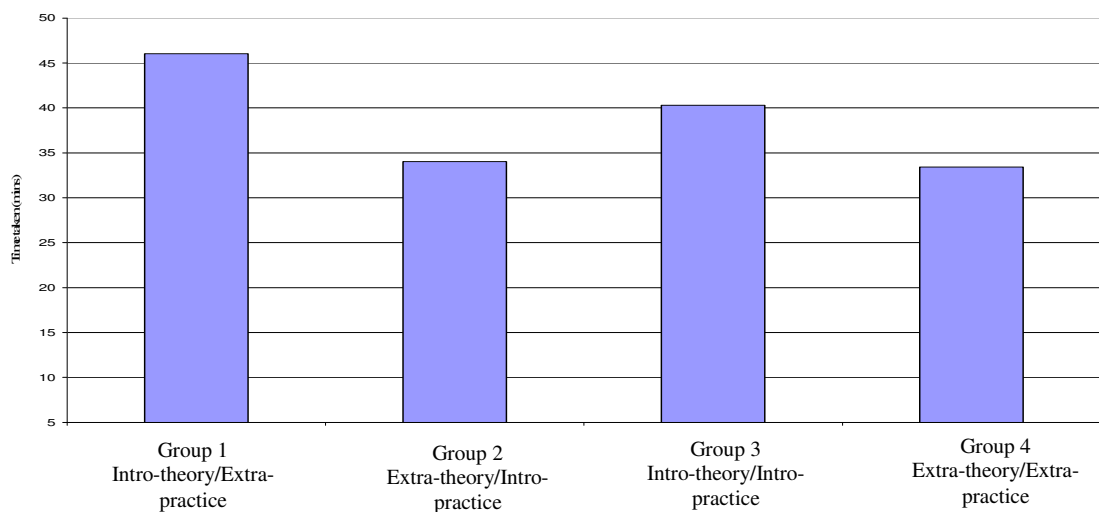
Figure 7.3 showed the overall time taken on this collaborative learning activity of four groups of learners with different types of personality combinations. It showed a considerable difference among the experimental groups. It can be seen that Group 1 (Full match) and Group 3 (Half match with all introverted) took more time than the other groups did. This pattern of learning seems to be much in line with the previous findings from Chapters 5 and 6, which pointed out that introverted learners might need more time to absorb all the details of different topics and express themselves in chat.

This was analysed by one-way between-subject analysis of variance, revealing that different groups of personality types resulted in the different performance on time taken ($F_{3,16}$=5.77, p<0.01). This was further examined by a Tukey-test, revealing that both Group 1 and Group 3 were significantly different from Group 2 and Group 4 which had no significant differences between them. It may be simply explained by the fact that the leading role of these two groups was assigned to the introverted learner.

Figure 7.4. Task performances (Correct answers %) of the 4 different groups

93
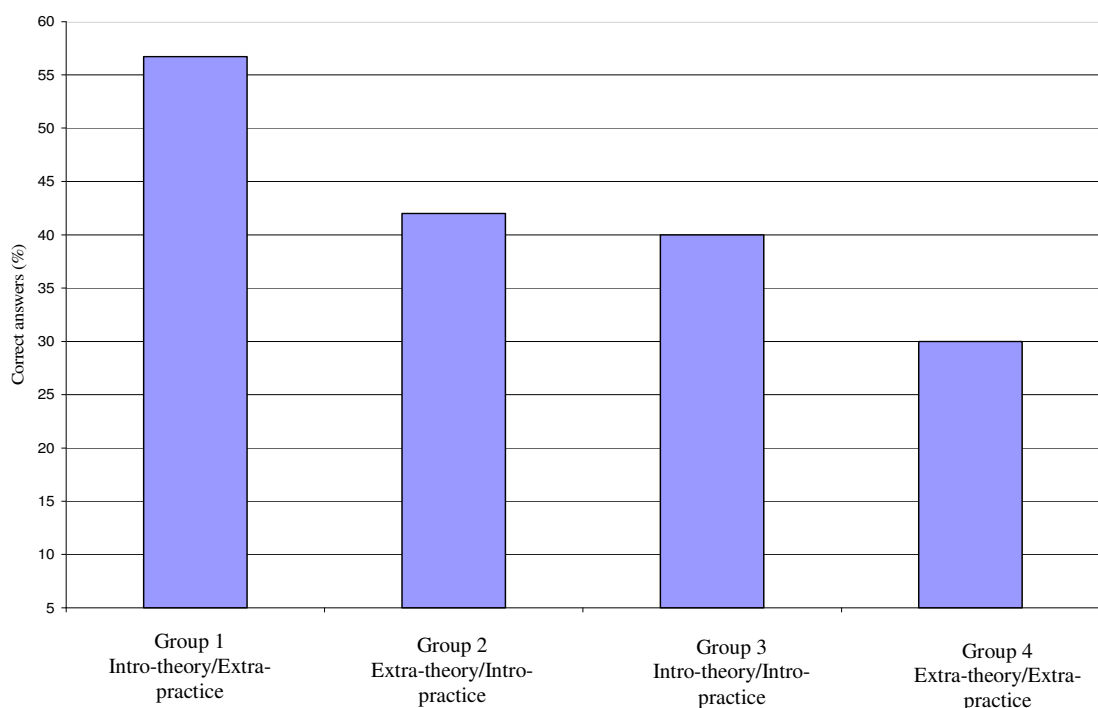
Figure 7.4 gives the most important outcome from this experiment. It showed that "Full match (introverted-theory/extraverted-practice)" outperformed the others in terms of correct answers, with a mean of 56.70 in Group 1.

A one-way between-subject analysis of variance found that different groups of personality types resulted in different learning performances ($F_{3,16}=3.55$, $p<0.05$). This was further examined by a Tukey-test, revealing that Group 1 was significantly better than the other three groups which had significantly lower level of comprehension from this collaborative learning experience. Thus it can be concluded that there was a significant personality effect in the different collaborative groups.

In addition, this experiment allowed the participants to freely navigate through the pages, so that the analysis of the revisits would give us a clear view of the collaborative learning experience. To do this, firstly, we categorised Nielsen's 10 heuristic rules into two. Rules 2, 4, 6 and 7 were considered as difficult ones, compared to the rest of the rules (1, 3, 5, 8, 9 and 10). Table 7.2 shows our classification of the rules.

Table 7.2. Two classifications of Nielson's rules

Easy rules	Difficult rules
1. Visibility of system status The system should always keep users informed about what is going on, through appropriate feedback within reasonable time**.** **3. User control and freedom** Users often choose system functions by mistake and will need a clearly marked "emergency exit" to leave the unwanted state without having to go through an extended dialogue. Support undo and redo. **5. Error prevention** Even better than good error messages is a careful design which prevents a problem from occurring in the first place. **8. Aesthetic and minimalist design** Dialogues should not contain information which is irrelevant or rarely needed. Every extra unit of information in a dialogue competes with the relevant units of information and diminishes their relative visibility **9. Help users recognize, diagnose, and recover from errors** Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution **10. Help and documentation** Even though it is better if the system can be used without documentation, it may be necessary to provide help and documentation. Any such information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.	**2. Match between system and the real world** The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order. **4. Consistency and standards** Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions. **6. Recognition rather than recall** Make objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate. **7. Flexibility and efficiency of use** Accelerators -- unseen by the novice user -- may often speed up the interaction for the expert user such that the system can cater to both inexperienced and experienced users. Allow users to tailor frequent actions.

Table 7.3. Numbers of revisited on both difficult and easy rules (mean/s.d)

	Number of revisits		
Groups	**Difficult rules**	**Easy rules**	**Total**
Group1 (6 pairs)	5 (2.38)	3 (2.58)	8 (0.14)
Group2 (5 pairs)	15 (4.86)	9 (6.11)	24 (0.88)
Group3 (4 pairs)	10 (5.21)	9 (9.22)	19 (2.84)
Group4 (5 pairs)	11 (5.20)	4 (2.67)	15 (1.79)

Table 7.3 showed the numbers of revisits that the different groups had throughout their collaborative learning activities. Looking at the face values, it can be seen that Group 1 (Introverted-theory/extraverted-practical) made fewer revisits to the pages than other groups. A Fisher-exact test supported this observation (Fisher, 1922).

This result can also be thought to underpin the assertion that heterogeneous grouping allows learners to share experiences, and reflect on the experiences of others while building understanding and aiding the process of learning and building the reactions and responses of others (Corich *et al*., 2004)**.**

7.3 Conclusions

The main hypothesis raised in the introduction of this chapter was that collaborative learning activities with those who have different personalities might enhance students' collaborative learning performance and make it more efficient. The experimental results pointed out that mixing the students who have different personality types would help them share their experience and cover up their weaknesses, given the appropriate allocation of their preferred learning material.

The first conclusion to be drawn was that (the findings from this study indicated that) the task performances of heterogeneous groups with different types of personality

were better than homogenous groups having the same type of personality, given the matching of each type of personality with learning material. Thus, if we could understand the strengths and weaknesses associated with the learners' attitude and preferences from the personality type, we would be more able to enhance their learning experiences. This shared experience and build knowledge based on what they already know helps to develop thinking skills such as critical and creative thinking to achieve the desired outcomes, enables learners to take responsibility for their learning, (Jacobs, 1988; Kinshuk & Lin, 2003; Sabine & Bekele, 2002).

It can be also concluded that integrating the collaborative work with personality differences would enhance the experience of learners participating in adaptive e-learning, reducing the time taken to perform their learning and increasing the quality of their performance through the interaction between them. However, the implementation of collaborative group work is still limited and needs more studies to be done before it can make a significant impact on our knowledge of the e-learning process.

PART IV. PERSONALITY TYPE IN THE PROPOSED USER MODEL

This part consists of two chapters. Chapter 8 describes how personality is incorporated in the proposed user model and finally conclusions are drawn regarding the thesis in Chapter 9.

CHAPTER 8. ENCOMPASSING THE PERSONALITY EFFECT IN ADAPTIVE E-LEARNING SYSTEMS DESIGN

Throughout this thesis, we have identified the effect of personality on e-learning systems, which could lead to the effective design of adaptive e-learning systems. In this chapter, we discuss a potential approach to encompassing the personality effect that we have identified from the previous chapters, in the development of adaptive e-learning systems. The main aim of this chapter is thus to explore whether the personality consideration in the user model would be able to dictate the learning performance of adaptive e-learning systems. The proposed user model in this chapter simulated the case in which learners were guided either into the matched or non-matched learning material for their personality type. The experiment empirically showed that encompassing the personality factor in the user model would improve adaptive e-learning systems.

Overview of the Chapter

Section 8.1 briefly reviews the literature on the personality aspect in the user model, and section 8.2 describes the empirical study introduced in Section 8.1. Finally, Section 8.3 discusses the lessons learnt from this empirical study and some conclusions are drawn in the final section.

8.1. Personality in the user model of adaptive e-learning systems

In the previous chapters, one of the main conclusions to be drawn is that the personality type has significant impacts on the learning performance. Following on the previous chapters, a subsequent question to be raised is how to encompass the personality effect in the design of adaptive e-learning systems this is central to this chapter.

Previous studies (please see Chapter 3 for more details) showed that the current user model has paid little attention to the personality aspect that we have confirmed in the previous chapters. There are many reasons for that (as have been stated in Chapter 3), for instance, it might not be economically feasible to collect such a great deal of personal data, partly because it is too time-consuming and mostly because it is still not clear what features should be considered for this purpose. Hence, only a few studies (Gilbert & Han, 1999; Grigoriadou *et al*., 2001; Kinshuk & Lin, 2004; Kwok & Jones, 1985; LSAS, 1999; Stash & De Bra, 2004) tried to integrate learning style into the adaptive application. It is therefore the aim of this chapter study to embody this personality feature in the design of the current user model, which has been overlooked in the early studies of adaptive e-learning systems.

Several empirical studies (e.g., Kinshuk & Lin, 2003; Stash & De Bra, 2004) demonstrated that an appropriate user model should categorise each individual by their own learning style at the very early stage of their learning, so in turn the adaptive e-learning system can effectively support different types of learners. Also, the previous finding of this thesis showed that classifying learner personality made it possible for the system to generate learning materials adapted to different types of personality (see Chapter 6). Therefore, an adaptive e-learning system proposed in this chapter mimics the ability to adapt new contents that match the user's needs according to the personality feature of each user's profile.

A brief experiment carried out in this chapter was to test whether encompassing the personality type in the user model can actually guide learners automatically to the correct learning materials. If so, it is worth noting how much that consideration can help the learners. Basically, the reliability of this system depends on the data that are given by the learner to identify his/her personality through a brief MBTI module.

8.2. A proposed user model with the personality type

A primary objective of this chapter is to explore a way of encompassing the personality effect identified in the previous chapters in designing adaptive e-learning system. Indeed, this can be simply done manually by written form-filling. Yet, this would be a possible obstacle or distraction to the effectiveness of adaptive e-learning systems. Hence, for this research, we simply developed a web-based module to identify the personality type of each learner, and the outcome of this module was used to dictate the learning material to follow. Of course, this approach seems to be problematic. For instance, there is no guarantee of that the MBTI model identifier will identify the right personality type of each learner without any proper consultation with registered psychologists. Yet, in the sense that the main point of this chapter is to show the effectiveness of the personality feature in the user model, for the following experiment, this compromise may be excusable. In the proposed user model, the generation of e-learning courses depends on the learner profile that includes user personality.

Figure 8.1 outlines the structure of our user model. To raise awareness of the personality in the user model, the other features that are generally being included, such as preferences and knowledge level and so forth have not been considered in the experiment.

Figure 8.1 A proposed user model
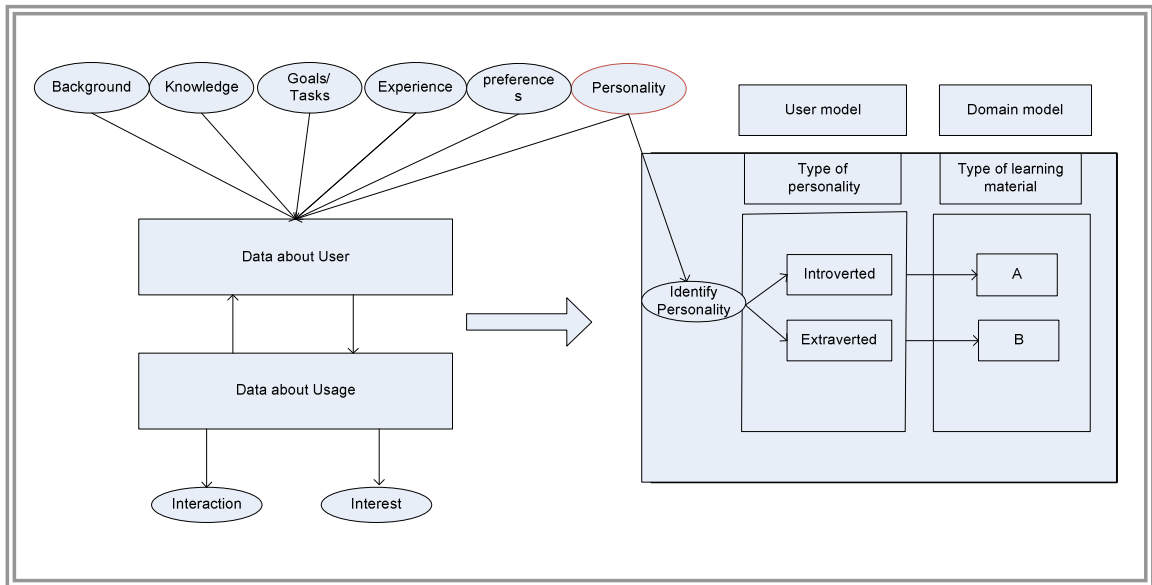
8.3 Experiment 6

8.3.1. Method

8.3.1.1. Participants

10 males and 2 females from Massey University took part in this experiment. They had

some homogeneity in that they were all undergraduates taking Computer Sciences (CS)

courses at the University. The homogeneity of the participants also considered their

previous learning outcomes in the other CS courses of more than B+ grade average and

their knowledge of programming skills (e.g., C, C++, and Pascal) within average. These

courses are compulsory for their progress in the undergraduate degree of Computer

Science. The sample size is too small because it was the end of the semester therefore it

was very difficult to find participants for this experiment, and we thought that this small

sample size would not cloud the approximation of the prototype system for identifying

the role of personality in the user model.

Table 8.1. The participants of Experiment 6

System	Introvert	Extravert	Total
Haskell 1	3	2*	5
Haskell 2	2*	5	7
Total	5	7	12

* Learners performed the material that did not match their personality

Table 8.1 describes the participants in this experiment. The assumption of the previous experiment (see Chapter 6), as well as for this study, was that Haskell 1 would be preferred by the introverted (because it matched their personality), while the extraverted would be more suited to Haskell 2**.** Therefore, if the proposed user model with the personality feature could guide the learner with their preferred system, their learning performance would be better.

Although the sample size of the participants in this experiment was very small, the purpose of this study is to provide an impression of the effectiveness of embodying the personality on learning performance, so this experimental setting would not cloud the findings from this experiment.

8.3.1.2 Apparatus

The two Haskell applications (i.e., Haskell 1 and 2) of Chapter 6 were reused for the experiment. A note is needed here. The outcomes of Chapter 6 were that the introverted favoured Haskell 1 and the extraverted, Haskell 2. Hence, it is hypothesised that the introverted who are automatically guided to Haskell 1 would benefit more than the extraverted who are directed to Haskell 1. This implies that the consideration of personality in the user model could possibly lead to better learning performance on adaptive e-learning systems.

Figure 8.2. The MBTI questionnaire test
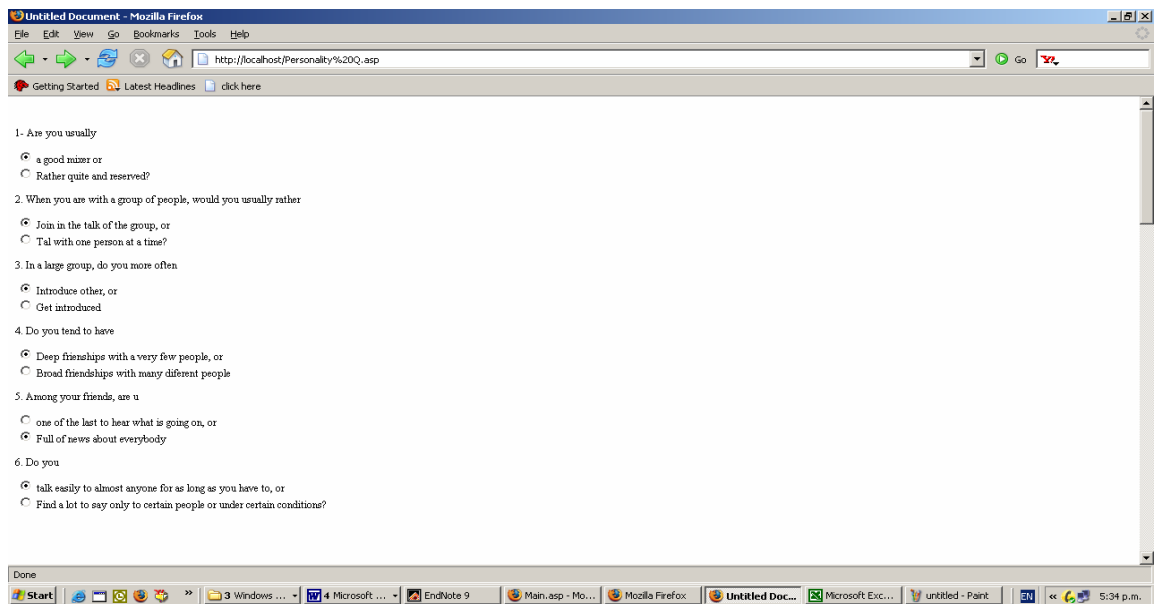
Figure 8.2 depicts the MBTI questionnaire page, consisting of 21 questions,

which were given to the participants before learning Haskell. Under each question there

are radio buttons for the learner to choose the one that fits his or her personality. After

the learners finished answering all the questions, the adaptive e-learning system

automatically guides them to either Haskell 1 or Haskell 2. For the experimental

purpose, in detail, 3 out of five introverted were assigned to use Haskell 1, and 5 out of

7 extraverted used Haskell 2. Other participants were allocated to the mismatched

systems, so they served as control groups. Figure 8.3 depicts the experimental setting.

Figure 8.3. The experimental setting

8.3.1.3. Experiment design

In this experiment, 2 (Haskell 1 / Haskell 2) by 2 (Introverted / Extraverted) between-subject design was considered. Both personality type and systems were independent variables. The dependent variables were time taken and correct answers.

8.3.1.4. Procedure

Firstly, participants were provided with the instructions regarding the experiment. These gave information about the experimental procedure, the purpose of the study, and the data protection policy. They were all seated in a laboratory where the proposed software of the adaptive e-learning system was installed on each computer. As the students first logged into the system, they had to answer the MBTI questionnaire test presented on the first page. The proposed software classified them automatically according to their personality, then directed the learners to either the right system that matched to their personality or otherwise the wrong system that did not match to their personality. All the participants were given sufficient time to learn all the materials with the system. At the end of the learning session, they were asked to answer 20 questions. Those questions were comprised of 10 multiple choice and 10 open-ended questions about what they had learnt from the adaptive e-learning system.

8.3.2. Results

Table 8.2. Summary of task performance in Experiment 6

System	Introverted		Extraverted	
	Time taken (mins.)	correct answer (%)	Time taken (mins.)	correct answer (%)
Haskell 1	42.60 (4.6)	63 (7.6)	50.60 (6.2)*	45* (0.0)
Haskell 2	47.70* (3.1)	50* (7.1)	30.60 (3.6)	65 (7.9)

*Learners performed the material that did not match their personality

Table 8.2 summarises the relationship between the type of personality and the learning material in terms of time taken and correct answers. It showed that introverted learners performed better with Haskell 1 (mean time taken = 42.60 min., correct answers = 63) than extraverted learners (mean time taken = 50.60, correct answer = 45). Also it showed that the extraverted learners performed better (mean time taken = 30.60, mean correct answers = 65) than introverted learners (mean time taken = 47.70, correct answer = 50) with Haskell 2. The findings were the same as those from Chapter 6. This clearly demonstrated that the personality consideration in the adaptive e-learning system would lead to better task performance.

The Mann-Whitten U-test was applied, because of the small sample size and the heterogeneity of the variance, for testing differences between the two independent variables; the personality (introverted and extraverted) and the system (Haskell 1 and Haskell 2). Regarding the time taken, it revealed a significant difference between the personality and learning system (Haskell 1 or Haskell 2). Similarly, in terms of correct answers it also indicated a significant difference between personality and learning system. In effect, the experiment showed that the personality feature in the user model would be crucial.

8.4. General Conclusions and Discussion

The aim of this chapter was to validate an idea for encompassing the personality type in the user model. The findings from this experiment showed that the introverted learners performed better with Haskell 1, whilst the extraverted learners performed better with Haskell 2. That is to say, this experiment empirically demonstrated that it is possible for a user model in adaptive e-learning systems to encompass the personality effect in an effective way. Thus, it is also possible to make it easier for the system to categorise learners and direct them to the right material to match their personality styles.

However, the small sample size adopted in this experiment would probably compromise the significance of the experimental result. It should be further investigated with more samples. Nonetheless, combined with the outcomes from Chapter 6, it seems to make sense that the user model with personality feature would lead to a better performance.

CHAPTER 9. CONCLUSIONS AND DISCUSSION

Throughout this thesis, we investigated the potential role of personality in adaptive e-learning systems, and how future adaptive e-learning systems could embody the personality feature to address each individual's differences. Originally, this research question arose from the author's personal experiences while teaching in a university in Oman, one of the Gulf States, where most of the students had different learning styles from those from a Western cultural background (Horikoshi, 1998; Lim, 2004). This experience suggested that the Omani students had rather different attitudes and communication styles with their teachers, which might result in different learning styles from those common in the Western students. For dealing with this difference, it was noted that the adaptive e-learning system should consider these different personality traits for an effective learning experience, which was central to the research question in this thesis.

There have been several studies on the user model for adaptive e-learning systems (Brusilovsky & Cooper, 2002; Brusilovsky *et al.*, 2001; de Vrieze, van Bommel, & van der Weide, 2004; Eklund & Brusilovsky, 1998; Eunjoo & Doohun, 2005; Henze & Nejdl, 2002; Kavcic, 2000; Kogan, 1971b; Messick, 1976a; Wenger, 1987), proposing a wide range of features, but none of them clearly pinpointed the role of personality in their own user model, which is the main contribution of this thesis. In crude terms, learner characteristics that have been given attention in the literature are *learners' backgrounds*, *knowledge*, *goals/tasks*, *previous learning experience*, *preferences, interests*, and *interaction style*. Some of these have been included in the user model to match their learning styles. Even though this approach has been successful to some extent, it seems to demand many system resources to identify the appropriate adaption

process. To have the correct adaptation for knowledge status, the system should monitor the student's entire learning log data, but if we can include the personality in the user model, more pervasive data on the student's own preference can be collected and used for the adaption process.

The main research question of this thesis was thus to investigate whether or not the learner's personality features may have certain effects on their use of e-learning systems, and if that is the case, how to embrace this feature in designing adaptive e-learning systems. And this, in turn, entailed the following related research questions:

- to investigate whether the different personality types of the learners (especially, the level of introvertedness) would have different effects on the learning performance of both traditional and adaptive e-learning systems (Chapter 4);

- to explore whether the other personality types (e.g., Sensing - Intuitive, Thinking - Feeling, and Judging - Perceiving) have consequences for learning performance in adaptive e-learning systems (Chapter 5);

- to investigate whether the learner's personality may influence preferences that can be used for structuring appropriate learning material (Chapter 6);

- to investigate the effects of the personality on the performance of a collaborative learning activity (Chapter 7);

- to explore whether the inclusion of the personality in the user model for adaptive e-learning systems would lead to better task performance (Chapter 8)

To conclude this thesis, Section 9.1 presents a brief summary of the findings from our research, encompassing the personality in the current user model, and relates that to its impact on learning performance using adaptive e-learning systems. Section 9.2 summarises the contribution of this thesis to the current research on the user model of

adaptive e-learning systems. Section 9.3 addresses the limitations of the thesis. Finally

section 9.4 discusses some implications of this research and makes some

recommendations for future work.

9.1 Summary of this thesis

In this section, we summarise the findings of the thesis, and what they imply for the

development of adaptive e-learning systems in the near future. Figure 9.1 shows the

overall structure of the thesis, and how each chapter was interwoven.

Figure 9.1. The overall thesis structure
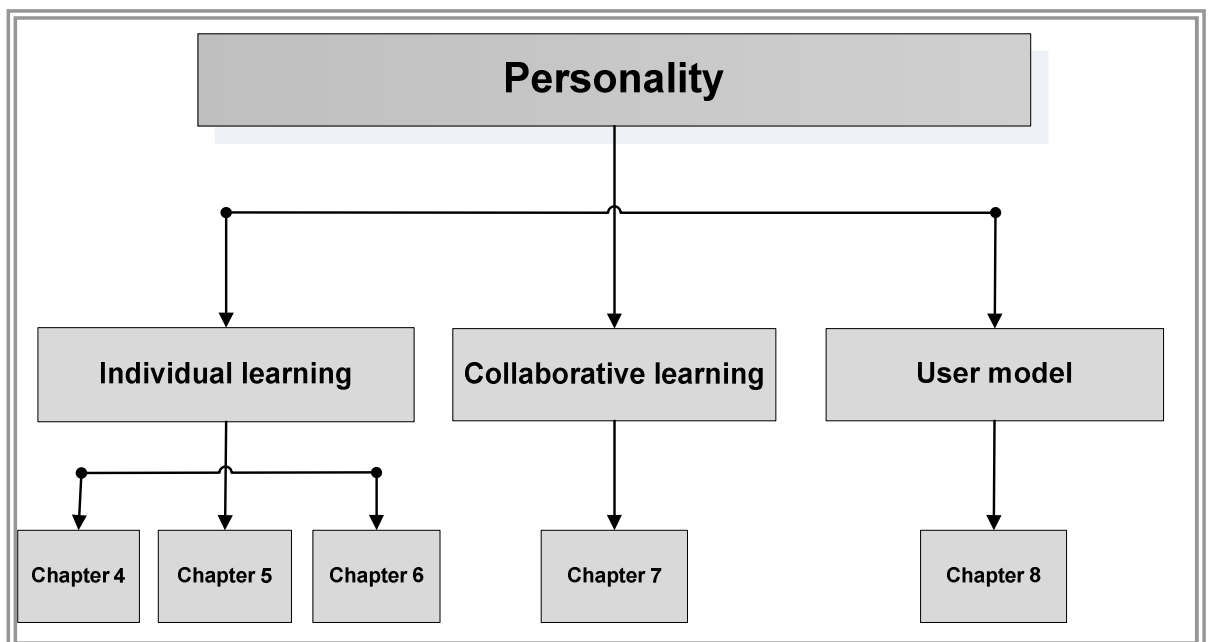
We considered the personality issues in three respects in this thesis. Firstly, the

personality effect in individual learning was investigated in Chapters 4, 5 and 6.

Secondly, the thesis reviewed the effects of the personality in collaborative learning

situations, assuming that the mixture of personalities in collaborative learning may

make a difference to the learner's task performance, which was discussed in Chapter 7.

Finally we empirically evaluated the personality effect in the user model for an adaptive

e-learning system, hypothesising that the personality feature can significantly enhance the learning performance with the adaptive e-learning system in Chapter 8.

Overall, firstly, we found that learners with different types of personality have different effects on their learning performance with adaptive e-learning systems. Secondly, we explored how to embody the personality features in the current user model, briefly proposing that the inclusion of the personality in the user model for adaptive e-learning systems would lead to better task performance.

Six experiments were carried out to determine whether different personality types could actually affect the use of adaptive e-learning systems. The first two experiments were carried out a Gulf States University. Experiment 1 was conducted to address the first question which is to understand the impact of personality on learning performance within a traditional e-learning system. In effect, a contribution of this experiment was to empirically confirm that traditional e-learning systems were not designed to support the personality difference. Consequently, Experiment 2 was conducted, intending to understand the impact of the personality type on the learning performance with adaptive e-learning systems. The results from this experiment indicated that different personality might have some effects on the learning performance with adaptive e-learning systems.

For an external validity test, the thesis extended the same experiment to another cultural context, though it was not the comprehensive triangulation. This, in turn, could be used to justify the results and generalise the findings of the two experiments 1 and 2. The other experiments were conducted in a Western University to investigate whether the different learning styles would have an impact on learning performance. Experiment 3 was performed to explore whether other personality types also have certain effects on learning performance in adaptive e-learning systems. The findings from this experiment confirmed the ones from Experiment 2 in the New Zealand context.

From Experiments 1, 2 and 3, we could conclude that learners' performances were significantly influenced by their personality differences, as they were educated by the traditional e-learning system. Moreover, it can be concluded that the personality factor, in particular, affected the learning performance in adaptive e-learning systems.

However, in order to rigorously validate the effect of personality, a following research question was to test whether or not the learner's personality may dictate their preferences for a particular style of learning material, as part of applications of using the personality feature. Experiment 4 was carried out to reveal this purpose. The findings from this experiment demonstrated that the task performances by the two different personality groups (the introverted and extraverted) were significantly affected by the two different types of teaching materials.

Moving from the concern with individual to collaborative learning, Experiment 5 was performed to explore the effects of personality on groups of learners incorporating collaborative learning. According to Soles and Moller (2001), it is necessary to find out the learning needs for each preference and in this experiment we endeavoured to meet these needs in an instance of collaborative work. The finding from this experiment indicated that the task performances of heterogeneous groups with different types of personality (introverted – theory and extraverted – practical) were better than homogenous groups having the same type of personality. This study suggested a practical implication for designing collaborative learning technologies in conjunction with the personality feature. Furthermore, it valued the personality effect in the adaptive e-learning system.

The main aim of Experiment 6 was to show empirically whether the personality consideration in the user model could dictate the learning performance of adaptive e-learning systems. A proposed user model in this chapter was designed to allow the learner to automatically be guided either into the matched or non-matched learning

material according to her or his personality type. The findings from this experiment showed that incorporating personality in the user model would be of practical value.

To sum up, this study demonstrated that personality differences do exist between learners, so that students' learning experiences should reflect this individual difference. As a consequence, this line of research would provide some implications for developing effective e-learning systems such as including the personality factor in the specification of the user model and providing the designers of educational materials with guidelines for how to meet the learning needs of each individual.

However, as our experiments are very limited, we cannot generalise the personality effect from this line of studies. Further studies need to be done before it can be considered as having a significant impact on the adaptive e-learning process, even though the findings from this thesis can prove useful in developing adaptive e-learning systems. This work may provide some directions for future research in this area and perhaps it opens the way to fit the collaborative learning style with learner's personality type, which could yet be considered a guideline for the design of effective e-learning systems.

9.2 Contributions

9.2.1. Contributions of the thesis to adaptive e-learning

By examining the personality trait which has been overlooked in the previous literature on the design of adaptive e-learning and including the personality feature in the current user model for better adaptation, this thesis significantly enhanced Brusilovsky's user model (2002), showing that identifying the personality feature in the design of e-learning systems would improve the learner performance in the learning process.

This study resulted in five contributions to current adaptive e-learning systems research:

1. Contribution to research on individual performance in e-learning

The study found that different personality types have different effects in e-learning systems. In order to characterise the adaptivity of the e-learning systems, the study compared the effectiveness of each system (non adaptive e-learning with adaptive e-learning system) in terms of MBTI personality type. It showed that personality type in the traditional e-learning systems may not have a significant effect on learning performance itself even though there is a certain relationship between personalities and learning style. In contrast it showed that adaptive e-learning systems are more sensitive to personality effect.

2. Contribution to research on personality effect

The research on personality trait in learning generally is not conclusive (Wicklein & Rojewski, 1995). It has long been considered in developing an effective e-learning environment but none of the studies clearly pinpointed the role of personality in the user model. Our studies in two tertiary e-learning contexts specifically showed significant differences in effect on performance with level of introversion/extraversion on MBTI scale, which was more salient than other personality types (Sensing - Intuitive, Thinking - Feeling and Judging - Perceiving).

3. Contribution to the learning material designs

On the basis of the new studies carried out in this thesis, instructional material designers are recommended to consider the personality trait as a tool for structuring the learning materials which can maximise learner potentials, thus enhancing the learner's learning performance. The study empirically identified the relationship between the personality type and the learning material structure, finding that task performances by different personality groups (introverted vs. extraverted) were significantly affected by two different material designs (depth-first vs. breadth-first).

4. Contribution to the performance of collaborative learning activity

It has been suggested that collaborative learning helps students through sharing their experience and strengths (Corich *et al.*, 2004; Gweon, Rose, Carey *et al.,* 2006). This study confirmed that collaboration between different types of personalities could motivate better collaborative learning experiences. The task performances of heterogeneous group of learners with different type of personality were better than those of homogenous groups of learners that have the same type of personality. Specifically, this study indicated that since different personalities have different learning strategies, collaboration using appropriately matched learning material improves group performance. This was found to be significant for pairs of introverted matched with extroverted learners.

5. Contribution to effective e-learning systems design

The study found that inclusion of personality in the user model would improve adaptive-learning systems. Although only at the prototype stage, the study empirically demonstrated that it is possible for a user model to encompass personality type in an effective way. Compared to the complexity of the previous studies using other personal characteristics (Felder & Brent, 2005; Ford *et al*., 2001; Holodnaya, 2002; Humanmetrics, 2006; Stash & De Bra, 2004) it would appear that this enables the system to categorise learners more efficiently and direct them effectively to appropriate instruction. The study implies that the user model in adaptive e-learning systems should accommodate learners' different learning styles.

We hope that the contribution will convince developers of e-learning systems to consider the personality feature in the current user model.

9.2.2 Contribution to pedagogy and teaching practice

The teaching challenge with which this research began should not be forgotten, as its contribution to pedagogy could be even more significant. This research contributes to ongoing debates about how to teach more effectively to different personalities and learning styles, and whether e-learning can do the job a sensitive teacher can do.

Initially the research sought a solution to a classroom instructor's problems, but while focussing on how to make e-learning more responsive to personality differences, it should not be surprising that it could have more general impact on teaching practice. Teachers acknowledge that knowing the personality of the learners helps the teacher match lessons to student's needs. This research clearly identifies a significant way that students (of any age) could be grouped (by level of extraversion), which could be beneficial for group work and the management of classes. English language teachers commented (personal communication, April 2007) that they could directly apply the design of collaborative learning in this study to their own teaching. These findings could also contribute to the Human Resources domain on selection and training for specific occupations, for example training the trainers of computer programmers.

9.3 Limitations

The following limitations of the study should be noted. Most of all, the small numbers of participants in Experiment 5 and 6 were the main limitation of this thesis. It is partly because the participants were voluntarily recruited, and partly because the experiments took quite a long time, so there were many instances of attrition. Secondly, the experiments in this study were limited to the two Universities samples (one from the Gulf States University and the other one from New Zealand), so that the results may not be widely generalisable to the broader population of other cultural contexts. Thirdly, we have not used any other content apart from the computer science courses, so if the

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course content is different, for example humanity courses, the result might vary. Fourthly, all the participants were from the Computer Science department, for the convenience of collecting data. IF a larger sample is taken the result may be different. Fifthly, more qualitative research is needed, for example on learners' feedback on their learning experience for more interpretation. Finally, although we used MBTI, currently more advanced psychological theory can be used such as the Keirsey indicator, which may provide a more candid and effective account of the personality issue, including information about certain types of intelligences, associated with the temperaments. Actually, based on Keirsey's personality study, ongoing research is planned to repeat the same experiment in other cultural contexts, using Keirsey's indicator instead of MBTI to justify the finding from the thesis.

Therefore, future research would go through the issues presented and gain new insights into the learners' learning process in order to generalise the findings of this thesis.

9.4 Future work

It is hoped that this thesis will serve as a springboard for future work in adaptive e-learning and pedagogy. The study in this thesis showed that the newly proposed user model that includes personality in the current user model significantly enhances the effectiveness of learning performance with adaptive e-learning. Yet, the understanding discussed in this thesis still requires more thorough validation and testing for a wide range of e-learning applications, in particular for adaptive e-learning systems.

In the near future, we are planning to perform all the experiments that have been done in this study with more participants to substantiate our findings considering the problems described in section 9.3. Also, they could be extended to embrace other cultural contexts in order to find out if the culture has any effect on using these systems.

For example, in other cultural contexts, more experiments are needed to explore whether other personality features apart from introverted and extraverted may affect learners' performance. Further research would test the effects of the proposed user model in this thesis on different content rather than those from the Computer Science discipline. We are also planning to approach to ELM-ART developers to combine this study in their design of adaptive e-learning systems. This may provide some directions for future research in this area and perhaps it opens the way to fit the learners' personality type for designing efficient e-learning systems.

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APPENDIX 1: EXPERIMENT 1

This appendix briefly describes how Experiment 1 was performed. Appendix 1.1 includes the short introduction of ELM-ART system. Appendix 1.2 includes the intro-Questionnaire which has been provided to participants about their background experience of programming in order to interpret data correctly. Appendix 1.3 presents the paper test. Finally, Appendix 1.4 includes some figures of the apparatus.

APPENDIX 1.1. SHORT INTRODUCTION ON ELM-ART SYSTEM

The following Table A.1.1 has been provided to each participant.

Table A.1.1. The general information of ELM-ART system

<table>
<tr><td>

Episodic Learner Model
The Adaptive Remote Tutor (ELM-ART)

Intro-questionnaire

ELM-ART is a new, *intelligent* system that allows for interactive learning via WWW. The development of the system is just in an experimental phase investigating different ways of knowledge-based support. Therefore, data gathered during working with this system are evaluated statistically (for scientific purposes only).

To interpret data correctly, we ask you to answer the following questions. In return you get the opportunity to work at all six lessons of the introductory LISP course. If you don't answer the questions, you will be able to play with the first lesson only. However, at any moment within the course, you can go to the intro page (the system's home page, that is the next page where you go to from here) and ask for the other lessons in the preferences section.

</td></tr>
</table>

APPENDIX 1.2. INTRO-QUESTIONNAIRE

The following table includes the questionnaires that have been given to each participant to fill in, at the beginning of their learning session. It is mainly used to gather information about learners' background experience.

Table A.1.2 Background experience questionnaires

Experience in		
Working with WWW browsers	**Programming**	**Using computers**
None	None	Never before
Little	LISP	Up to 20 hours
Something	Pascal, C, C++, Basic	20-100 hours
Much	Others	More than 100 hours

APPENDIX 1.3. THE PAPER TEST

The following table shows the test questions that have been given to participants after

they learnt the LISP material.

Table A.1.3. Test questions

Questions	Options	
(XY)Z)	Atom / List/ No LISP-Expression	
ALPHA	Atom / List/ No LISP-Expression	
(IS THIS AN ATOM)	Atom / List/ No LISP-Expression	
The character string may be an atom, a list, or an incorrect lisp expression. Check the correct description	()	Atom / List/ No LISP-Expression
	7	Atom / List./ No Lisp-Expression
	T	Atom / List/ No LISP-Expression
Which of the following statements are correct?	T	Atom / Symbol / Number / List /No Lisp-Expression
Which of the following statements are correct?	()	Atom / Symbol / Number / List/ No LISP-Expression
Is the character string a number?	27.6-	Yes / No
Is the character string one LISP atom?	XYZ	Yes / No
Is the character string a nested List?	(13(ab))	Yes / No
Is the character string one LISP Atom?	(1x 2y 3z)	Yes / No
Is the character string one LISP atom?	453	Yes / No
Is the character string a List?	1A	Yes / No
Is the character string a List?	)r s t u(	Yes / No
Is the character string a nested List?	((jenny))	Yes / No
Is the character string a number?	-2,0 Dollar	Yes / No
Is the character string one	Group-A+B	Yes / No

LISP atom?		
Is the character string a nested List?	(a(b(c(de))f))g)	Yes / No
Is the character string a List?	-0.3	Yes / No
Is the character string a nested List?	(XYZ)	Yes / No
Is the character string one symbolic atom?	Jack-jenny	Yes / No
Which of the following statements are correct	)(	Atom / Symbol./ Number / List/ No LISP-Expression
Is the character string a number?	-0,4e+4	Yes / No
Is the character one Lisp atom?	(c0	Yes / No
Is the character string a List?	(Group A+B)	Yes / No
Is the character string a nested List	13(ab)	Yes / No
Is the character string a List?	Ab cd efg	Yes / No
Is the character string a number?	+1.7E-2	Yes / No
Is the character string a nested List	((ATOM)	Yes / No
Is the character one Lisp atom?	7+69	Yes / No
Is the character string a nested List	13(ab)ab	Yes / No
Is the character string a number	Jacj.tom(a)	Yes / No

Is the character string a List?	(+7.6(+4.3-2.1 0.5))	Yes / No
Is the character string a nested List	((one 1) (two 2)(three) (four))	Yes / No

APPENDIX 1.4. SOME FIGURES OF THE APPARATUS

The following figures give insights into how Experiment 1 was conducted. The software had the same learning contents as ELM-ART except for the adaptive mechanism.

Figure A.1.4.1. The login page
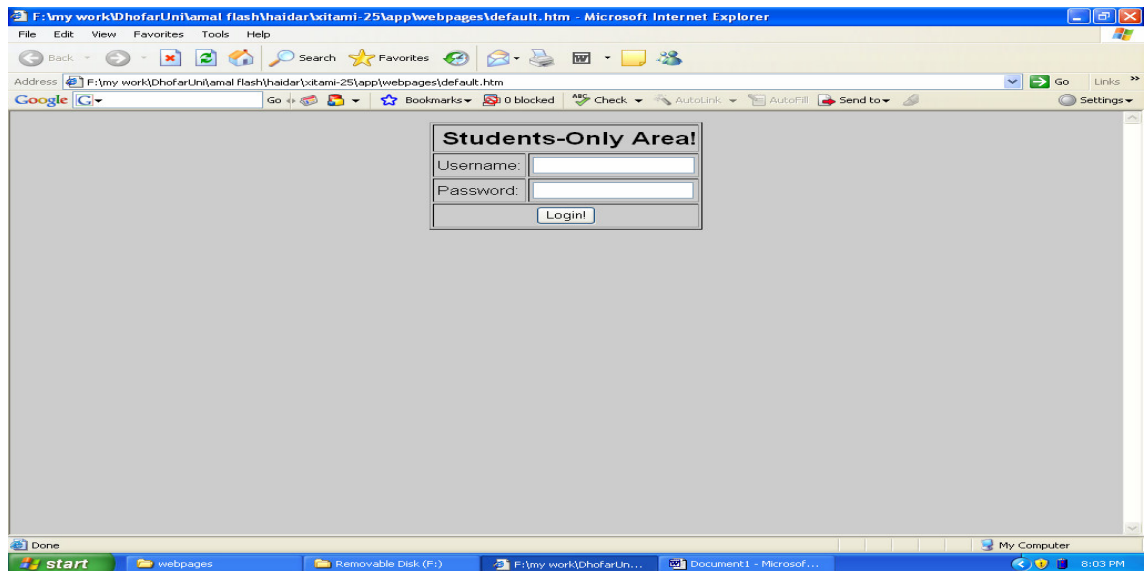
Figure A.1.4.1 depicts the login page, when 'login' button is clicked; the LISP course appears, as shown in figure A.1.4.2.

Figure A.1.4.2. Chapter1: Lesson 1
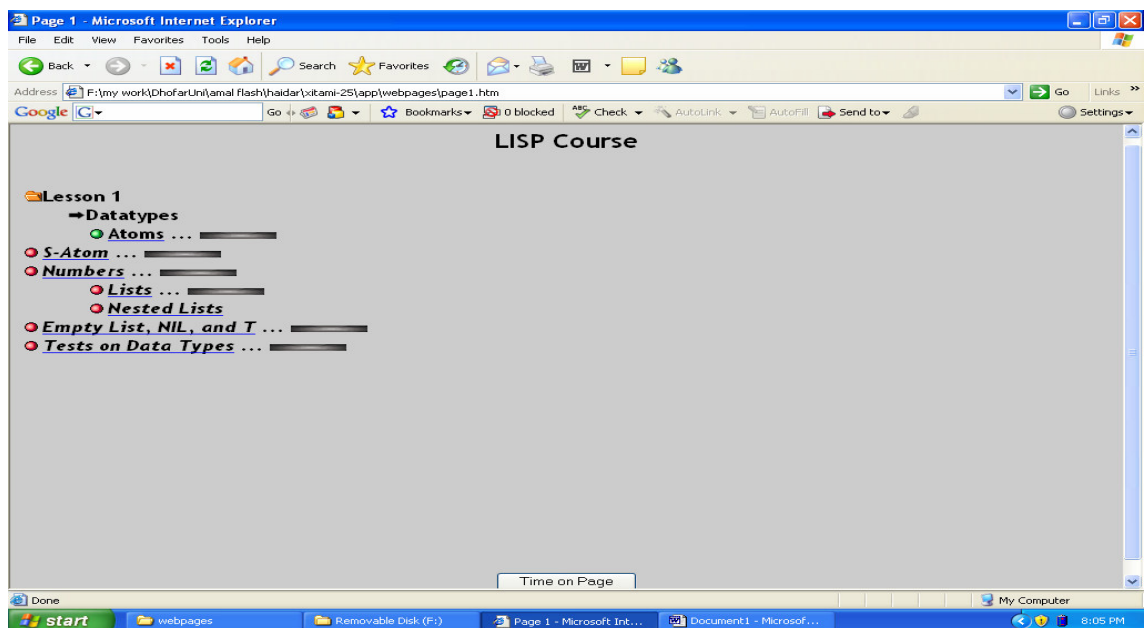
Figure A.1.4.2 depicts the first page of LISP. It shows the outline of lesson 1 concepts.

Figure A.1.4.3. Atom page
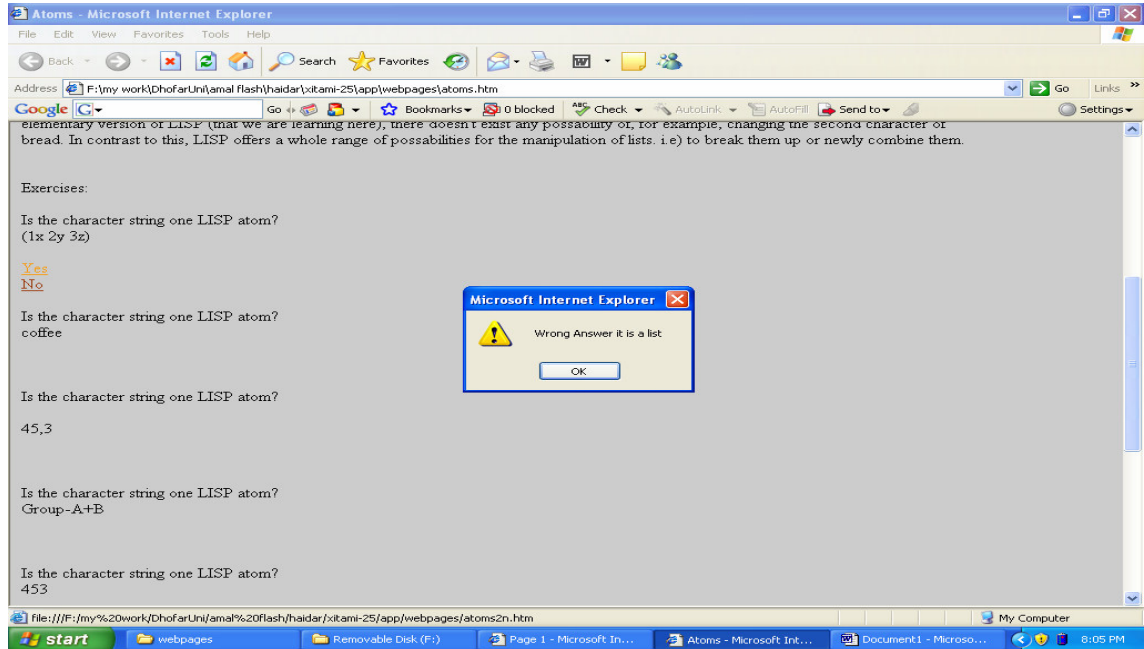
Figure A.1.4.3 depicts the Atom page of LISP. It consists of learning material of the concept atom, followed by some examples for the learner to experiment with, if the learner clicks the wrong answer he/she will receive an alert massage to warn him that he chose an incorrect answer.

Figure A.1.4.4. Symbolic page
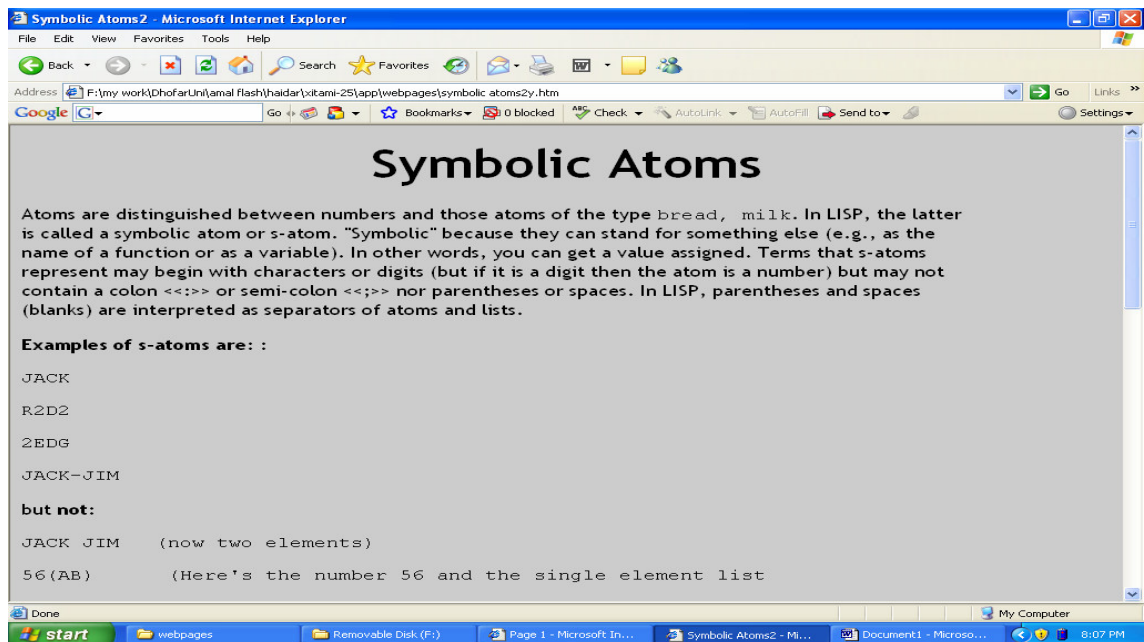
Figure A.1.4.4 depicts the learning material of the symbolic atom page. When the

'Next' button is clicked, the next page appears

Figure A.1.4.5. Symbolic page with alert message
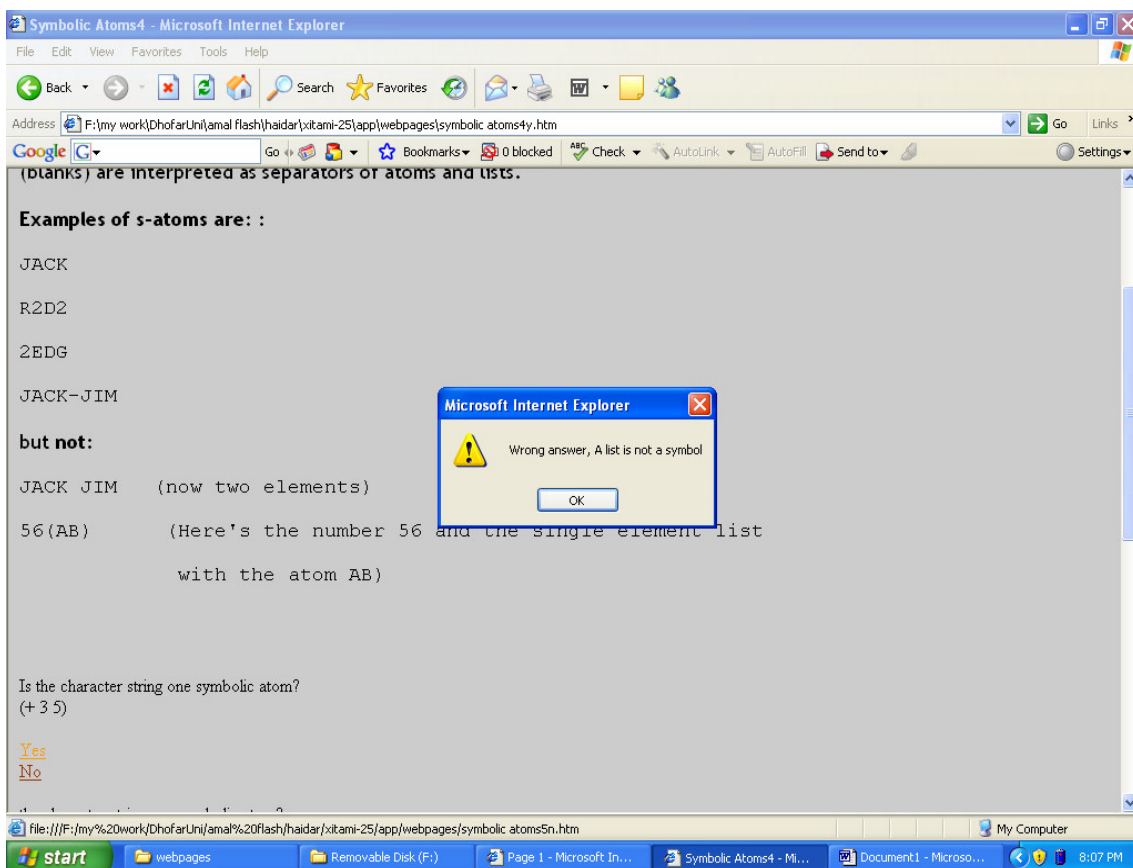
Figure A.1.4.5 depicts the symbolic atom page with the alert message. When the

'Next' button is clicked, the next page appears.

Figure A.1.4.6. Numbers page
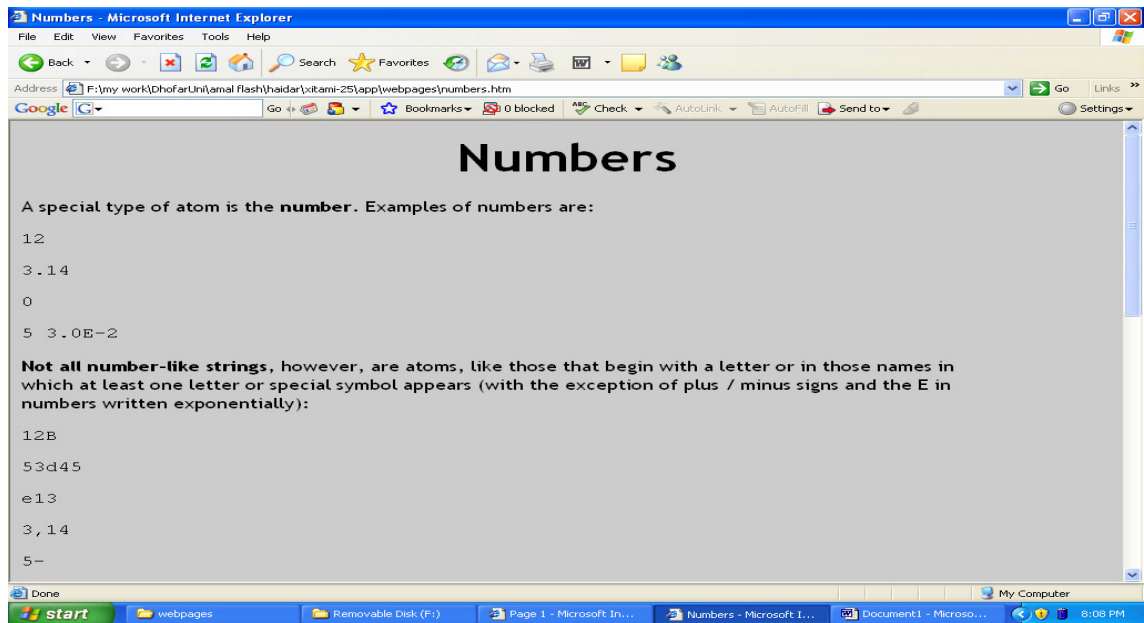
Figure A.1.4.6 depicts the number page. When the 'Next' button is clicked, the

next page appears.

Figure A.1.4.7. Lists page
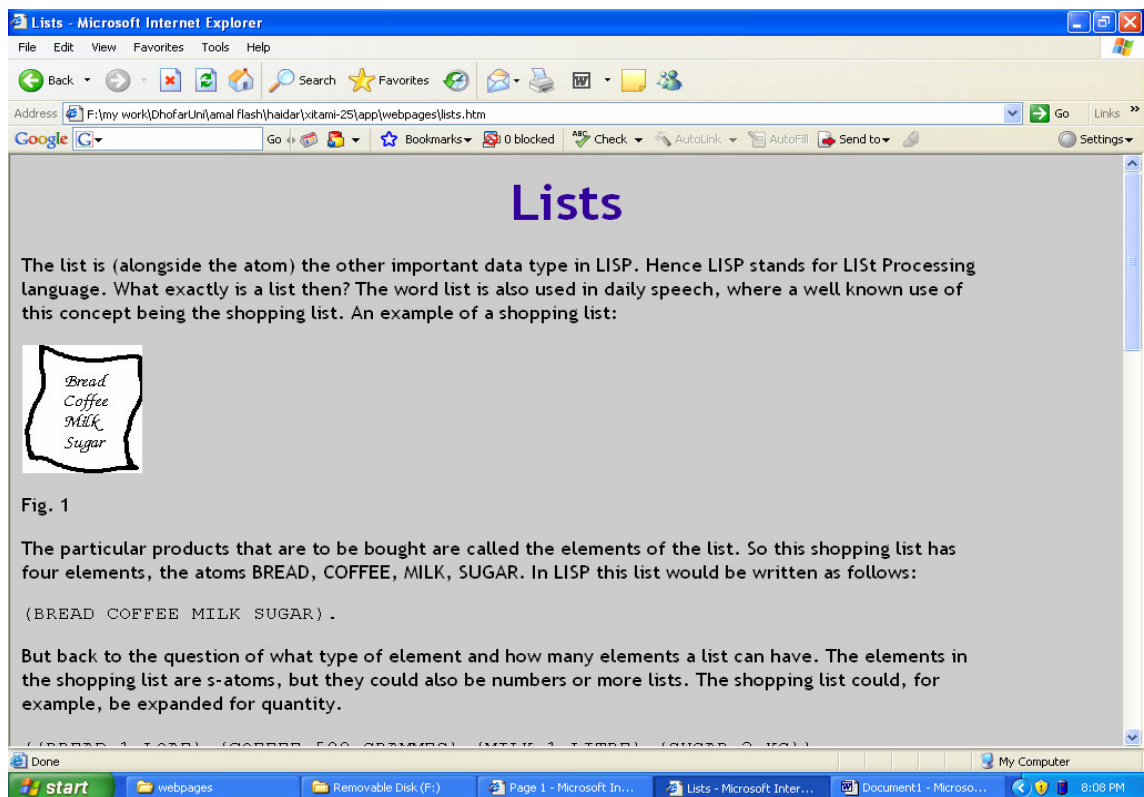
Figure A.1.4.7 depicts the lists page. When the 'Next' button is clicked, the next

page appears.

Figure A.1.4.8. Nested Lists page
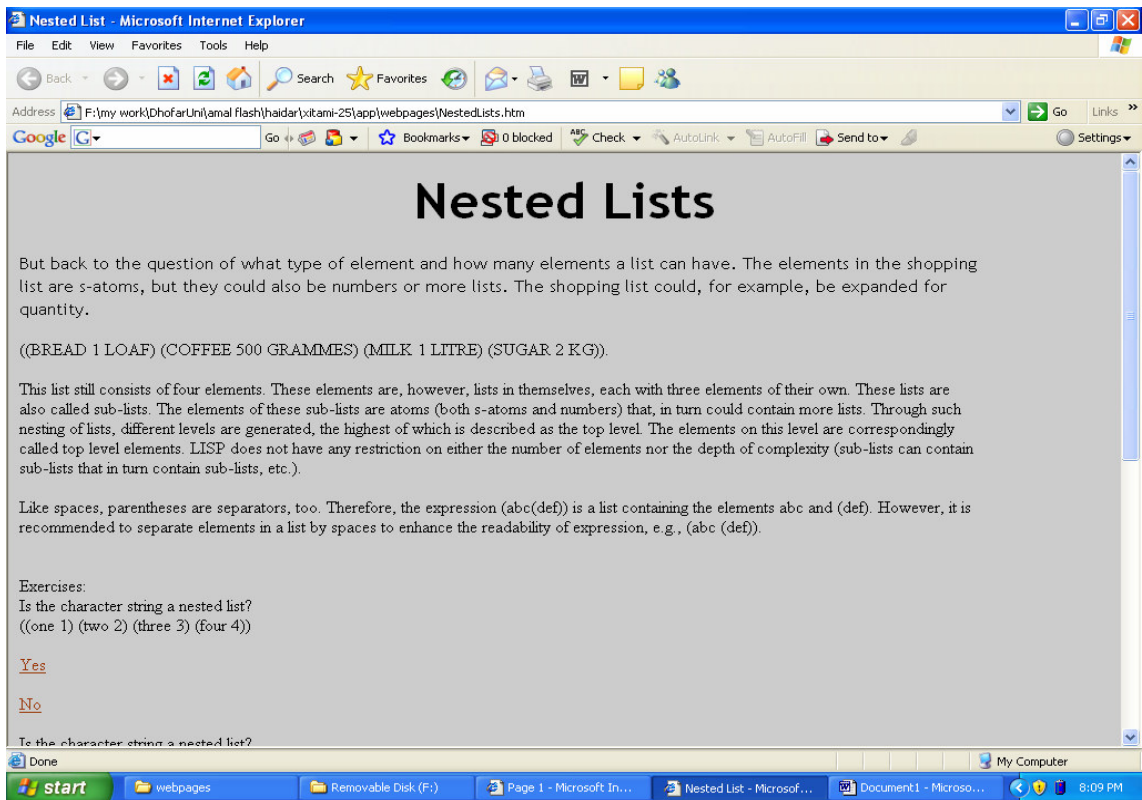
Figure A.1.4.8 depicts the nested lists page. When the 'Next' button is clicked, the next page appears.

Figure A.1.4.9. Empty Lists page
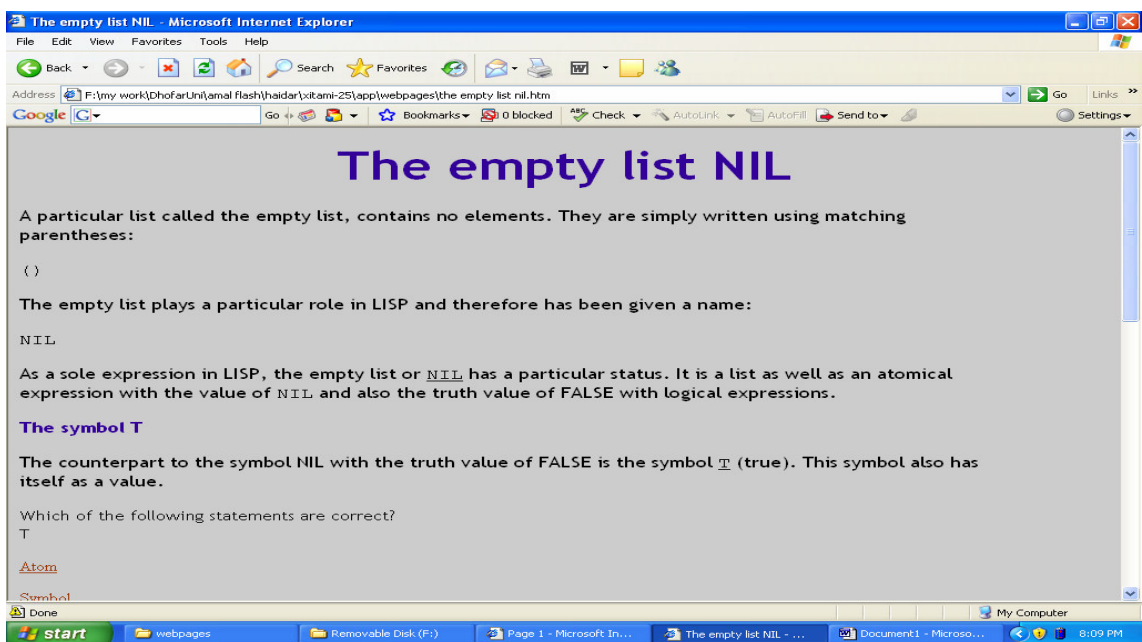
Figure A.1.4.9 depicts the empty lists page. When the participant successfully completes reading the whole pages, figure A.1.4.10 appears with the test questions.

Figure A.1.4.10. Tests page
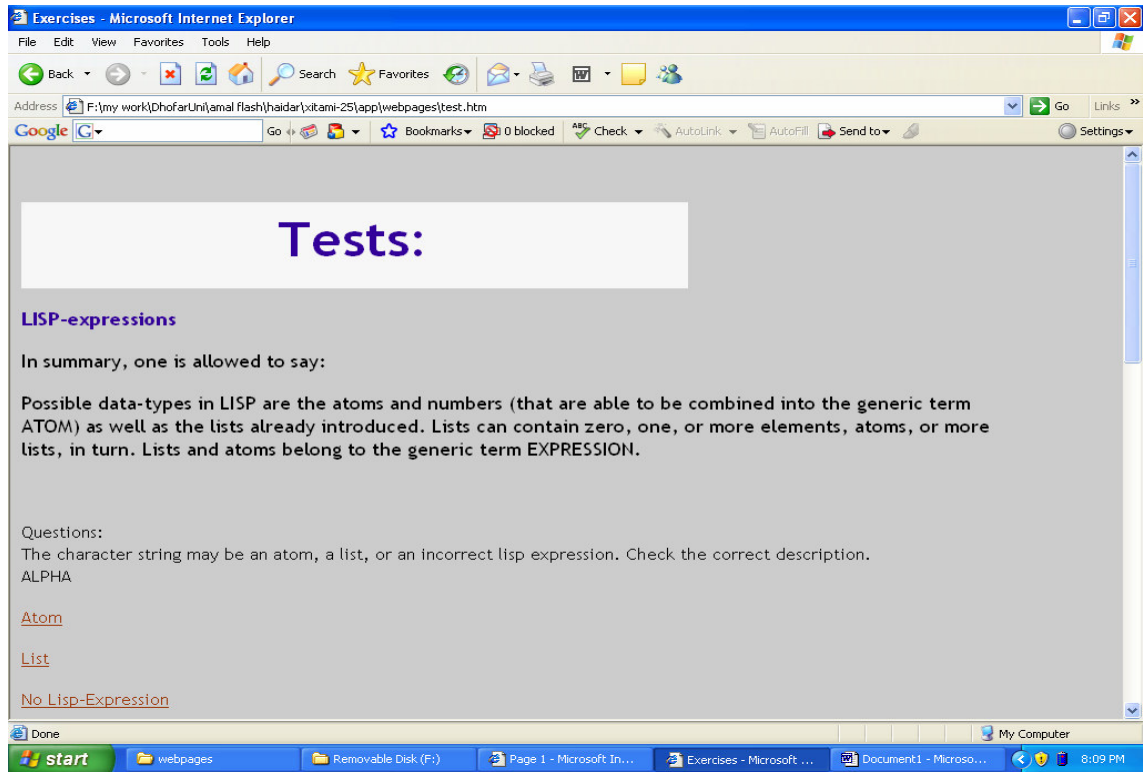
Figure A.1.4.10 depicts the tests page. When the participant successfully completes the test question, he/she can click the 'Submit' button to exit from the system.

APPENDIX 2: EXPERIMENTS 2 and 3

This appendix briefly describes how Experiments 2 and 3 were performed. The introduction and the intro-Questionnaire of the adaptive e-learning system ELM-ART are the same as the previous experiment using the traditional e-learning system except for the adaptive mechanism. That is to say the adaptive e-learning system has the adaptation process for each individual difference.

Appendix 2.1 includes the introduction part of ELM-ART and the intro questionnaire web page to gather information about each participant. Appendix 2.2 includes experiments 3 and 4 web pages with some figures of the apparatus ELM-ART that have been used for both experiment 2 and 3.

APPENDIX 2.1. THE INTRODUCTION WITH THE INTRO QUESTIONNAIRE WEB PAGE

The following Table A.2.1 has been provided for each participant.

Figure A.2.1. The intro questionnaire web page

When the 'Submit' button in Figure A.2.1 is clicked, the first page of the LISP course appears.

APPENDIX 2.2. EXPERIMENTS 3 AND 4 WEB PAGES

The following figures give insights into how these web-based experiments have been conducted.

Figure A.2.2.1. LISP course (introduction)
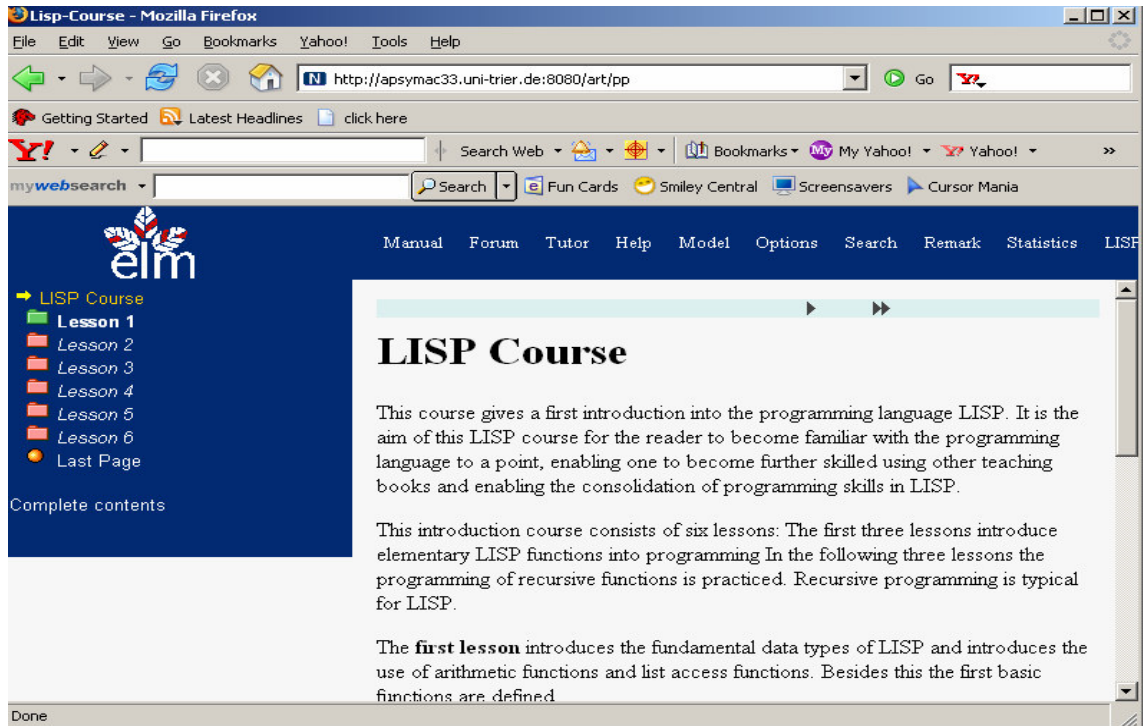
This depicts the introduction to the LISP course. When 'Submit' button in Figure A.2.2.1 is clicked, figure A.2.2.2 the first page of the LISP course appears.

Figure A.2.2.2. LISP course (lesson 1)
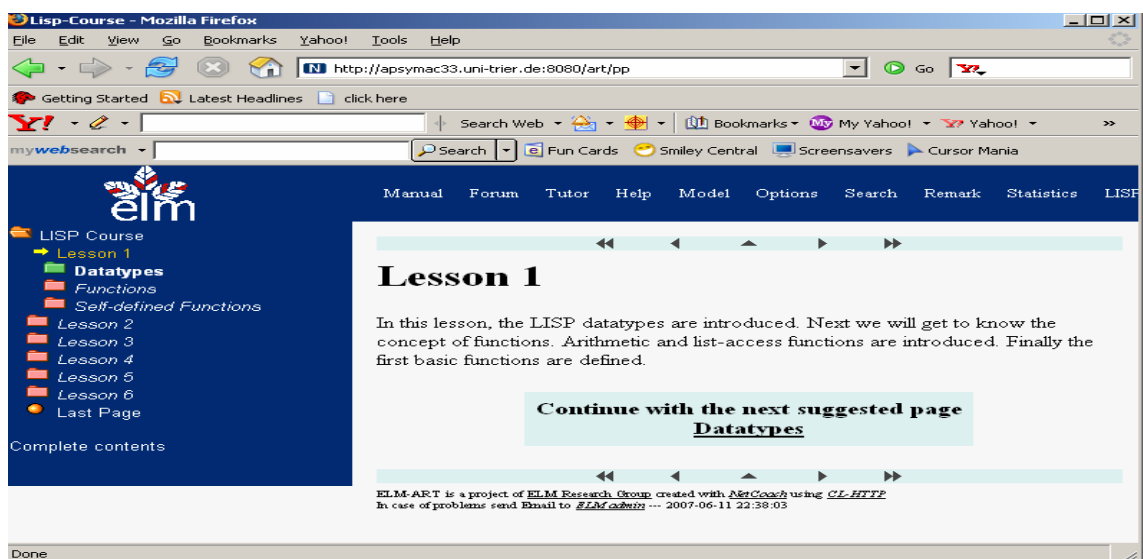
Figure A.2.2.2 depicts lesson 1 with the annotation link suggested by the system for the participant to follow.

Figure A.2.2.3. LISP course (datatypes)
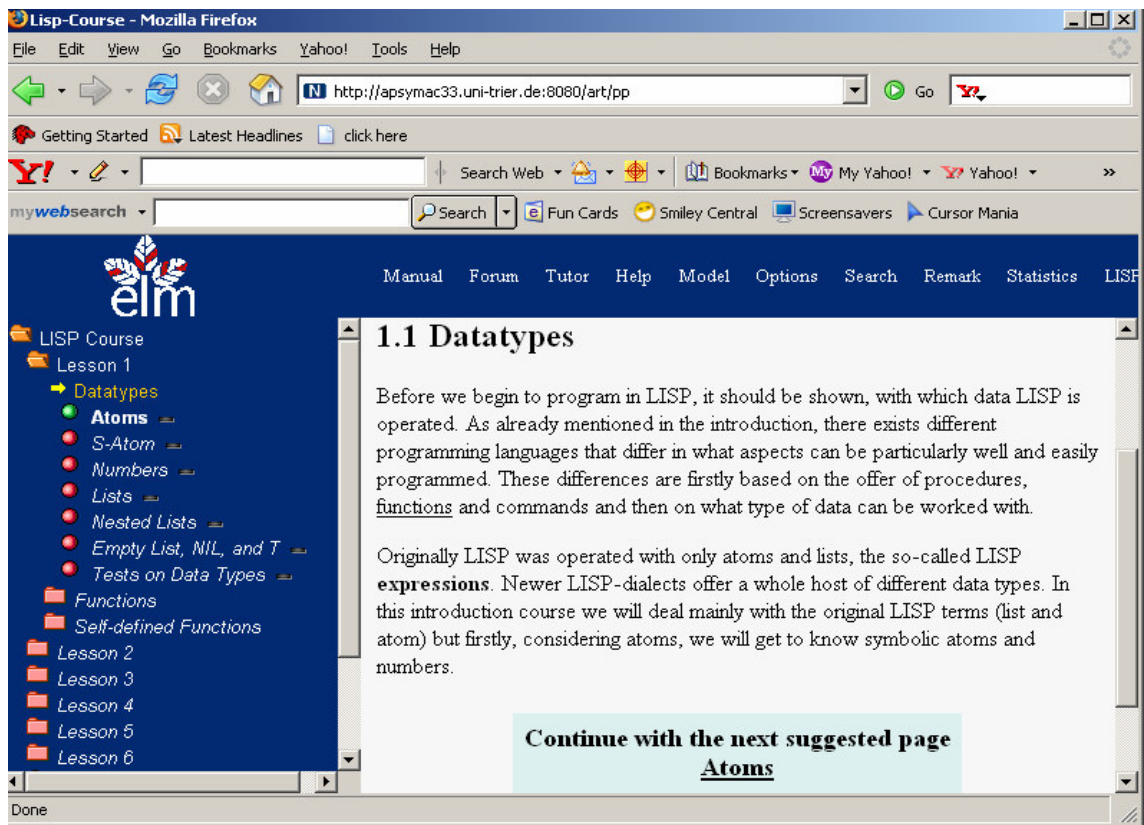
Figure A2.2.3 depicts the datatype page with the annotation link suggested by the system for the participant to follow.

Figure A.2.2.4. Atom
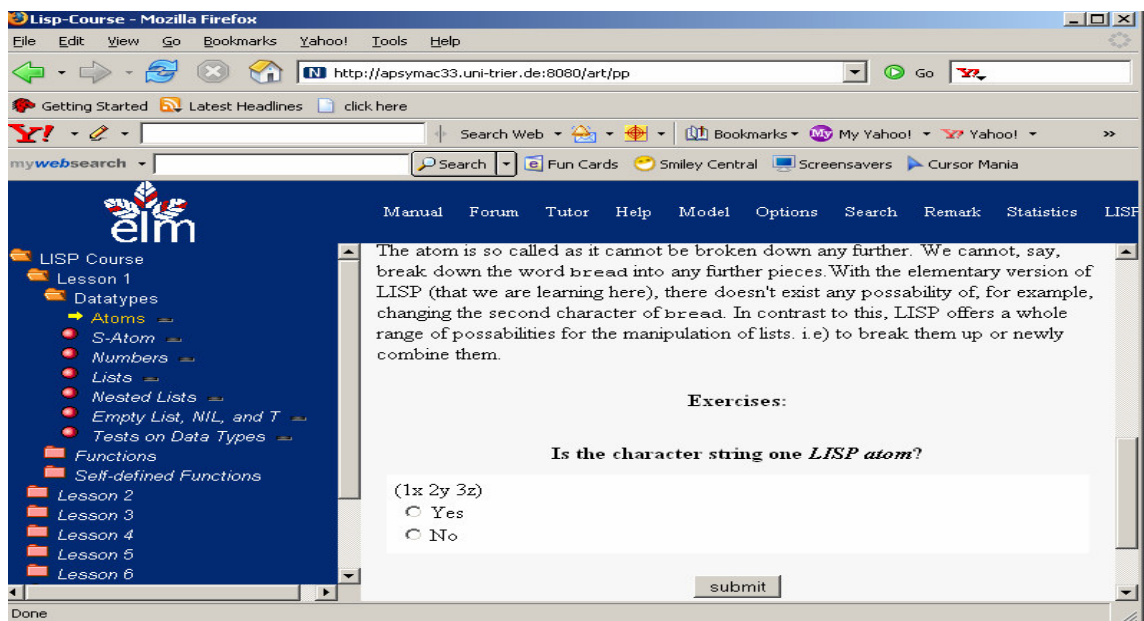
Figure A.2.2.4 depicts the learning material on atom. When 'Submit' button in Figure A.2.2.4 clicked, the error message as shown in Figure A.2.2.5 appears.

Figure A.2.2.5.Error message
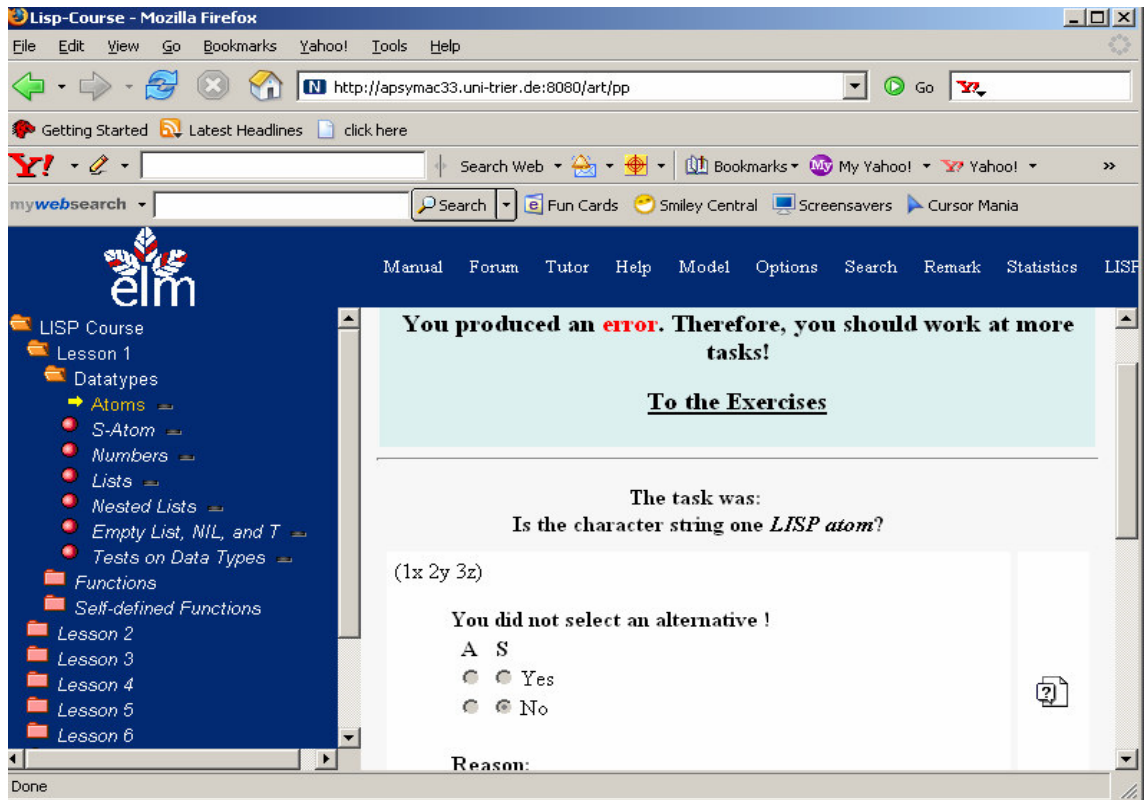
Figure A.2.2.5 depicts the error message from the system advising the participant

to work on more tasks.

Figure A.2.2.6. More exercises suggested by the system
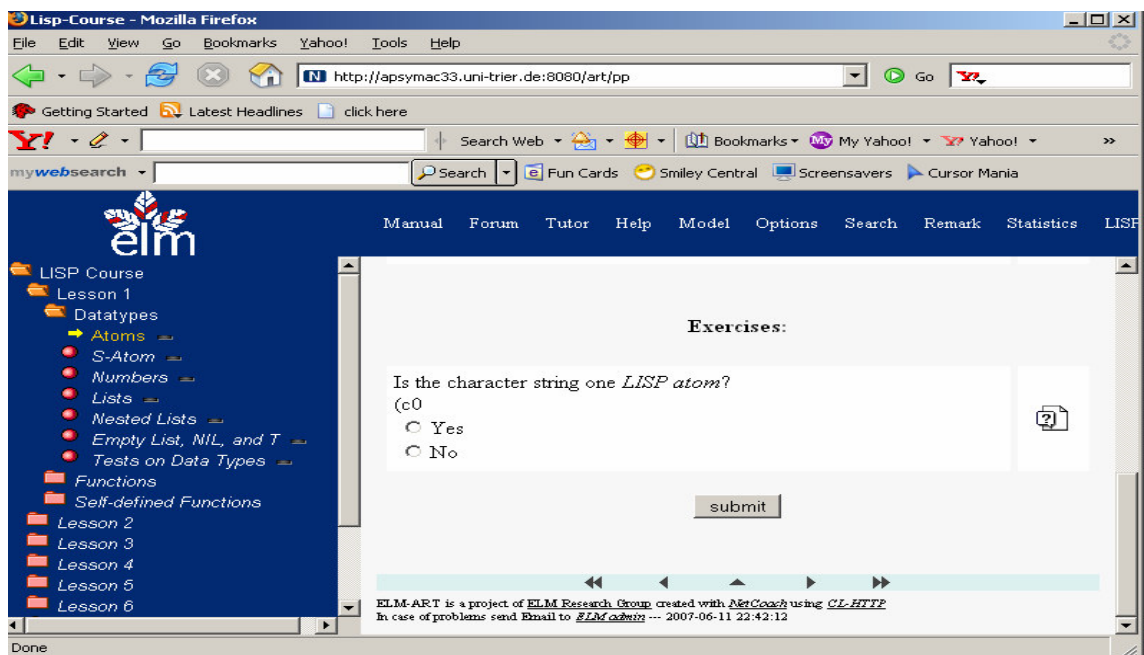
Figure A.2.2.6 depicts the exercise page. If the participant clicks the 'Submit'

button with the right answer, the correct message as shown in Figure A.2.2.7 appears.

Figure A.2.2.7. Correct message from the system.
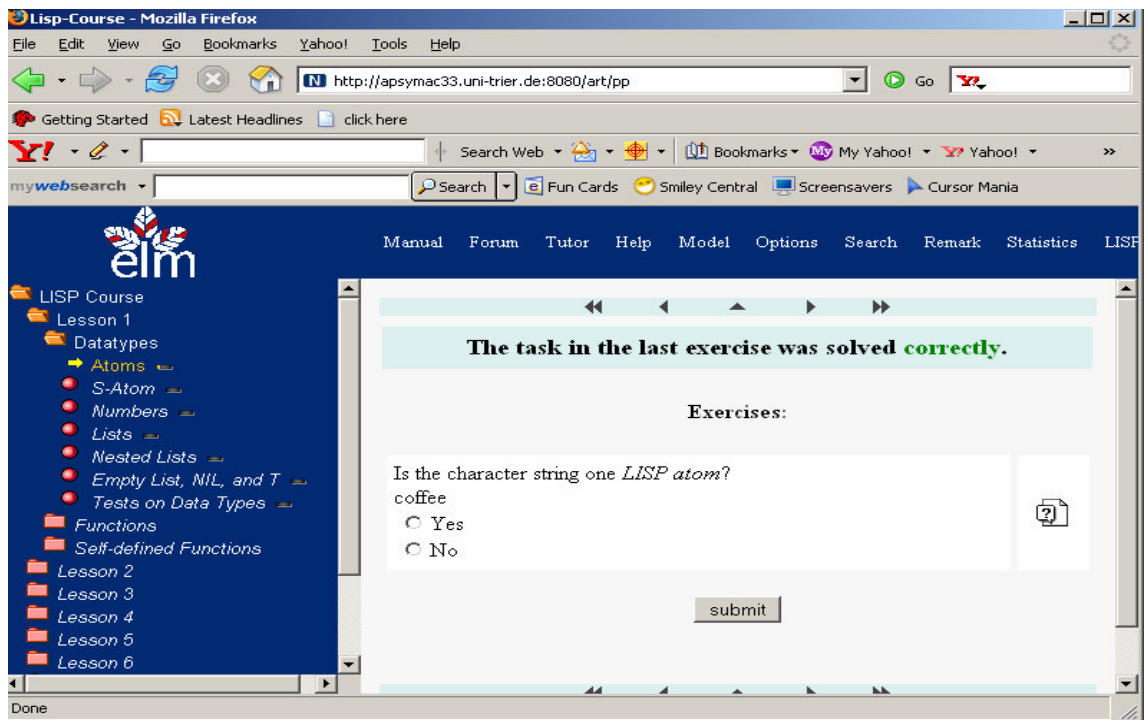
Figure A.2.2.7 depicts the system message to the participant, so that the

participant can move on to the next task. On the other hand, if the participant submits

wrong answers and tries to move to the next concept, he/she will receive the next

message as shown in Figure A.2.2.8.

Figure A.2.2.8. System warning message
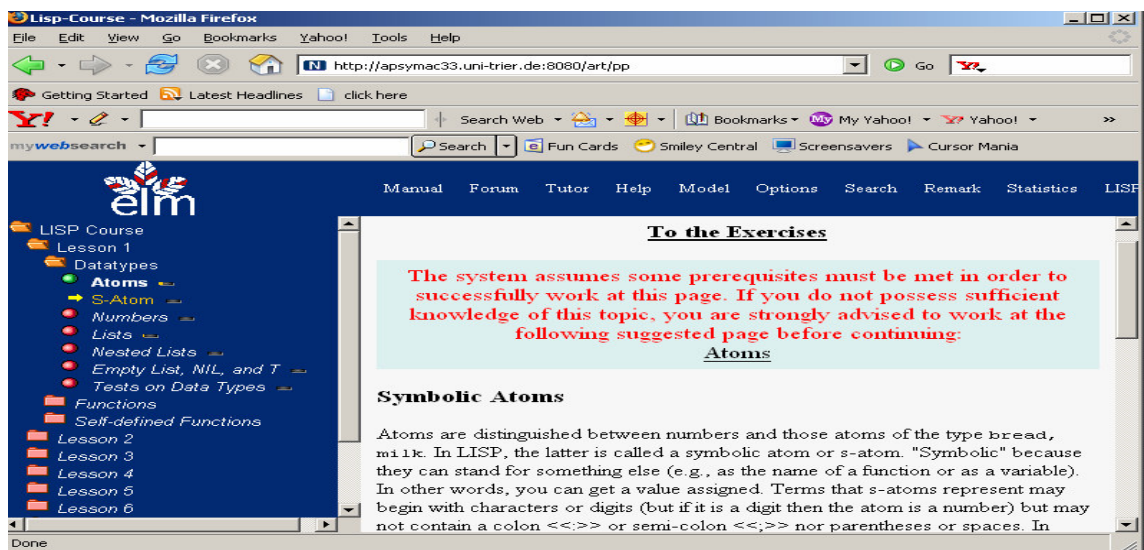
Figure A.2.2.8 depicts the system message to the participant. The system is

advising the participant not to move before he/she possesses sufficient knowledge on

the topic that the participant has been working on.

Figure A.2.2.9. System warning message
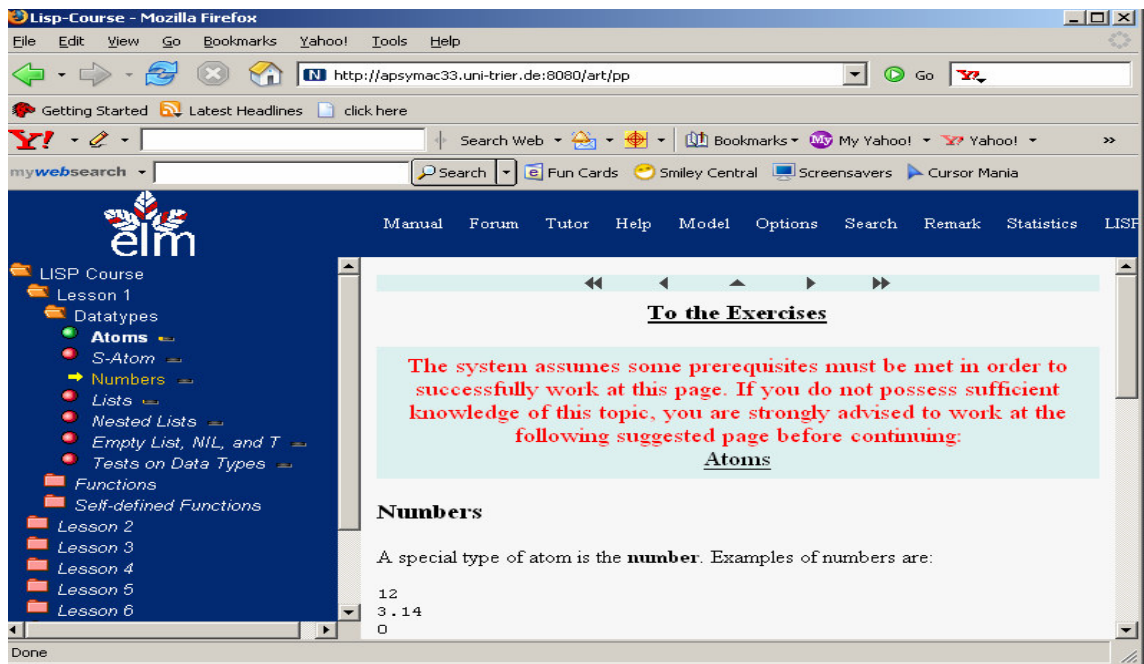
Figure A.2.2.9 depicts the system warning message. The system gives the same warning if the participant tries to move to another concept and he/she does not yet fulfil the requirements.

Figure A.2.2.10. Test web page.
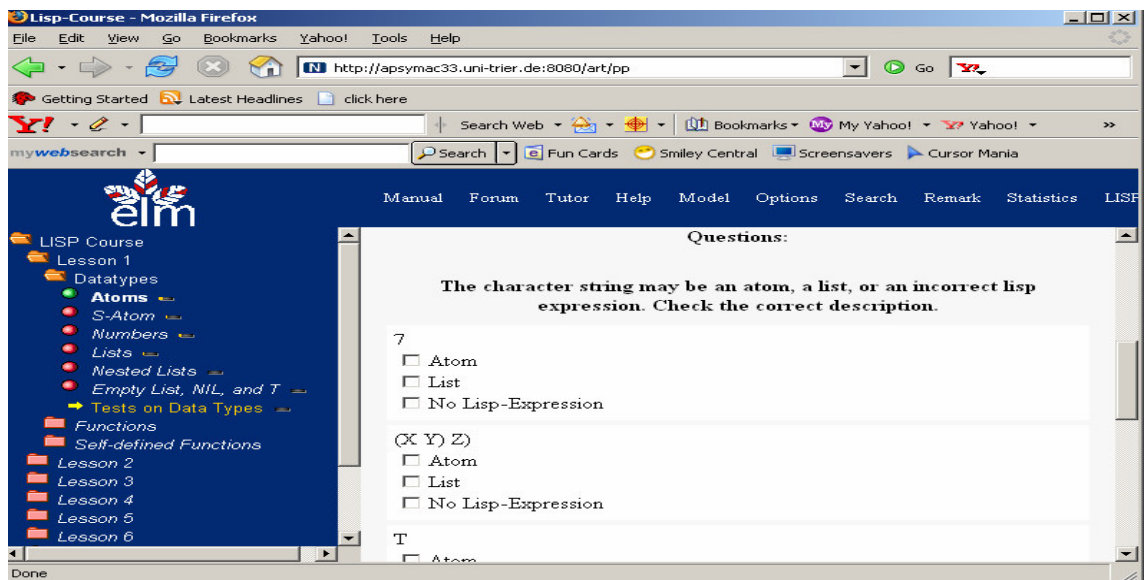
Figure A.2.2.10 depicts the last page of the datatypes with the test questions. The participant can click 'Submit' after the successes he/she made through the entire concepts.

APPENDIX 3: EXPERIMENT 4

This appendix briefly describes how Experiment 4 (Chapter 6) was performed.
Appendix 3.1 includes a short introduction to the Haskell system with the declaration of
Experiment 4. Appendix 3.2 includes the experiment web pages. Appendix 3.3 includes
some figures of the apparatus. Finally, Appendix 3.4 presents the paper test.

APPENDIX 3.1. INTRODUCTION ON HASKELL

The following figure A.3.1 depicts the welcoming web page with the main purpose of
the experiment. When the 'Yes' button in Figure A.3.1 is clicked, the login page as
shown in Figure A.3.2.1 appears. The 'No' button allows participants to leave the
experiment at once.

Figure A.3.1. Instruction web page

APPENDIX 3.2. EXPERIMENT WEB PAGES

The following screenshots give insights into how this web-based experiment was conducted.

Figure A.3.2 1 depicts the login web page. When the 'Submit' button is clicked, Figure A.3.2.2 appears.

Figure A.3.2.1. The login page
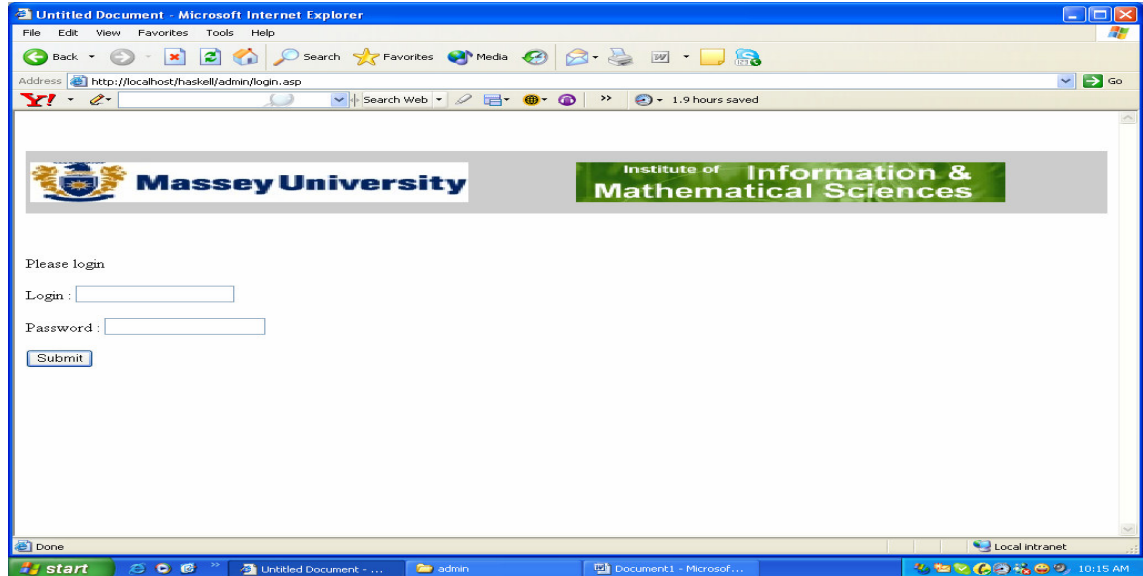
Figure A.3.2.2. Welcome page
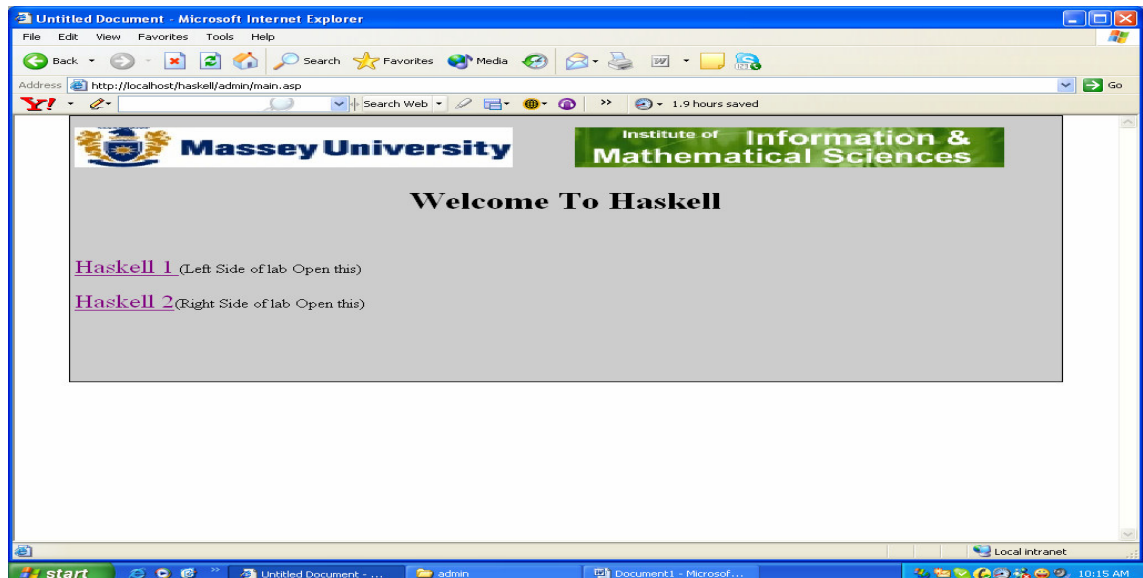
Figure A.3.2.2 depicts the two alternative links of Haskell 1 and Haskell 2. Half of the participants have Haskell 1 and the others have Haskell 2. When the 'Haskell 1' link is clicked, Figure A.3.2.3 appears. Otherwise Figure A.3.2.4 appears.

Figure A.3.2.3. The structure of Haskell 1
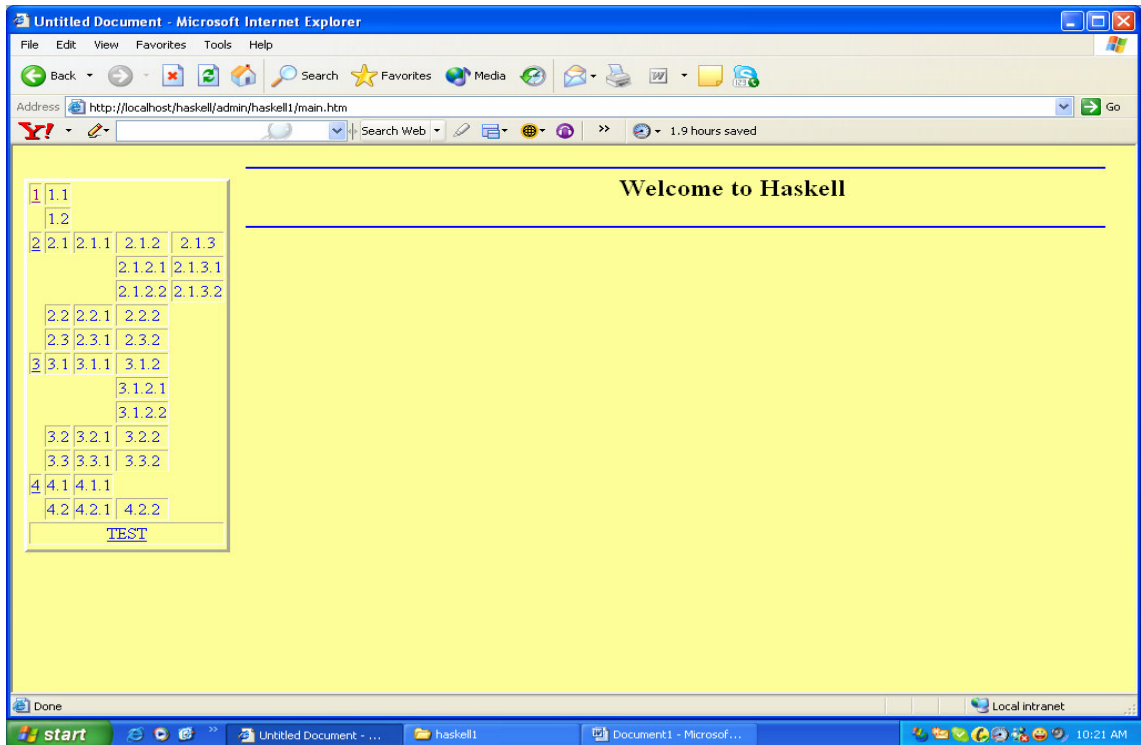
Figure A.3.2.4. The structure of Haskell 2
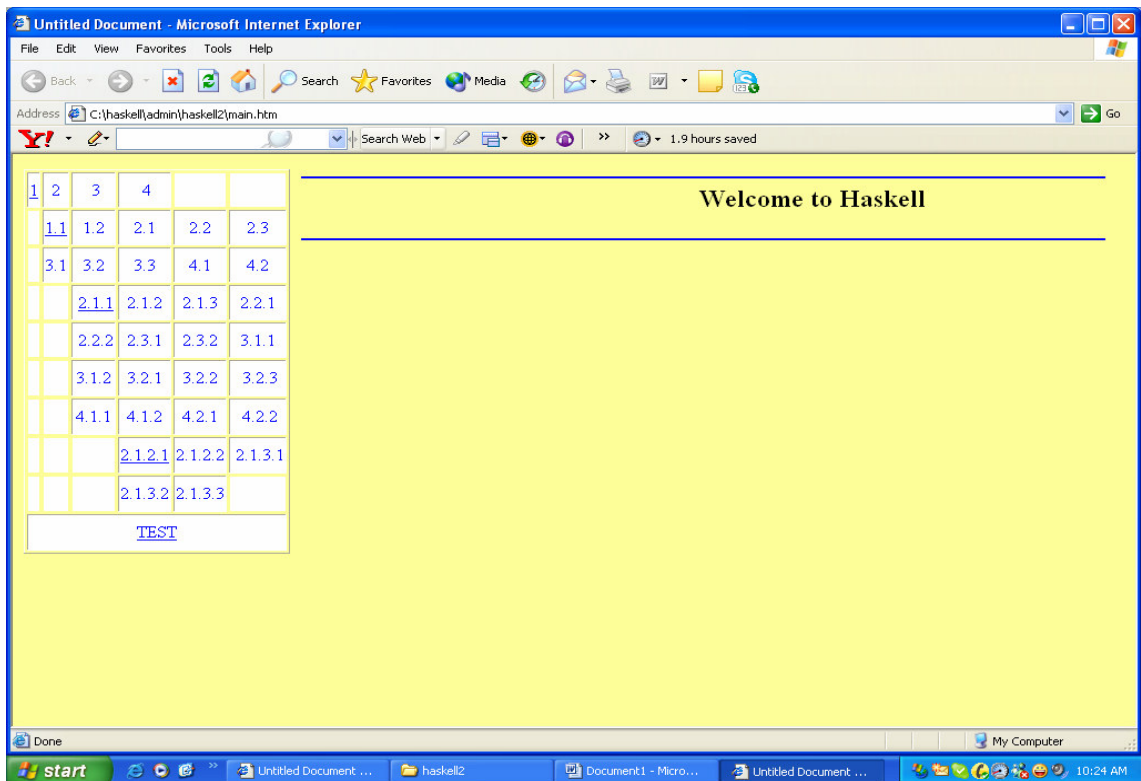
APPENDIX 3.3. Some figures of the apparatus.

The following figures give insights of how this experiment was conducted to examine the relationship between learner's personality type and learning material structures. Two systems Haskell 1 and Haskell 2 were designed to teach Haskell; the learning material is the same only differ in the order of content presents. Figure A.3.3.1 depicts the first page from Haskell 1. When the 'next' button is clicked, figure A3.3.2 appears.

Figure A.3.3.1. Introduction page for Haskell
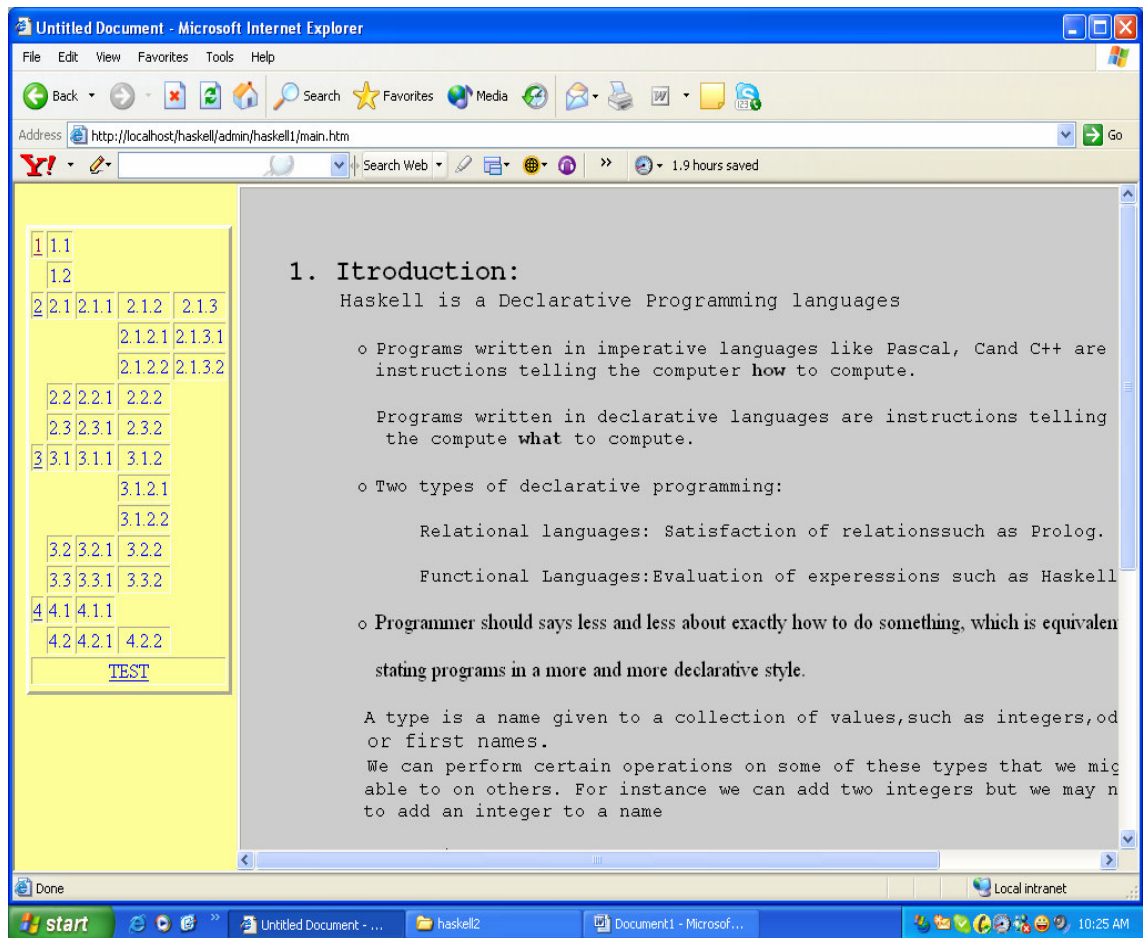
Figure A.3.3.2. Types concept page
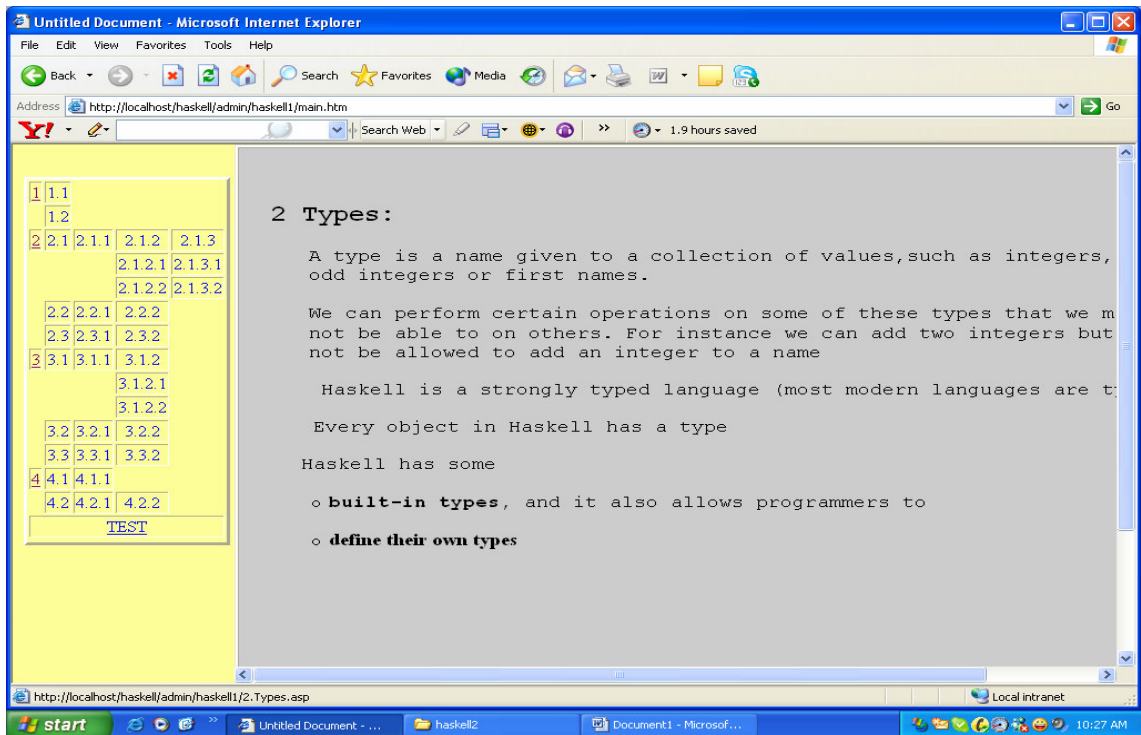
Figure A.3.3.2 depicts the learning material of the type concept page. When the 'next' button is clicked, figure A.3.3.3 appears.

Figure A.3.3.3. Functions concept page
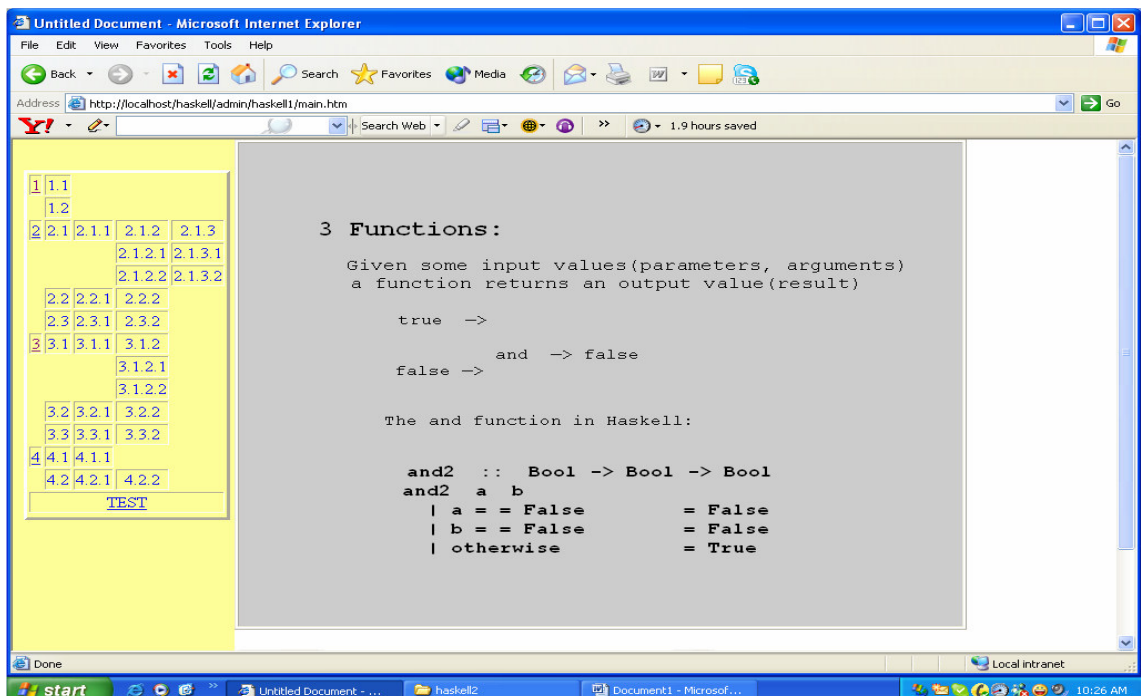
Figure A.3.3.3 depicts the learning material of the functions concept page. When the 'next' button is clicked, figure A3.3.4 appears.

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Figure A.3.3.4. List concept page
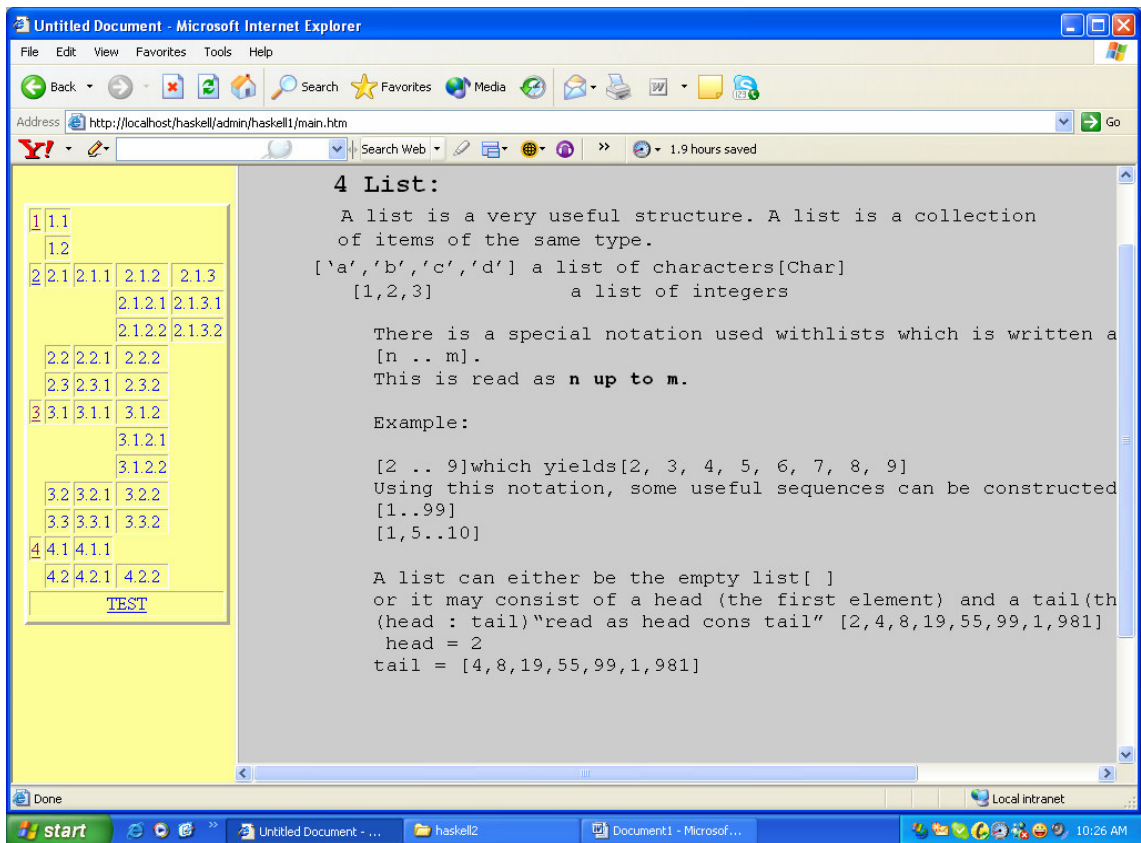
Figure A.3.3.4 depicts the learning material of the list concept page with some examples. When the 'next' button is clicked, figure A.3.3.5 the simple list page appears.

Figure A.3.3.5. Simple list concept page
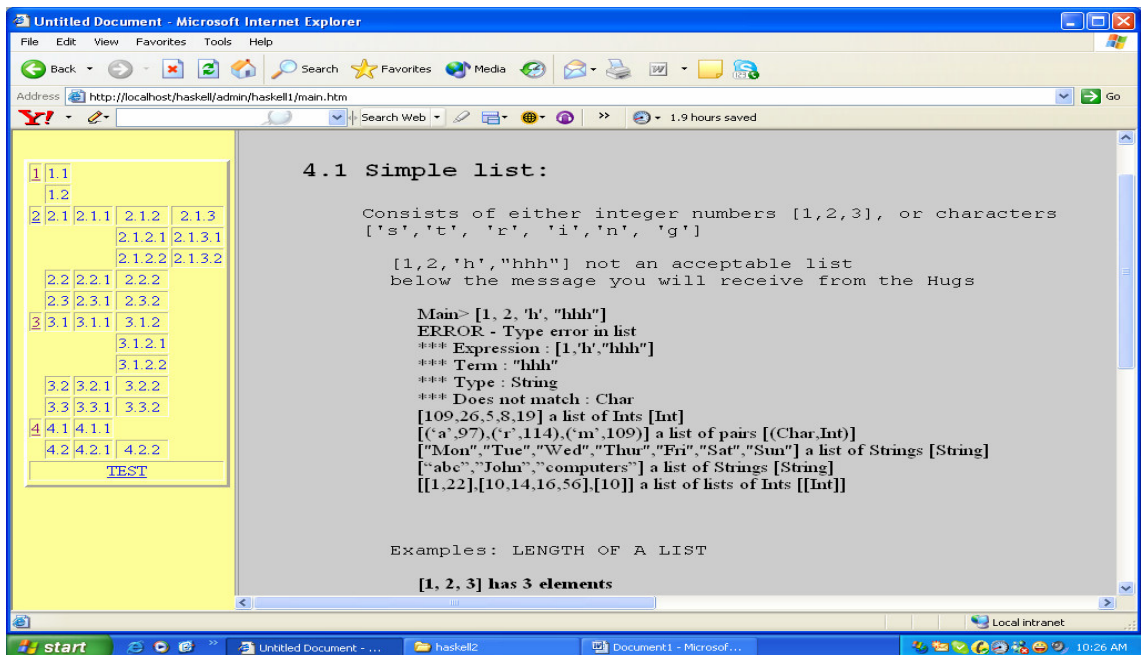
Figure A.3.3.5 depicts the simple list concept page. When the 'next' button is clicked, figure A.3.4.2 the test questions appear.

APPENDIX 3.4. HASKELL TEST

The following table shows the test that has been given to participants after they have learnt the Haskell material

Table A.3.4.1. Test questions

Questions	Options
Q1) Haskell is a declarative programming language that is	a. more efficient than C and C++ b. a functional programming language c. more time consuming to write programs d. less efficient but require less time to program.
Q2) What is the result of entering this expression	a. 140 b. 22 c. 102 d. 120
Q3) The following function tests for **IsChar:: Char-> Bool** **IsChar = not (IsDigit ch)**	a. a Boolean b. a character c. a numeric value d. a digit
Q4) Given the list [4] **Head [4]**	a. [] b. 4 c. error d. none of the above
Q5) Prelude> head [1,3,4,6]	a. [3,4,6] b. 1 c. [1] d. [1,3,4]
Q6) The result of **[8,15..11]**	a. [8] b. [8, 15] c. [] d. error
Q7) The result of head [4] [0, 0.2,..1]	a .4 b. [0,0.2, 1] c. [0. 0.2, 0.8, 1] d. none of the above
Q8) The result of Prelude>3 div 2 is	a. 2 b. error c. 1 d. 3
Q9) Find the sum of the numbers between A A and B when A and B are given.	

You may use the built-in function sur	
Q10) What is wrong with the following code **Result:: Char** **Result=10+40**	
Q11) Write a function to filter and return odd numbers from the list [1..10]	
Q12) Is it possible to write a function to add up A-Z if so write that function	
Q13) Define a function cube to raise an integer to the power 3	
Q14) Write the ASCII code of F-L	
Q15) Write built-in function to convert upper-case letters to lower-case letters	
Q16) Write a function to print "Institute of Information and Mathematical Science"	
Q17) Write a function to print 72a11kell Write the output of the function	
Q18) What is the result of entering this expression **Prelude>['a', 'c'..]**	
Q19) Use the function (take) to select the first 10 elements of this list [1,5..]	
Q20) Why would this expression produce error [1,2]:3	a. element can only be added to the beginning of a list using the cons operator b. the right hand argument to cons is not a list c. square brackets used here will cause error d. both a and c

Figure A.3.4.2. The test questions web page
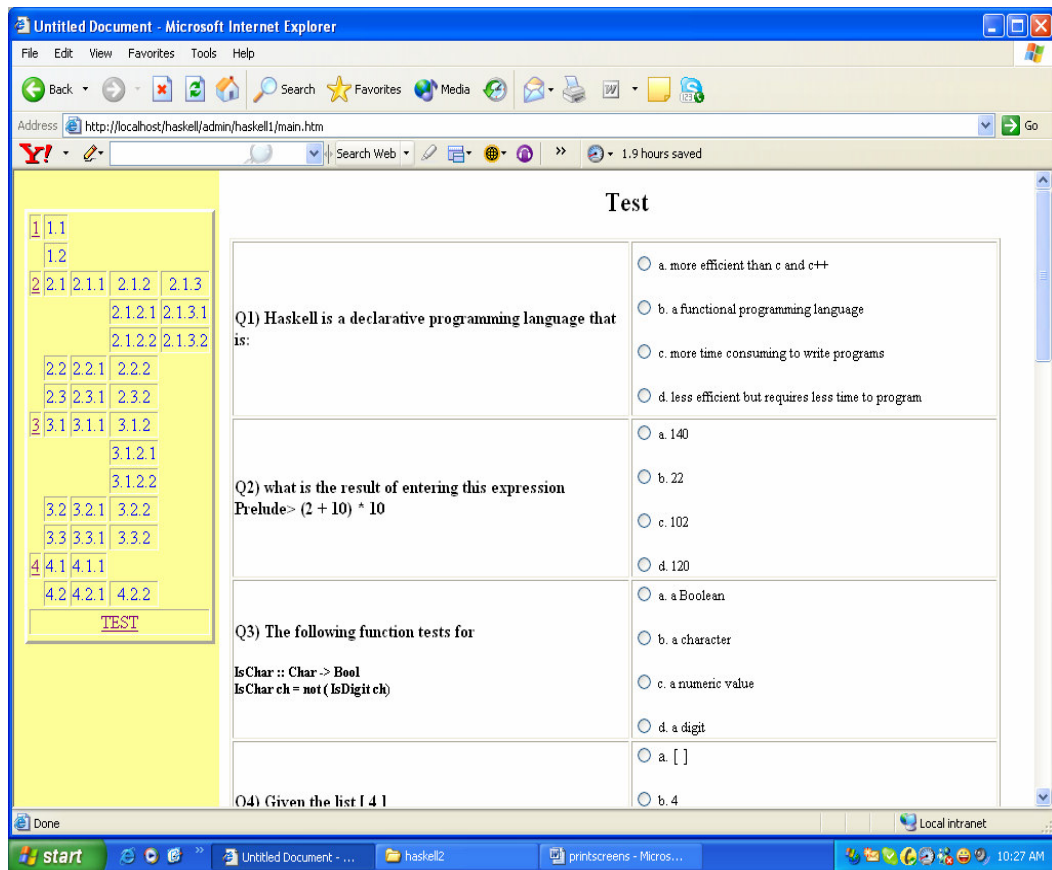
Figure A.3.4.2 depicts the test questions. After the participants finish answering

all the questions, they can click the 'Submit' button to exit from the system.

APPENDIX 4: EXPERIMENT 5

This appendix briefly describes how Experiment 5 (see Chapter 7) was performed. Appendix 4.1 includes the login instruction part to the developed system. Appendix 4.2 includes some figures from the theory and the practical part windows: with the chatting facilities that have been designed for collaborative learning procedure that has been developed for this purpose.

APPENDIX 4.1 LOGIN PROCEDURE

The following figures give insights into how this web-based experiment has been conducted

Figure A.4.1.1 depicts the initial web-page of experiment 5. It consist of a declaration the participant has to read and if he/she accepts, when yes is clicked, figure A.4.1.2 appears

Figure A.4.1.1 The welcome page
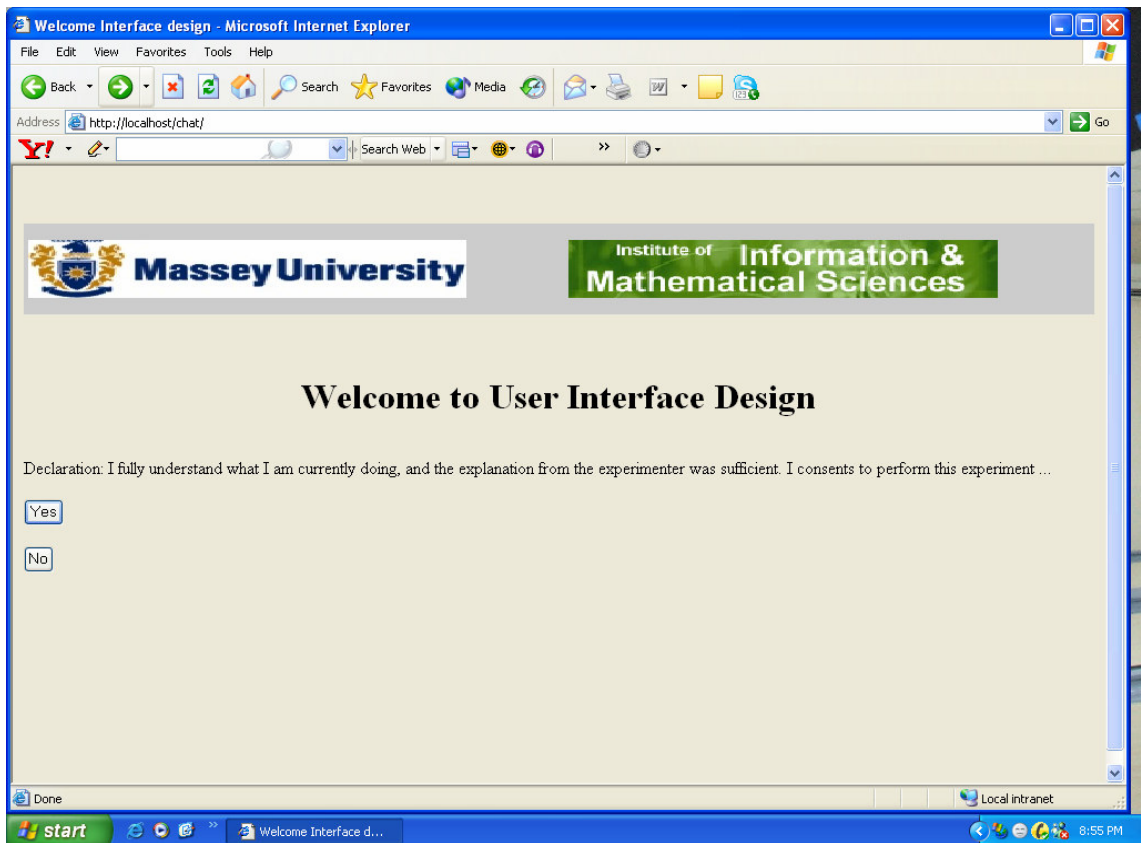
Figure A.4.1.2. The personal information page
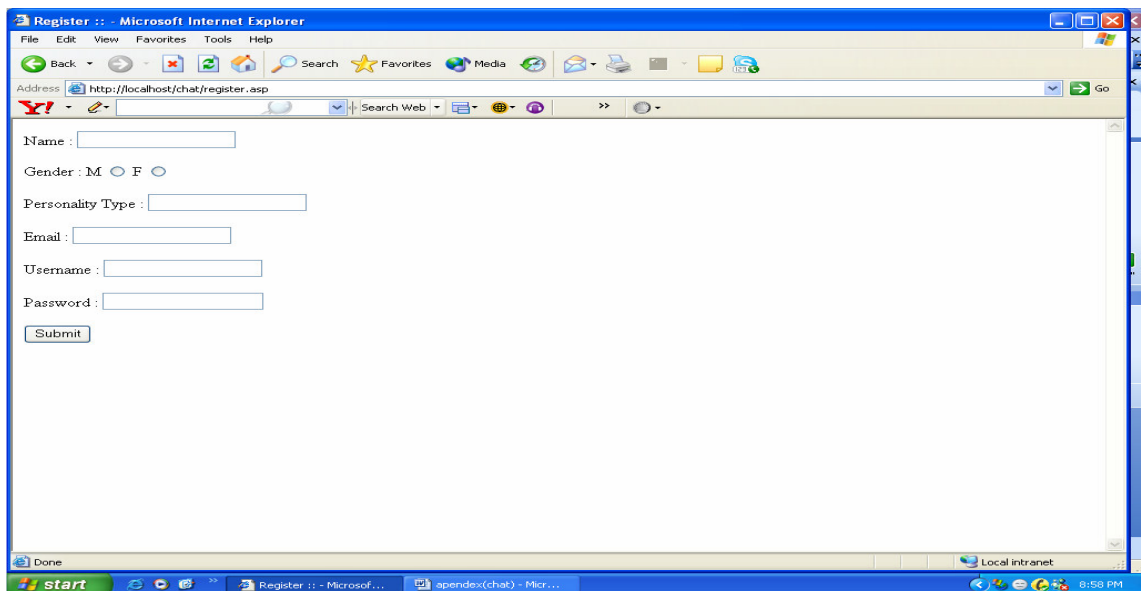
This asks the participants to fill in their personal information, which is mainly used to gather information for each participant. When the participant clicks the 'Submit' button, Figure A.4.1.3 appears.

Figure A.4.1.3.relogin page.
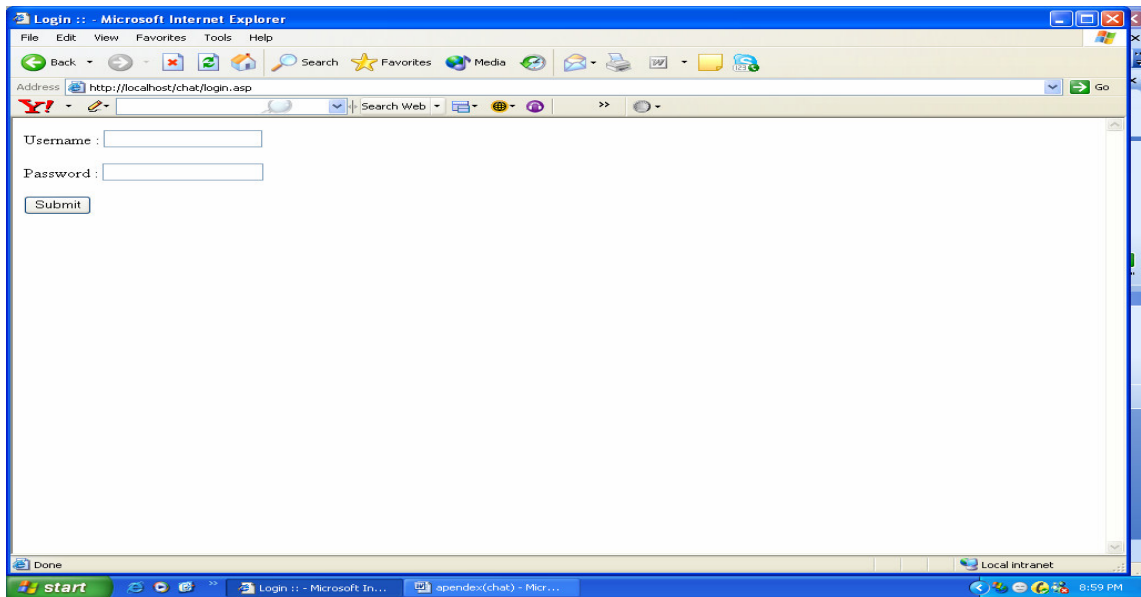
It shows that the participant has to enter the username and password to double check it for more security. When the participant clicks the 'Submit' button, Figure A.4.1.4 appears.

Figure A.4.1.4. Interface design
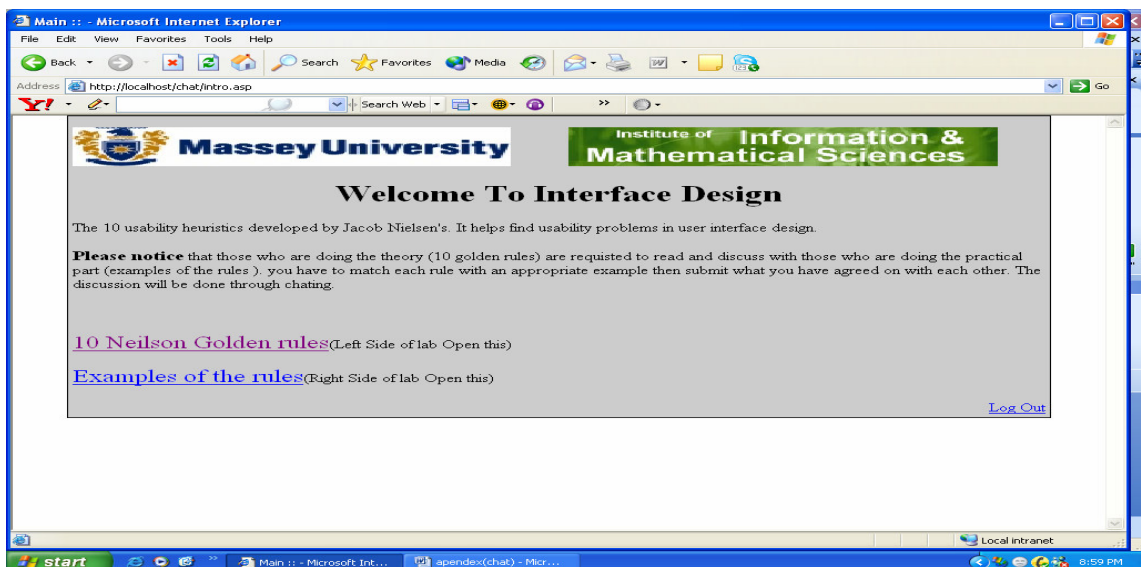
It shows the two alternative links to the theory and the practical part of Nielson rules. When the participant clicks on the first link (10 golden rules) figure A.4.2.1 appears, otherwise Figure A.4.2.2 (examples of the rules) appears.

APPENDIX 4.2. Some figures from the theory and the practical part windows

The following figures give insights into the chatting windows between two learners for

the collaborative learning procedure that has been developed for this purpose.

Figure A.4.2.1. The first theory rule
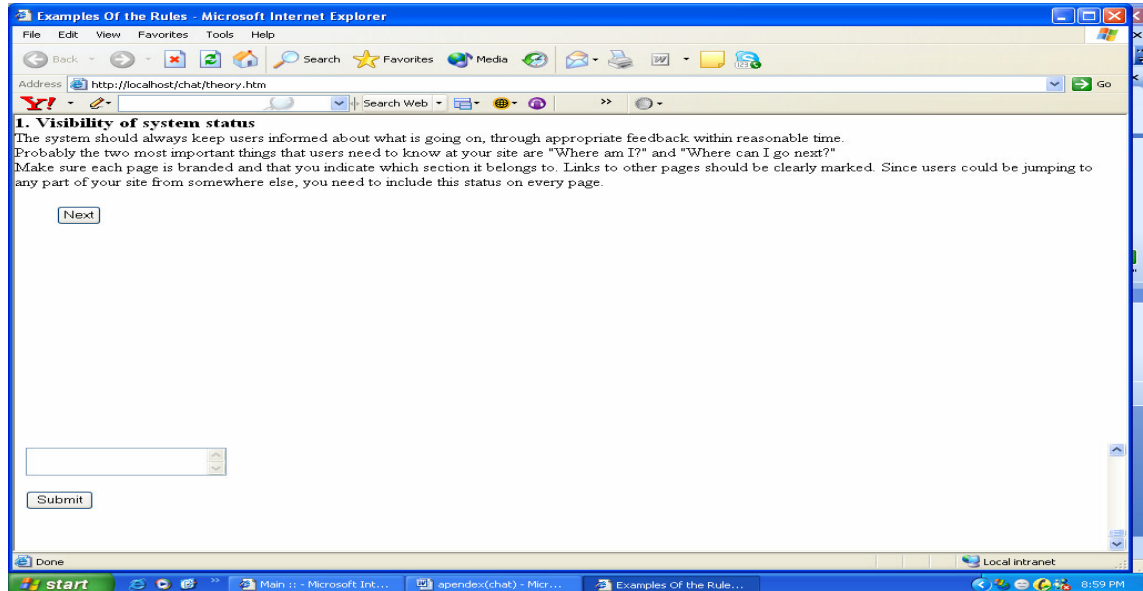
It depicts the first theory rule for the interface design with the chatting facility

screen for collaboration between two participants. Each participant used this chatting

board to explain the rule to his colleague. When submitted the other figure appears with

the example that has been sent by his colleague.

Figure A.4.2.2. One of the examples for rule 1
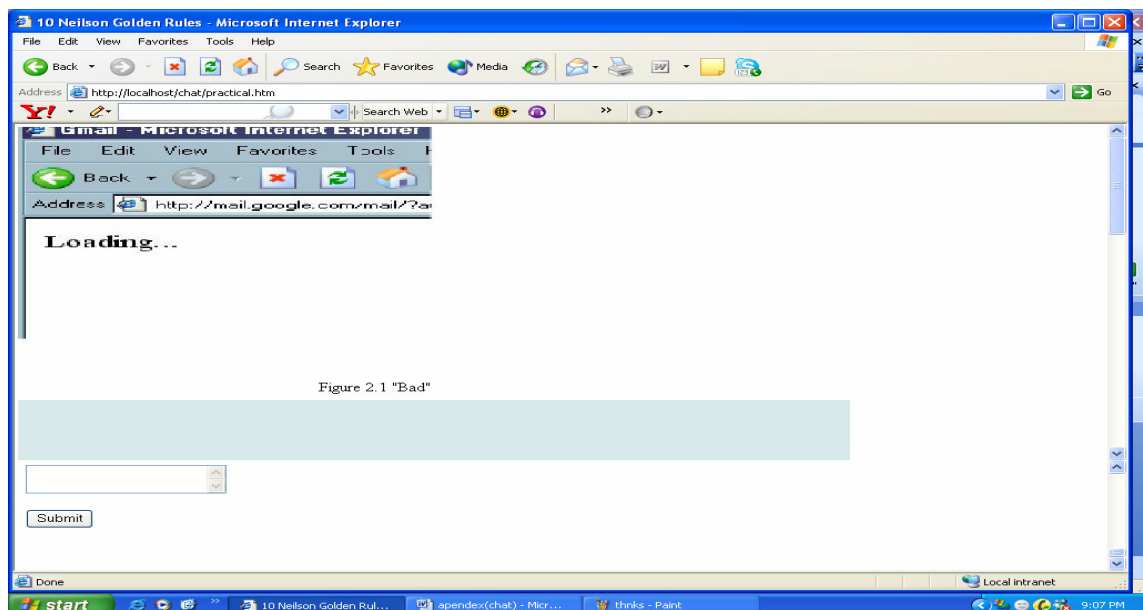
This figure depicts the example that has been suggested by his colleagues which either matches or mismatches the first rule.

Figure A.4.2.3. Another example suggested for rule 1.
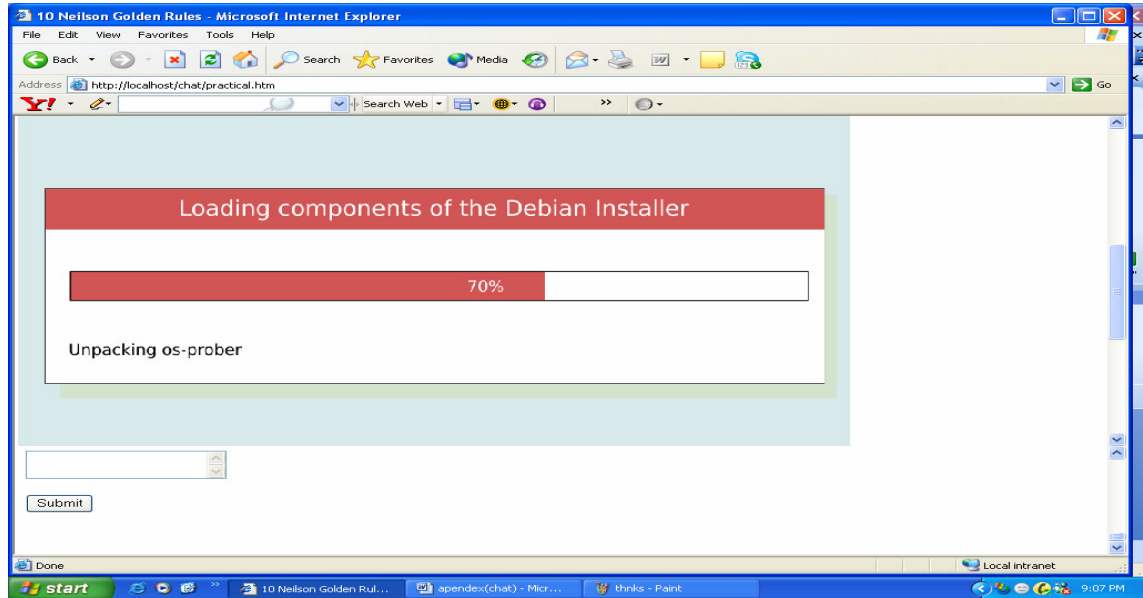
This screenshot depicts the next example that has been suggested by his colleague which either matches or mismatches the first rule. The procedure continues until they agree on one of the examples, so that they can move to the next rule.

Figure A.4.2.4. Rule 2
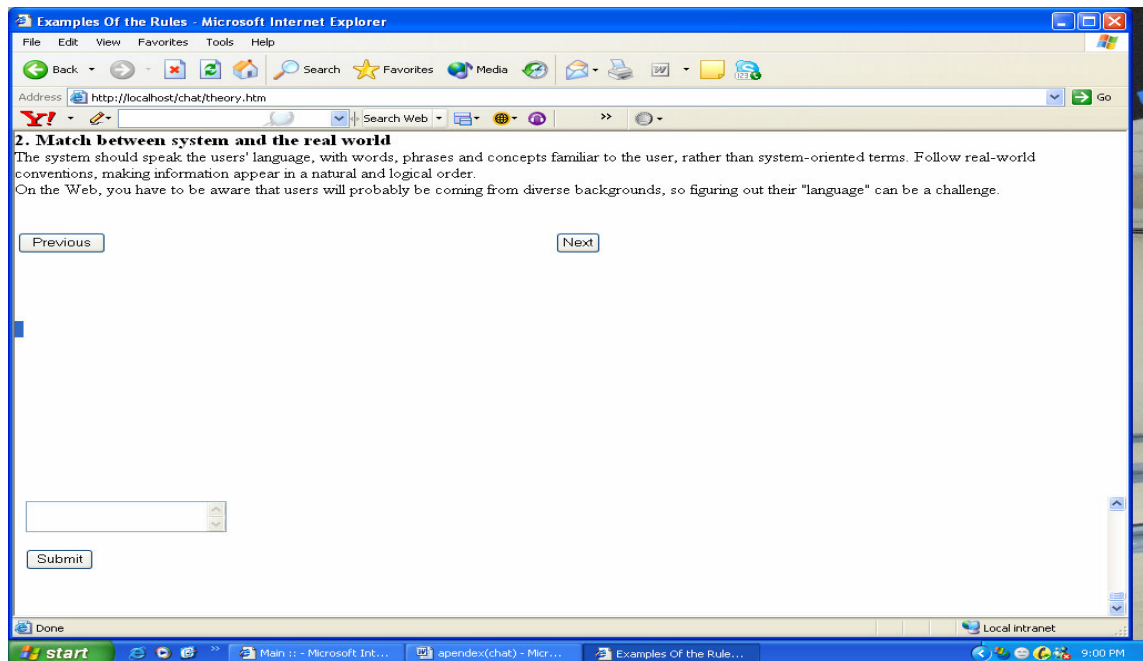
This depicts the second rule. The participant will use the chatting board to explain the rule in his own words and send it to his colleague. When submitted the other figure appears with the example that has been sent by his colleague.

Figure A.4.2.5 One of suggested examples for rule 2

It depicts the example that has been suggested by his colleague which either matches or mismatches the second rule.

Figure A.4.2.6 another suggested example for rule 2
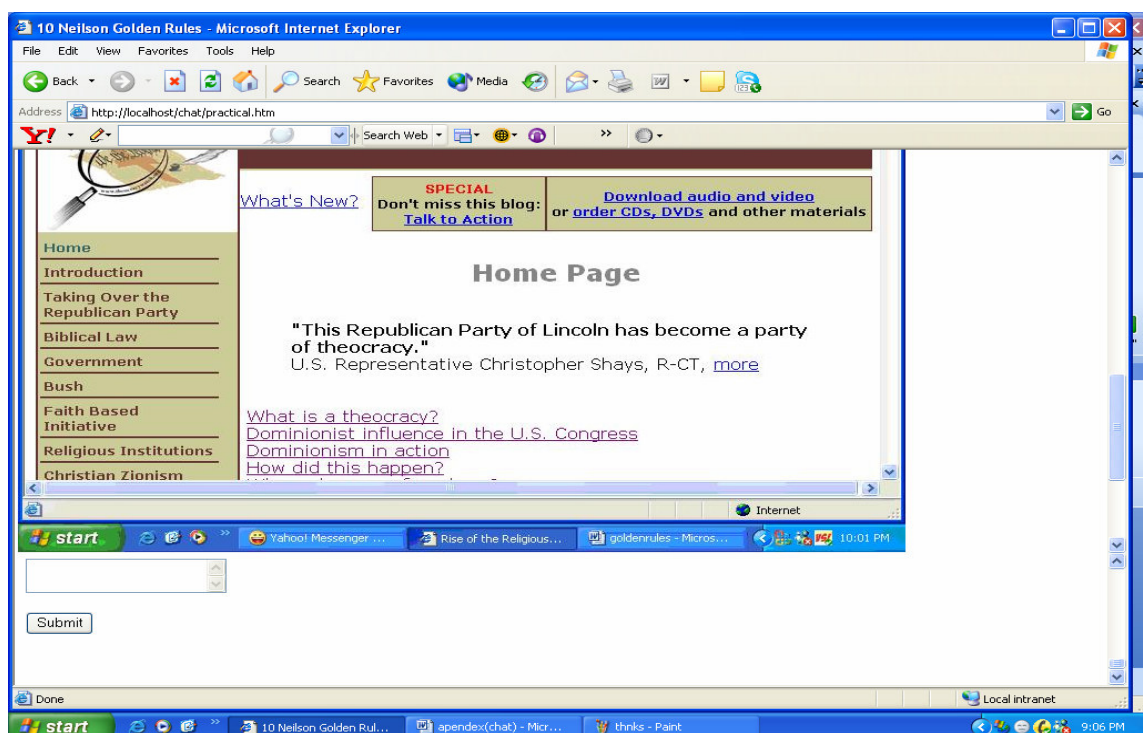
It depicts the next example that has been suggested by his colleague which either matches or mismatches the first rule. The procedure continues until they agree so that they can move to the next rule.

Figure A.4.2.7. Rule 3
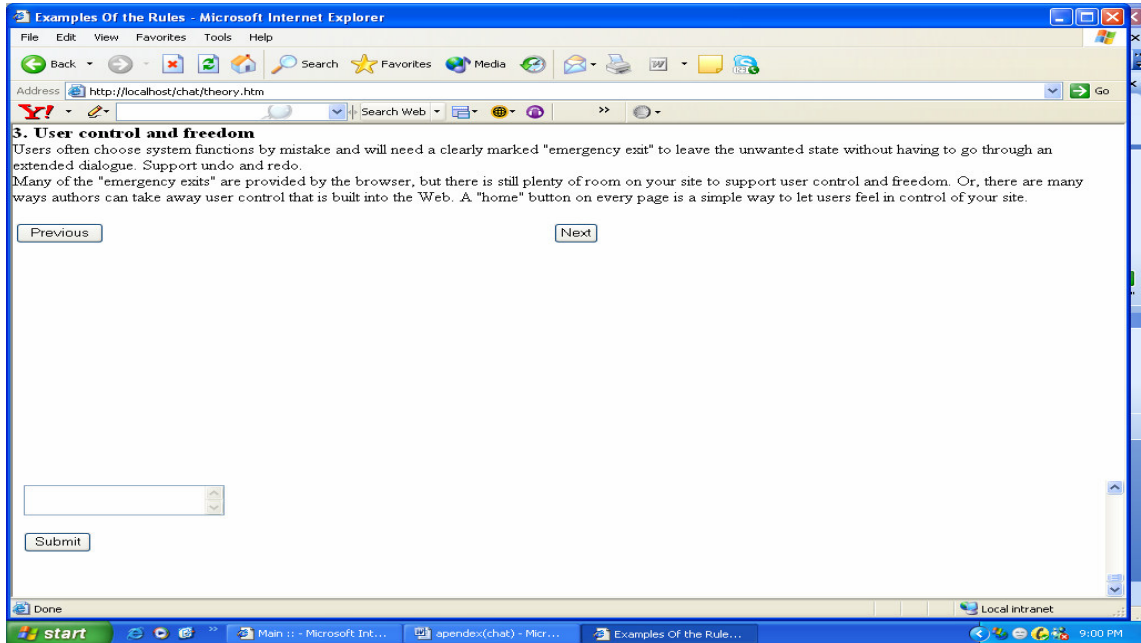
Figure A.4.2.8 One of the suggested examples for rule 3
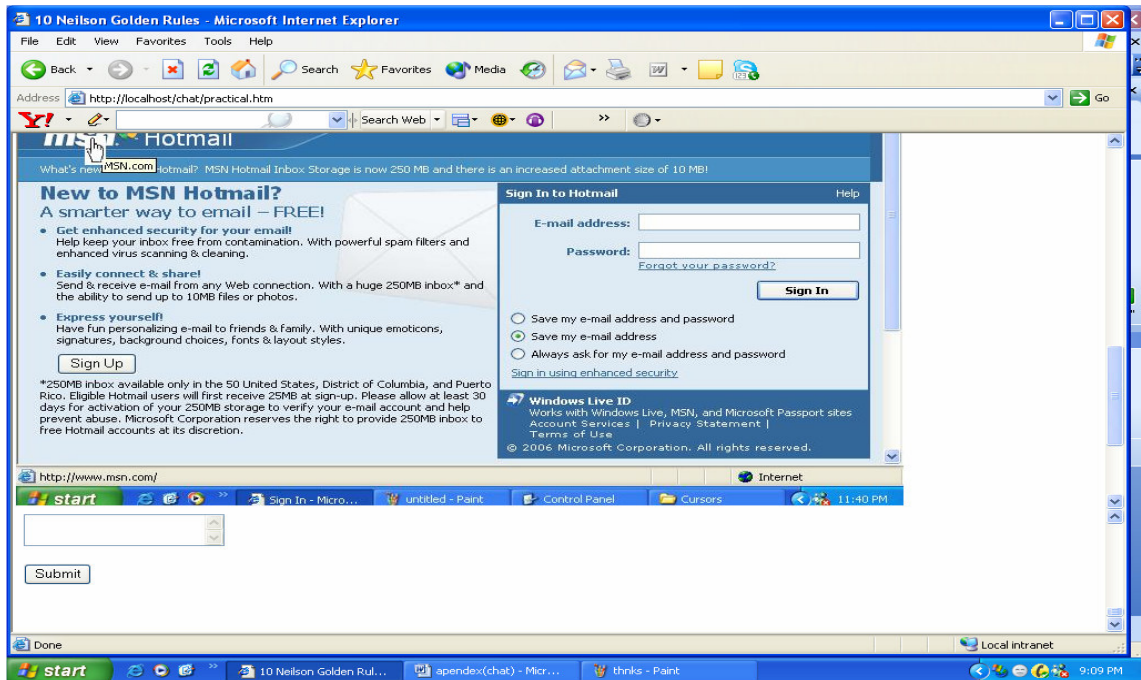
Figure A.4.2.9 another suggested example for rule 3
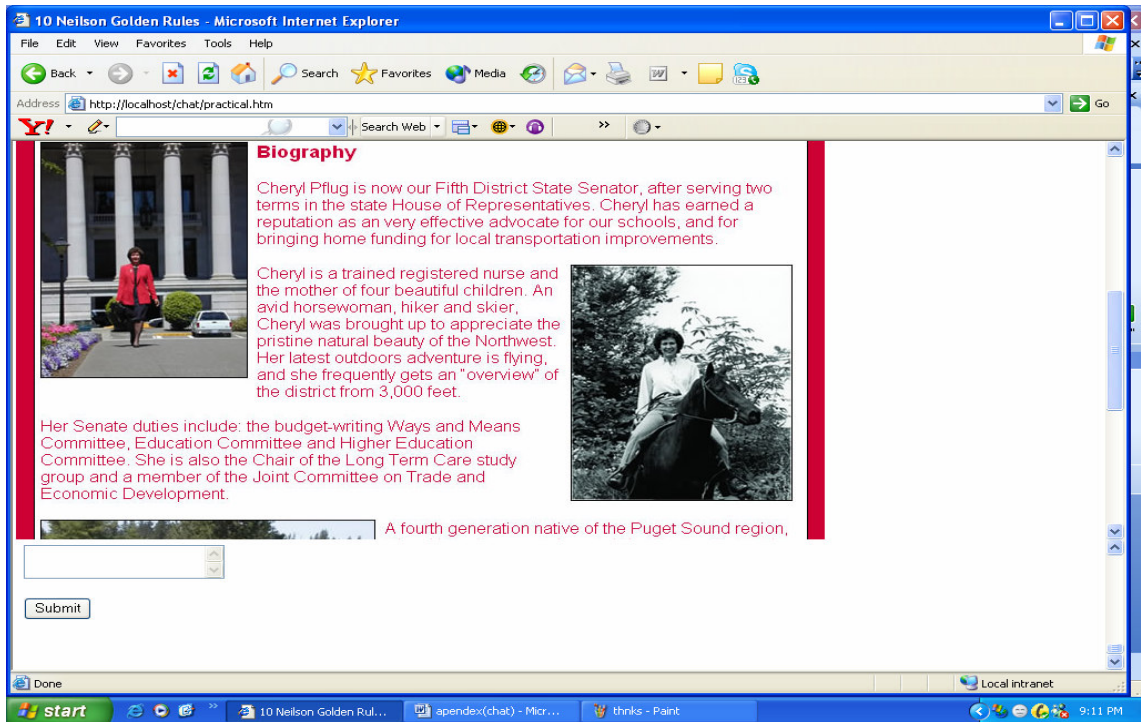
Figure A.4.2.10. Rule 4
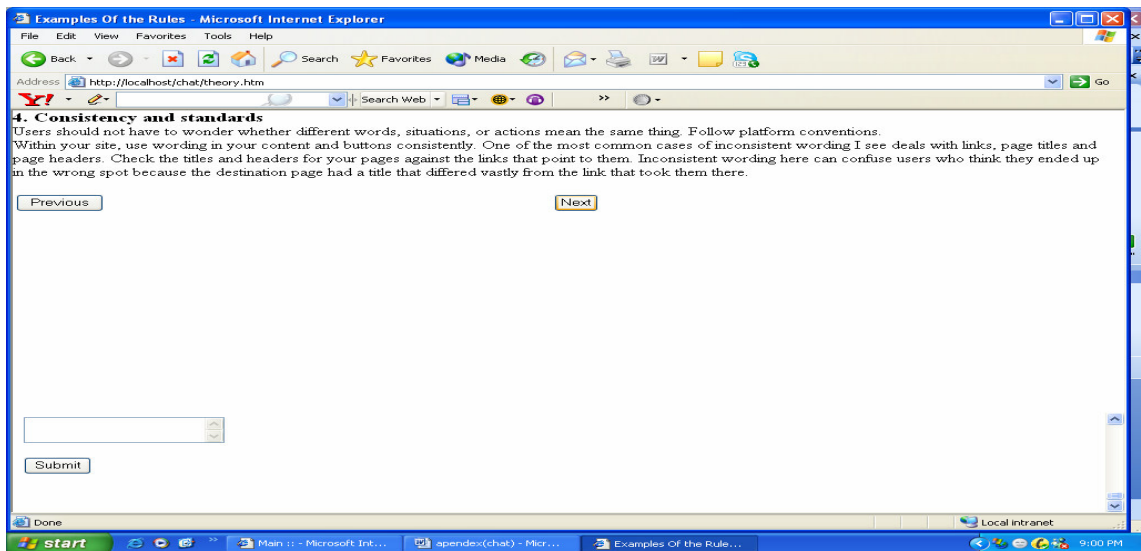
Figure A.4.2.11 One of the suggested examples for rule 4
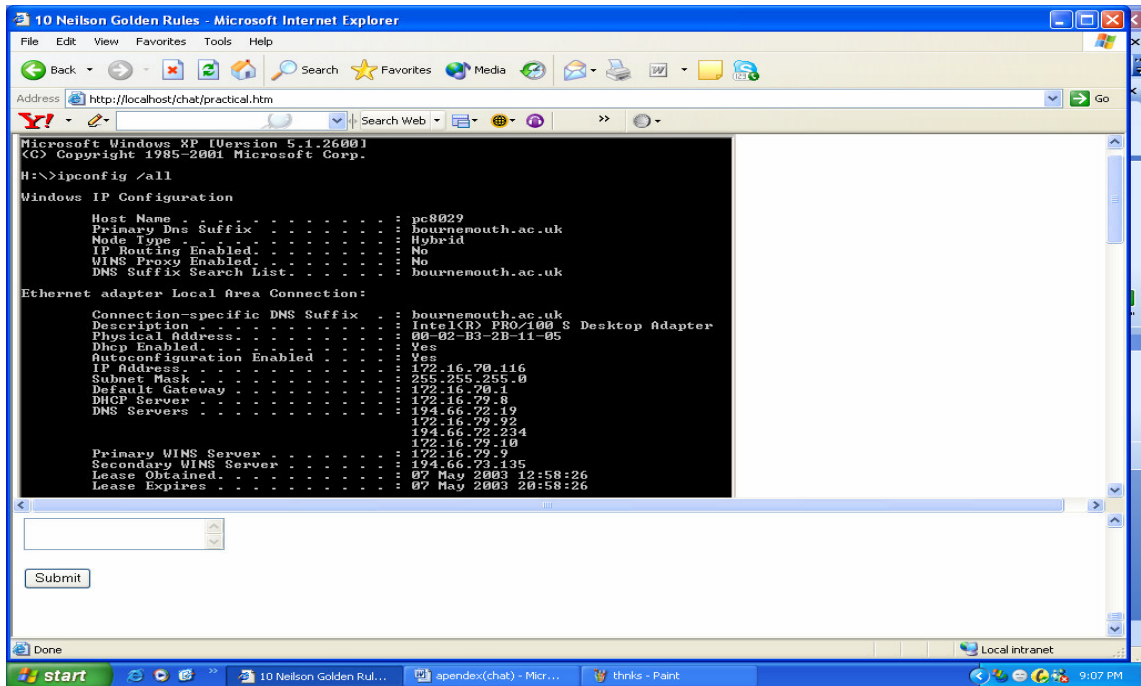
Figure A.4.2.12 another suggested example for rule 4
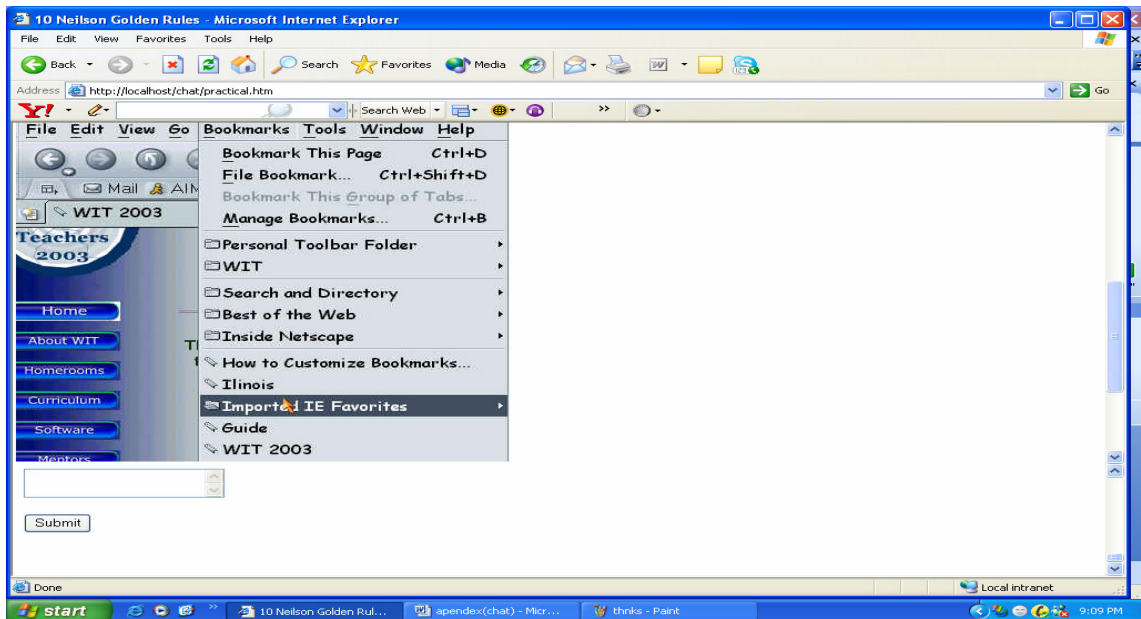
Figure A.4.2.13. Rule 5
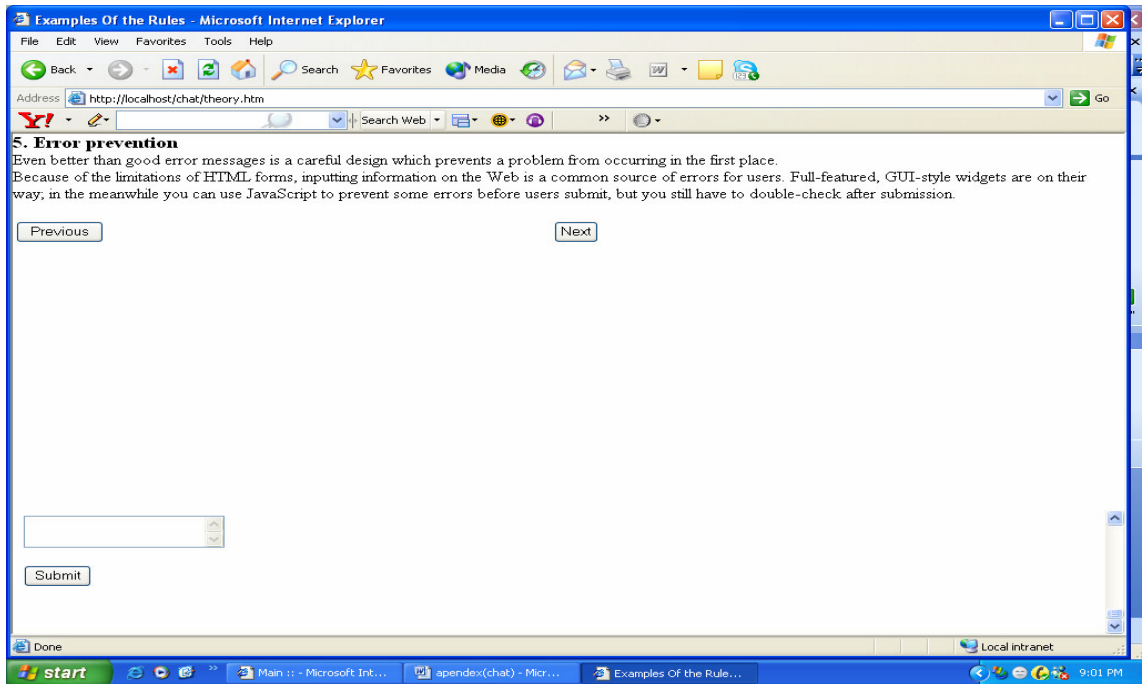
Figure A.4.2.14 One of suggested examples for rule 5
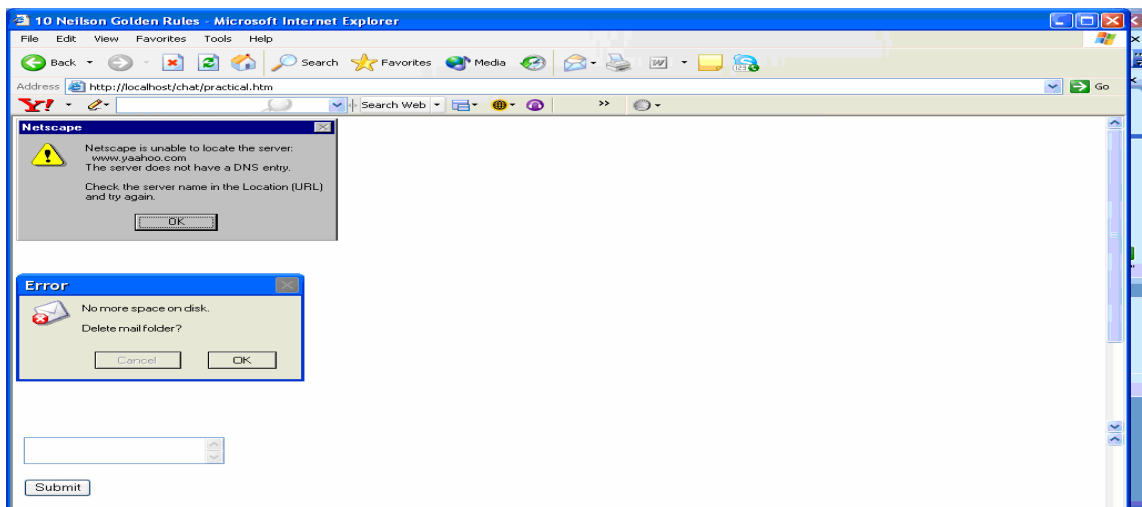
Figure A.4.2.15 another suggested example for rule 5
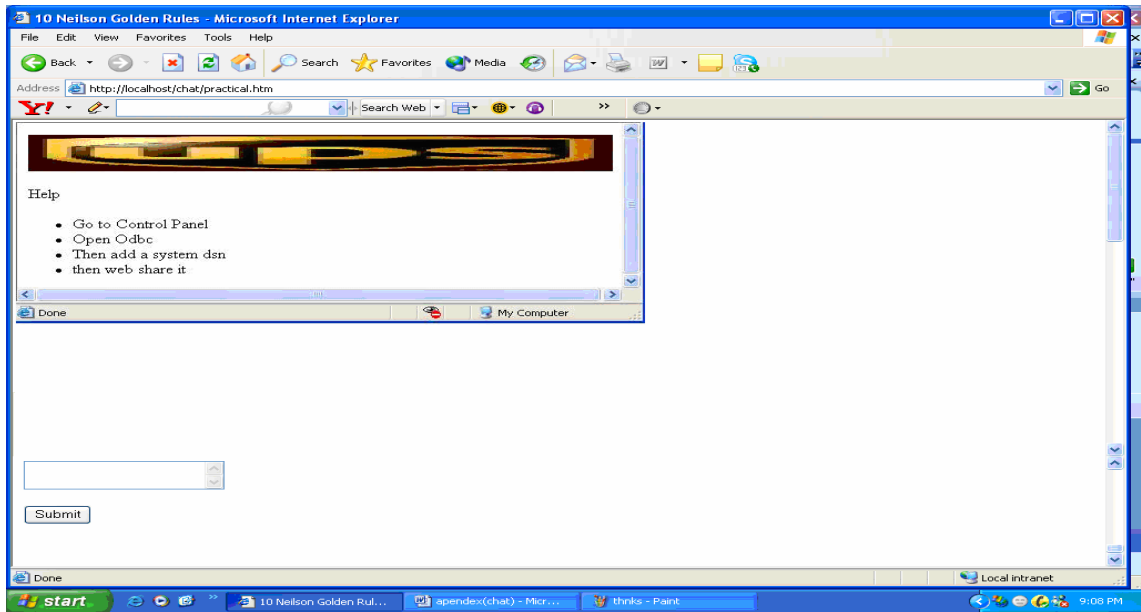
Figure A.4.2.16. Rule 6
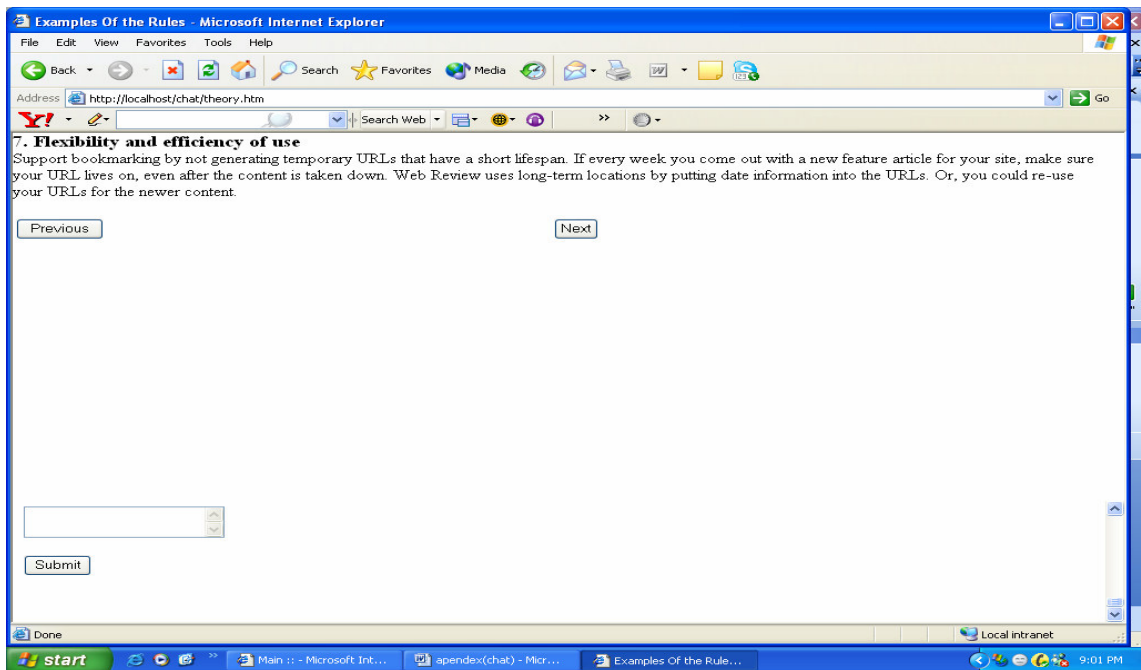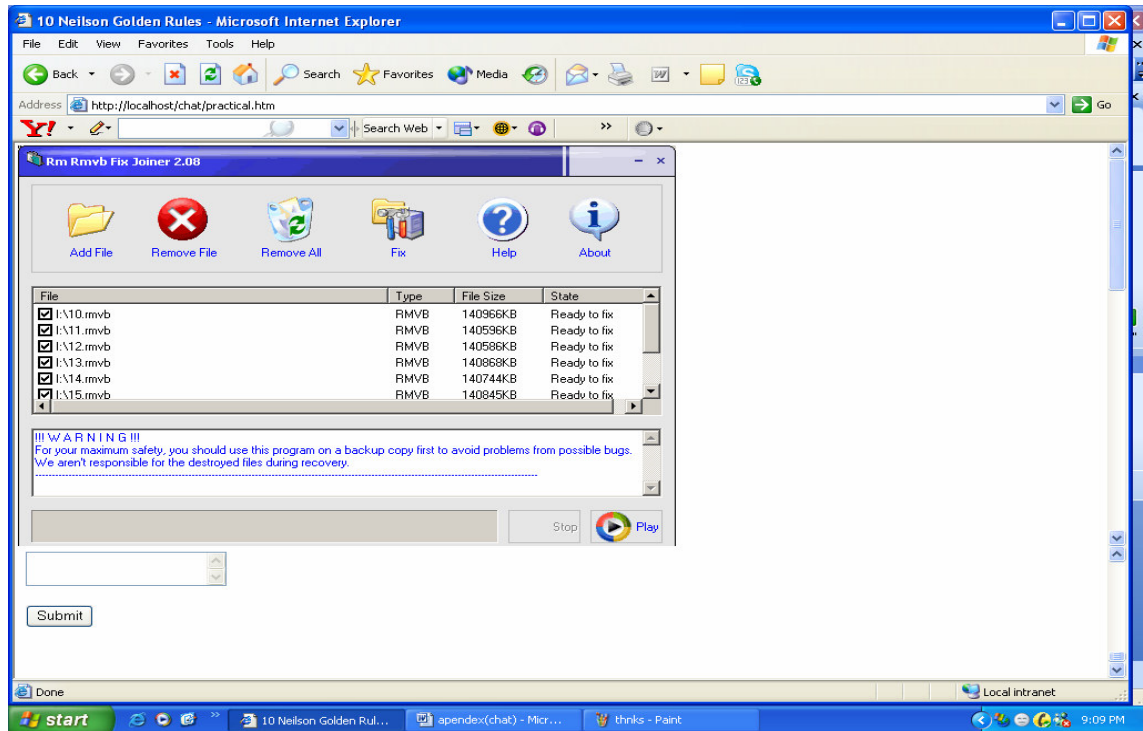
Figure A.4.2.17 One of suggested examples for rule 6

Figure A.4.2.18 another suggested example for rule 6

The two participants will keep chatting till they reach rule 10.
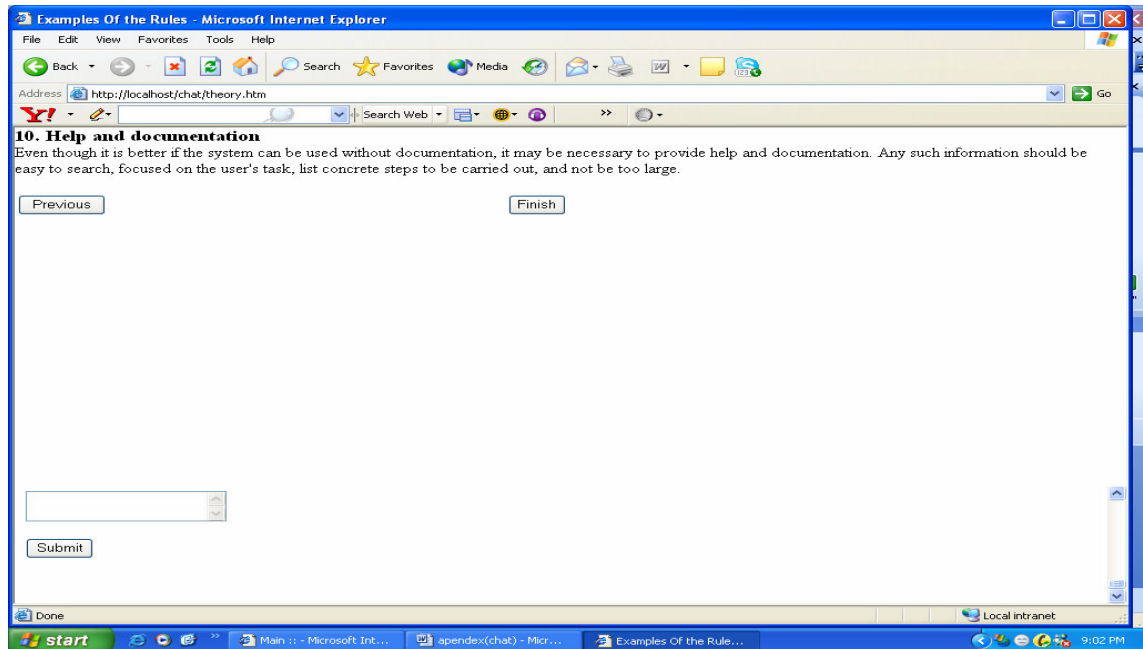
Figure A.4.2.19. Rule 10

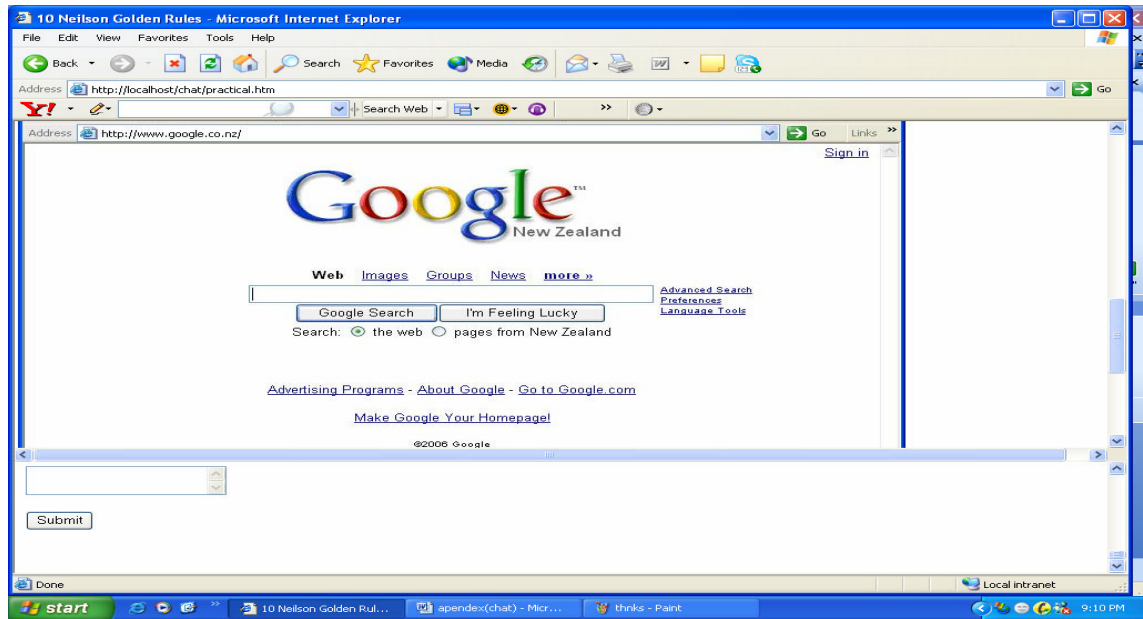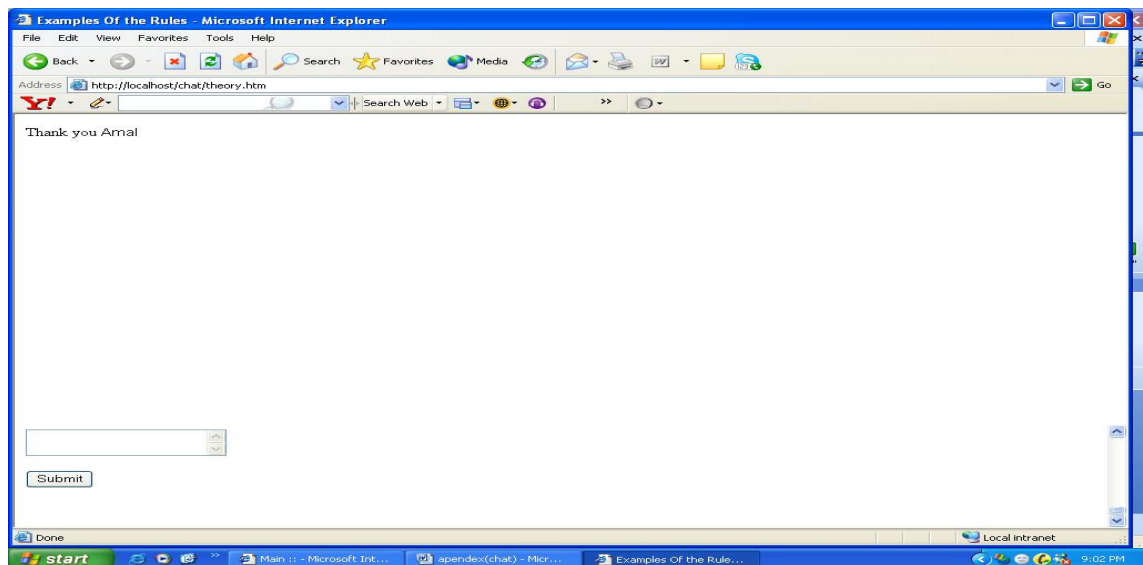**Figure A.4.2.20 One of the suggested examples for rule 10**

Figure A.4.2.21 Thank you page

It depicts the last web page: when 'Submit' is clicked the participant can leave.