Cognitive Trait Model for Adaptive Learning Environments

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"If we understand the human mind, we begin to understand what we can do with educational technology."

- *Herbert A. Simon*

Abstract

Among student modelling researches, domain-independent student models have usually been a rarity. They are valued because of reusability and economy. The demand on domain-independent student models is further increased by the need to stay competitive in the so-called knowledge economy nowadays and the widespread practice of lifelong learning. On the other hand, the popularity of student-oriented pedagogy triggers the need to provide cognitive support in virtual learning environments which in turn requires student models that create cognitive profiles of students. This study offers an innovative student modelling approach called cognitive trait model (CTM) to address both the needs mentioned above.

CTM is a domain-independent and persistent student model that goes beyond traditional concept of student model. It is capable of taking the role of a learning companion who knows about the cognitive traits of the student and can supply this information when the student first starts using a new learning system. The behaviour of the students in the learning systems can then be used to update CTM.

Three cognitive traits are included in the CTM in this study, they are working memory capacity, inductive reasoning ability and divergent associative learning. For the three cognitive traits, their domain-independence and persistence are studied and defined, their characteristics are examined, and behaviour patterns that can be used to indicate them are extracted.

In this study, a learning system is developed to gather behaviour data of students. Several web-based psychometric tools are also developed to gather the psychometric data about the three cognitive traits of students. In the evaluations, Cognitive trait modelling is then applied on the behaviour data and the results are compared with the psychometric data. The findings prove the effectiveness of CTM and reveal important insights about the three cognitive traits.

Keywords: Cognitive trait model, working memory capacity, inductive reasoning ability, divergent associative learning, psychometric tools, student model, adaptive learning systems

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CHAPTER 1

General Introduction

1.1 Introduction

The Nobel Prize winner and a pioneer in artificial intelligence, Herbert A. Simon, stated in a speech presented at the 1997 Frontiers in Education Conference that

> *"What we must avoid above all is designing technologically sophisticated hammers and then wandering around to find nails that we can hit with them. That is a great temptation for all of us who are involved with computer technology; for computers can do really fascinating things when they are not being stubborn; and we would like to see how we can use those potentialities in education. But I submit that we are not going to succeed in that unless we really turn the problem the other way around and first specify the kinds of things students ought to be doing: what are the cost-effective and time-effective ways by which students can proceed to learn. We need to carry out the analysis that is required to understand what they have to do - what activities will produce the learning - and then ask ourselves how the technology can help us do that."*

Herbert Simon pointed out that *understanding the students* is a prerequisite of effective application of educational technology. The aim of education technology is to help student learning by using technological innovations, but technology alone does not guarantee learning (Bransford, 2000). The title of this dissertation "Cognitive Trait Model for Adaptive Learning Environments" is set out as an attempt to understand the students for the purpose that learning systems can adapt to the characteristics and needs of students.

Understanding the students is not a completely new concept. About 2500 years ago, Confucious (551-479 BC) had already actively practised it. Socrates (470-399 BC) used the dialectic mode of teaching so that he could know the students' levels of understanding. What is new here is the context of learning. Instead of understanding the students from face-to-face interaction with them, we wish to be able to develop methods to understand the students from their interactions with computerised learning systems. It is easy to use computers to log the activities, grades, and other achievements of students when they are using learning systems. These data about the students potentially contain information about them. With proper analysis, valuable information about students could be extracted to help their learning. In fact, many researches had been done using student data log to find information about students (e.g. Nykänen, 2006; Lu, Wu, Wu, Chiou, and Hsu, 2005; El-Sheikh & Sticklen, 1998).

This study sets its focus on cognitive characteristics of students. Three cognitive characteristics are included: they are working memory capacity, inductive reasoning ability and divergent associative learning. Researches about the cognitive characteristics, such as working memory capacity and inductive reasoning ability, even though they have been quite well documented, are still mostly studies in laboratory contexts (e.g. Cantor and Engle, 1993; Laumann, 1999; Gorman and Gorman, 1984; and Engle et al. 1999). This study aims to harvest the rich results from these laboratory studies and apply them to the use of educational technology so that technologies are best utilised because of the "understanding about students".

One important phenomenon that affects many aspects of our day-to-day life, including education, is the so called *knowledge economy*. The main contributor of the knowledge economy is *globalisation* (Friedman, 2005). Knowledge economy and globalisation are features of the temporal environment that the work of this study is conducted in. They are also the reasons why this research work is needed and relevant. Discussion on these phenomena in the next section sets the context of this study and delineates a few important requirements of this study.

1.1.1 Knowledge Economy and Life-Long Learning

Statistics indicated that the information stored in the world doubles every 2.8 years (Keegan, 2000). The problem every country faces now is not how to create more information, but how to locate and utilise available information. This amazing phenomenon brings on the dawn of a so called *knowledge economy* within which market transactions are facilitated or even driven by knowledge. Knowledge is acquiring more of the properties of a commodity (Houghton, & Sheehan, 2000).

Three drives for the knowledge economy are identified (Wikipedia Contributors, 2006):

1. Globalisation: markets, products and source of labour are more global;
2. Information and knowledge intensity: 70% of workers in developed economies are information workers; and
3. Computer networking and connectivity: Internet has reduced the barrier of physical distance between people to many aspects of people's life (doing business, communication, learning etc.).

Friedman (2005) pointed out that there are three different stages (versions) of globalisation:

1. Globalisation 1.0 (the years 1492 to 1800): where the world was driven by countries and armies competing and fighting for resources;
2. Globalisation 2.0 (the years 1800 to 2000): the world was driven by multinational companies. Two important drives in this stage were falling transportation and communication costs; and
3. Globalisation 3.0 (the years beginning in the year 2000): the world is driven by the empowerment of individuals.

The dynamic forces globalising the world are different in these three versions: in version 1, they are countries; in version 2, they are companies; and in version 3, they are individuals and small groups. Globalisation 3.0 is enabled by the vast amount of information and connectivity in computer networks (Friedman, 2005).

Globalisation does not only apply to goods or services but to job market as well. In developed countries, workers are facing competition from overseas workers; companies are outsourcing their business operations (e.g. call centres) to overseas; and factories are shifting to overseas countries where cheaper labour can be found.

However, Friedman (2005) pointed out that the impact of global labour market competition has little effect on three categories of workers: the *specialised*, the *anchored*, and the *really adaptable*. A worker with specialised skill cannot be easily replaced. Someone who is deeply anchored in the local market is less affected by globalisation. An adaptable worker can easily take on other opportunities when adversity in the current employment arrives. Friedman stressed: "adaptability through education is key to economic security" in Globalisation 3.0 (Friedman, 2005, p239). Freidman did not mean that only fresh graduates are adaptable, rather he emphasised on continuous education in a sense of life-long learning.

Not only individuals are aware of the importance of education and the value of human capital, corporations like General Electric (GE) spend \$500 million on training and education every year, and overall \$62.5 billion was budgeted for formal training by U.S. organisations in 1999 alone (Keegan, 2000). Corporations, similar to individuals, are more and more required to absorb and keep updated the new information through on-the-job or private training in order to stay competitive. Life-long learning has become a common practice for a wide range of careers ranging from engineers to sales representatives and doctors to farmers.

1.1.2 Electronic Learning

Electronic learning (eLearning) answers to many requirements of life-long learning: it allows learners to learn when they want to, and where they want to (Takiya, Archbold, and Berge, 2005; Sampson, Karagiannidis, and Cardinali, 2002).

One of the main advantages of eLearning over traditional instructor-led training is its ability to provide individualisation and adaptivity to suit the learner's needs. Adaptive learning systems can adapt the learning content and presentation according to the characteristics of the learners (Jonassen & Wang, 1990; Costa et al., 1991; Beaumont, 1994). They aim at providing individualised courses similar to the one-to-one privilege from a private tutor.

However, in order for learning system to provide adaptivity, it has to know about the learners: profiles of learners are needed. Learners' profiles are obtained through a process called student modelling and the profiles are often called student models (Nykänen, 2006; Lu, Wu, Wu, Chiou, and Hsu, 2005; El-Sheikh & Sticklen, 1998; Hume, 1995; Zhou & Evens, 1999).

A student model representing a chosen set of attributes of a learner is the result of the student modelling process. Adaptive learning systems can then provide adaptivity based on the information in the student models. Different kinds of student models are compared and discussed in details in chapter 2. What needs to be pointed out now is the fact that most of the existing student models focus on the performance of the learner on specific domain content (e.g. Lu et al., 2005; Brusilovsky et al., 1998; Staff, 2001). For example, they model which unit, skill, or knowledge has been learned to what degree. Adaptivity based on performance models can be in the form of guiding the learner to the next most suitable learning task. This type of model is called performance-based model.

A performance-based model profiles a learner's performance in a domain, course, or learning unit. It is an essential requirement for learning systems to provide performance-based adaptivity. However, after the completion of the course, the performance-based student model becomes of little use if not totally useless at all. It leads to our speculation about whether it is possible to have a student model that can be retained for different domains (i.e. domain-transcending), and valid for a longer-period of time (i.e. persistent)?

"Domain-transcending" could be construed as if a learner had done a course in eCommerce and the student model created in that process can also be used in Information Technology, Programming, World History, and so on. "Persistent" denotes a period longer than usual 6-monthly or 1-yearly duration of a course. It could be 3 years, 10 years, or 30 years. The time duration (3, 10, 30 years) is not meant to be a definite limit. A learner may take a couple of year break from study or a learner could enrol in a correspondent course because of career requirement 10 years after graduating from university. The aim is that the student model created can still be valid and can reflect the attributes of the learner that it is modelled for.

In this study three attributes of learners are chosen. They are believed to fit the domain-transcending and persistent requirements. The three attributes are: *working memory*, *inductive reasoning ability* and *divergent associative learning*. Because of their cognitive orientation and their persistently influential power in many aspects of learning (like personality traits persistently influencing personal behaviours), they are called *cognitive traits* and the student model that profiles learners' cognitive traits is called *cognitive trait model*. The three cognitive traits are briefly introduced next.

1.2 A Brief Introduction to Cognitive Traits

Working memory capacity, inductive reasoning ability and divergent associative learning are the three cognitive traits used in this study. They are each discussed in more details in chapters 6, 7, and 8 respectively. This section gives a very brief introduction of them to familiarise the reader with what each of them refers to when the research questions are formulated.

Working memory capacity refers to the transient memory storage to activate a limited amount of information for a short time (Bunting, Conway, and Heitz, 2004; Kane and Engle, 2003). Information perceived needs to be stored in this transient memory storage for later processing. In reading a sentence, words/phrases read earlier are stored in working memory so that they could be combined with words/phrases read later to make sense of the complete sentence. In doing arithmetic operations like (3 x 9 + 3), the products of earlier operations (3 x 9 = 27) are stored in working memory to be processed later (27 + 3 = 30).

Inductive reasoning ability refers to the ability to generalise an abstract entity from instances (Holland, et al., 1987; Heit, 2000). The abstract entity could be a rule, a theory, a principle or a model to explain certain phenomenon. Inductive reasoning ability is a significant factor for problem solving, concept learning, mathematics learning, and development of expertise (Harverty et al., 2000).

Divergent associative learning refers to the characteristic of learning that develops links between new concepts and existing concepts. Its operation is divergent (Kolb, 1984; Runco, 1991) and the products of its operation are associations (Laumann, 1999; de la Iglesia, 2004).

Because 1) we posit the research works about the cognitive traits as works in the field of cognitive psychology, and 2) two different opinions exist about what is cognitive psychology, we would like to extend current discussion now to brief descriptions of related schools of psychology. In addition, because of the close relation between Philosophy and Psychology, philosophical thoughts relevant to current study are also introduced next in section 1.3 .

1.3 Pertinent Philosophical and Psychological Thoughts

Many of the literature reviewed in this study is psychological in nature. There is a need to introduce different schools of psychology and philosophy that are relevant to this study. The discussion in this section serves as background information for discussions in later chapters.

1.3.1 Rationalism and Empiricism

An important polarity in Western intellectual history has been the debate between the philosophies of *Being* and *Becoming* (Leahey, 1997). The philosophy of Being asserted that the underlying reality of the universe was an unchanging substance: pure Being. The followers of this philosophy think that the phenomenon of change is an illusion of human mind. A well known spokesman of the philosophy of Being was Pluto who proposed the famous idea about "Form". Pluto maintained that there exists a realm of Being in which Forms exist. What are observed by human senses are copies of the Forms: for example, all right-angle triangles are copies of the Form of the Right-Angled Triangle, and every courageous act resembles the Form of Courage. For the philosophy of Being, the appearance of the universe is Becoming but the reality of the universe is Being.

For Pluto, true-knowledge must be true at all times and at all places, knowledge claims have to be rationally justifiable. Because the physical world is always in a state of becoming and human perceptions are tainted by preconceptions (personal, cultural, etc.), therefore truth, and the knowledge of it, cannot be derived directly from perceptual observations. One, therefore, should rely on pure logic to obtain knowledge. This approach to philosophy was later known as *rationalism*.

On the other hand, advocates of Becoming do not believe in the existence of such static truth (Leahey, 1997). They maintain that the only truth is that anything is in the process of becoming something else. Heraclitus was the spokesman of the philosophy of Becoming. His well-known saying "no one ever steps in the same river twice" very well describes the core meaning of this philosophy.

For the philosophy of Becoming, the appearance of the universe is Being but the reality of the universe is Becoming. Unlike his teacher Pluto, Aristotle regarded that human senses were only passive and conforming to the perceived forms and therefore were reliable and unerring. To Aristotle, perception is the starting point to knowledge. This view of Aristotle's created the foundation of what is known as *empiricism.* A true empiricist would claim that one should stay as close to experience as possible in order to obtain true knowledge.

1.3.2 Atomism

Atomist proposed that all objects are composed of infinitesimally small atoms (Leahey, 1997). This was a very advanced view among ancient Greeks (invented about 430 BC). The name *atom* and the atomist view have proven immensely fruitful in modern Physics. The influence of atomists is not only visible in the studies about the physical nature (such as Physics, Chemistry), but also in studies about human nature and understanding (Psychology).

Psychological atomism viewed that complex ideas, such as House, are composed of simpler ideas, such as Brick, Door, and Window. The collection of simple ideas is grouped together, by means of association, to form the complex ideas.

Views from of atomism are also quite apparent in many studies about human abilities. Guilford (1971) proposed in his structure-of-intellect (SI) model that human intellect consists of 120 hypothetical abilities. Researches, such as Klauer (1996), Harverty et al. (2000), and Zhu and Simon (1987), also broke inductive reasoning down into smaller steps or sub-tasks.

The methodological approach of this study is not purely atomistic, that is this study does not aim to decompose each cognitive trait into its sub-parts or sub-traits. Atomistic view helps the search for manifestation of cognitive traits by the fact that the functions of sub-parts are often simpler than that whole of each cognitive trait and therefore easier to be identified. For example, hypothesis generation was identified as a sub-task of inductive reasoning (Harverty et al., 2000), and student behaviour pattern for hypothesis generation is easier to find than that of the inductive reasoning. Therefore, influence of atomist view can also be seen in this study.

1.3.3 Humanism

The focus of humanism is on humans. Humanists believe that humans are different from animals and therefore cannot be studied mechanically as behaviourism does. Humanist also believes that humans should not be studied analytically using isolated behaviours; "man is much more than a concatenation of biological and learned reflexes or reflexive units" (Hillner, 1984, p236).

Humanists concern about human as a unique, irreducible individual being. "The model of man is himself, ... The only reality for man is that which he experiences" (Hillner, 1984, p236). The claim "Of all things, the measure is man" from Protagoras (approximately 490-420 B.C.) spells out the central idea of humanism and endorses a *relativistic empiricism* (Leahey, 1997). Relativistic empiricism has both an empiricism focus, which says truth lies in the immediate human experience, and a relativistic focus, which points out that truth, because it is based on experience, is relative to each perceiver (Leahey, 1997).

There are also elements of relativistic empiricism in this study. The element of empiricism is the use of student behaviour data. The element of relativism is that although each different theory of a cognitive trait holds a certain degree of truth about the cognitive traits of students, the degree of truth is relative to each student. Although the definition of relativistic empiricism of this study is seemingly different from that of the original definition (see Leahey, 1997, p43-44), the two different definitions can be linked by a causal relationship by using Vernon's (1979) definition of intelligence. This relationship will be discussed in more details in chapter 3.

1.3.4 Structuralism

Structuralism is the first school of psychology (Hillner, 1984). It focuses on the content and structure of the mind, not its dynamics or functioning. The goal of structuralist study is to analyse conscious experience into its elements. Unlike other branches of psychology that take overt behaviours into account, structuralists only acknowledge mental elements of conscious experience. Therefore, only introspection is regarded as the source of study object in pure structuralist point of view.

1.3.5 Functionalism

Functionalists focus on the dynamics and functioning of the mind, not its content or structure (Hillner, 1984). The objects of study in functionalism are the operations and functions of the consciousness. The aim of functionalist study is at an abstraction of mind in terms of mental activities such as thinking, feeling, imagining and perceiving. Functionalists are not studying conscious mental activities as an end in itself; rather, the conscious mental activities are treated as the adaptive function of the mind. Adaptive function of the mind refers to how the mind assists human beings adjusting to the environment. The adjustment takes the form of behaviour changes. Behaviours are therefore necessary as external references to what is going on inside the mind.

The approach of current study about taking the behaviours as external references to the mental activities is similar to that of the functionalist. The hypothesis, proposed in chapter 18, that student behaviours and their learning styles are shaped by their cognitive capacities also have signs of functionalist thought.

1.3.6 Behaviourism

Behaviourists treat organisms as black boxes. Radical extreme of behaviourism does not tolerate any referents to the mental activities (Hillner, 1984). For radical behaviourist, "any significant or relevant psychological events is resolved in terms of a stimulus or response" (Hillner, 1984, p143). Radical behaviourism has been gradually replaced by a re-emphasis on the mental activities which is now called cognitive psychology (Leahey, 1997).

1.3.7 Cognitive psychology

Hillner (1984) pointed out two views about the domain of cognitive psychology. In the first view, the domain of cognitive psychology coexists with the domain of psychology because any psychological phenomenon involves one or many cognitive processes. In the second view, the domain of cognitive psychology is limited to only the study of human symbolic thought which includes epistemic meaning, propositional knowledge, and reasoning. The first view is called the general view and the second one is called the limited view in this discussion.

The assumptions of innate structures that govern human cognitive operations belong to the limited view. Leahey (1997) called this view the new structuralism. Examples of works in this category include Chomsky's innate grammatical rules of language, and Piaget's generic epistemology. They believed that any human behaviour pattern can be explained by reference to abstract structures which were believed to be logical or mathematical in nature (Leahey, 1997).

The information processing model of human cognition presumes the general view of cognitive psychology. This view has more emphasis on the overt behaviours than the limited view. Unlike behaviourists, cognitive psychologists do not take overt behaviours as the end of study, but only as means to understand the cognitive processes within (Hillner, 1984). This is a stance we take in this study.

The fields of artificial intelligence and computer simulation psychology are included in the general view of cognitive psychology. Researchers in these fields presuppose that all information processing systems, no matter human or machine, operate according to similar principles and therefore constitute a single field of study, namely cognitive science (Leahey, 1997).

The information processing model of cognitive psychology has a deep impact on this study. In fact, the selection of the three cognitive traits is based on the information processing model. More discussion on this regard will be presented later in this dissertation.

1.4 Research Question, Treatment and Methodology

Two factors, which are 1) The domain-transcending and persistency requirements to meet the need of life-long learning, and 2) the significant influence and pertinence to many aspects of learning, have lead to the selection of the three cognitive traits, namely working memory capacity, inductive reasoning ability and divergent associative learning, in this study. It is now relevant to discuss the main research question. First of all, we would like to ask:

Question 1-1: *How to model the three cognitive traits, namely working memory capacity, inductive reasoning ability and divergent associative learning?*

In this study, we are interested in how to model students' cognitive traits in learning systems. There are however, many different types of learning systems ranging from solitary (Virvou et al., 2000) to collaborative learning (Karacapilidis et al., 2000), from web-based hypermedia systems (Kayama and Okamoto, 2001) to standalone virtual reality learning environments (Norhayati, and Siew, 2004; Muirhead and Juwah, 2004), from emphasising conceptual knowledge (Dori and Barak, 2001) to procedural skills (Lu et al., 2005). A particular methodology might be usable in one type of learning system but useless in another. We therefore are not aiming at developing a method to model cognitive traits for all types of learning systems. In this study, the scope is set to web-based hypermedia learning systems with emphasis on conceptual knowledge for solitary learners. By addressing the scope of study, Question 1-1 becomes Question 1-2**Error! Reference source not found.**:

Question 1-2: *How to model the three cognitive traits, namely working memory capacity, inductive reasoning ability and divergent associative learning, in web-based hypermedia learning systems with emphasis on conceptual knowledge for solitary learners?*

Both the goal and the scope of this research are stated in Question 1-2. The goal is to find out a method to model the three cognitive traits in learning systems. The scope is set to "web-based hypermedia learning systems with emphasis on conceptual knowledge for solitary learners". This type of learning systems is hereafter called the *target-systems.* The learning system discussed in chapter 14 is an example of target-systems.

Question 1-2 presents the main research question of this study. Treatment to this question is discussed next.

1.4.1 Treatment to Research Question

The research question of this study is how to model students' cognitive traits in target-systems. This section describes a proposed approach, as a treatment to the research question, to model cognitive traits. The methodological part of this study, i.e. the evaluation and validation, is discussed in section 1.4.2 .

The approach of this study has the following steps:

- Step 1. Study and understand the characteristics of each cognitive trait.
- Step 2. Identify *patterns of behaviours* or *characteristics of students* that could be used to indicate the student's cognitive traits. And because patterns of behaviours or characteristics of students are manifestation of cognitive traits are ways the cognitive traits manifest themselves, they are called *manifestations of trait* (MOTs).
- Step 3. Monitor and log the student's behaviours in the target-systems.
- Step 4. Analyse the student's behaviour log, match behaviours with MOTs and use the matched MOTs as indications of cognitive traits.
- Step 5. Take the indications of cognitive traits from Step 4 with consideration of previous record of the student to calculate new values of cognitive traits.

Step 1 involves a comprehensive literature review about the cognitive traits. Steps 3, 4 and 5 take place for each learning session. A learning session begins when the student logs in the learning system and ends when the student logs out. Step 3 happens during the session, whereas steps 4 and 5 happen after the logout.

Step 2 produces an important output of this study. Some MOTs found in Step 2 are themselves behaviour patterns. For example, students with low working memory capacity tend to do linear navigation (Huai, 2000). The MOT, i.e. linear navigation, is a behaviour pattern that can be tracked in the behaviour log in Step 4. On the other hand, some MOTs need to be translated into behaviour patterns. For example, high attentional control ability indicates high working memory capacity (Engle et al., 1999). The MOT "higher attentional control ability" could be translated into a behaviour pattern "able to perform simultaneous task", which can then be tracked in the student behaviour log. The behaviour patterns that can be tracked in the student log are called *implementation patterns* (IPs) in this study because they are implemented in the target-systems.

However, some MOTs are not translated into behaviour patterns because there are no commonly available elements in target-systems that the MOTs can be translated to. For example, the MOT "classification ability" is found to relate to divergent associative learning positively. But in typical conceptually oriented hypermedia systems (e.g. Kayama and Okamoto, 2001), there is no suitable element that this MOT can be translated to. It is conceivable that it is more likely that this MOT can be translated into a behaviour pattern in a simulation-based learning environment where the main learning content is procedural skill.

The outputs of this study with respect to *indications of cognitive traits* can therefore be separated in two layers, a theoretical layer and a practical layer. The theoretical layer contains the MOTs. MOTs are abstract descriptions about what can be used to indicate cognitive traits. Many of them are directly extracted from other researches. Using the previous example "higher attentional control ability indicates higher working memory capacity", the relation between attentional control and working memory was the conclusion of Engle et al.'s (1999) study using 11 memory tasks, 2 intelligence tests, and a verbal ability test. The MOTs are general and abstract and can be applied to different types of learning systems. Therefore, they are placed in the theoretical layer.

Another layer of the *indications of cognitive traits* is the practical layer. The practical layer contains the implementation patterns (IPs). The IPs are more specific to target-systems and may need to be re-worked/re-translated if they are to be ported to other type of learning systems.

Separation of the theoretical layer and the practical layer makes it easy to use cognitive trait model in a new system. If the new system is very similar to the target-systems, the IPs covered in this study can be directly used in the new system. However, if the new system is very different to the target-systems, for example a procedure-skill-oriented virtual reality learning system, different IPs might need to be translated from MOTs that are suitable for the new system.

Another important output of this study is the cognitive trait model (CTM). In general, the term CTM in this study can refer to either the cognitive student profiles or the combination of the technical components that are used to create the cognitive student profiles. The process to create the cognitive trail model is called *cognitive trait modelling*. Steps 3, 4 and 5 together are counted as cognitive trait modelling.

In this study, the approach to infer students' cognitive traits is by observations instead of self-report (such as questionnaire). One could use explicit questioning techniques to elicit information from the learners. However, researches have pointed out several disadvantages of using questionnaires, for example, possibility of cultural bias (Heine & Lehman, 1995), acquiescent responses (some participants are prone to accept propositions/suggestions put in front of them) (Ray, 1983), and inter-group bias (Navarrete, Kurzban, Fessler, & Kirkpatrick, 2003). Decisions need to be very carefully made to avoid biases if the questionnaire approach is used to obtain the student attributes.

Learners' behaviours (interaction paths) in the learning systems are 1) guided by their beliefs regarding what they perceive as the most suitable way for them to learn, 2) limited by their cognitive capacities. Thus, if one wishes to find out the cognitive traits of learners, the author believes that analysing learners' behaviours would be a more reliable approach than the questionnaire approach.

The above is the description of general approach that we intend to follow to address the research question. It outlines the logical steps to approach the research question and the reason why observations are preferred to questionnaire. The next section describes the methodology of this study.

1.4.2 Methodology

The most important task of this research is to study and validate cognitive trait modelling. Valid cognitive trait modelling ensures valid cognitive trait model.

One of the very important ingredients of cognitive trait modelling is the *indications of cognitive traits*. The indications of cognitive traits are separated into the theoretical layer and the practical layer. As said, the manifestations of traits (MOTs) are the indications of cognitive traits in the theoretical layer, the implementation patterns (IPs) are the indications of cognitive traits in the practical layer. Both layers need validation.

Because there are three cognitive traits in this study and each cognitive trait includes several MOTs (and the corresponding IPs), it is therefore logical to take a bottom-up approach – to validate the MOTs and IPs before validating cognitive trait modelling. This is because if we use the wrong indications to infer students' cognitive traits, the end result of cognitive trait modelling would not be optimal even if other mechanisms are right.

The task to validate the MOTs and the IPs has to be separated into two sub-tasks because MOTs and IPs reside in different layers. In this study, the theoretical layer is validated conceptually by using a computer simulation and the practical layer is validated empirically using experiment data. The validation in the theoretical layer mainly examines whether cognitive trait modelling can successfully combine different MOTs to produce better representations of the cognitive traits than any single MOT could.

The validation of the practical layer requires data from both cognitive trait modelling and psychometric measurements. The former data is obtained from the application of cognitive trait modelling on students' behaviour log in the learning systems. The latter data is made available through the psychometric tools that we have developed in this study. Statistical analysis, especially correlation analysis and comparison of sample means (T-test), is employed to study and evaluate each of the IP individually in the practical layer.

After the evaluations in the practical layer of the indications of cognitive traits, cognitive trait modelling itself is evaluated. This evaluation is the practical version of the theoretical validation, that is, whether cognitive trait modelling can successfully combine different IPs to produce better representations of the cognitive traits than any single IP could. This evaluation requires both the data from cognitive trait modelling and the data from psychometric measurements. Statistical analysis is again used to perform this evaluation.

1.5 Dissertation Structure

Based on the steps of the treatment to the research question and the methodology, this dissertation is organised as follows. Chapter 2 reviews literature for the context of this study. Important areas reviewed include adaptive learning systems, student modelling and adaptive framework.

After given the background of this dissertation in chapters 1 and 2, chapter 3 describes about the general description of cognitive trait model and its overall structure. Two important components used in CTM are semantic relation analysis and multiple portrayal network. They are both innovations of this study and are described in chapter 4 and chapter 5 respectively.

Chapters 6, 7 and 8 are devoted for the discussions the three cognitive traits, namely working memory capacity, inductive reasoning ability and divergent associative learning respectively. On the basis of extensive literature reviews on the cognitive traits, indications of cognitive traits, that is the MOTs, are enumerated. Translations of MOTs into IPs are also presented in these three chapters.

After the identification of MOTs, the theoretical validation of this research is presented in chapter 9. The validation utilises a computer simulation and examines whether cognitive trait modelling is capable of combining different MOTs to form better representations of cognitive traits.

Chapters 10, 11 and 12 then present several psychometric measurement tools. These tools are used to gather psychometric data that is required in the statistical analysis to evaluate cognitive trait modelling. Chapter 13 studies the relationships between the three cognitive traits from the data obtained from the psychometric tools.

Chapter 14 describes the learning system that is used to gather the behaviour data that cognitive trait modelling will apply to. The data is stored in student behaviour log in the database. Because the same learning system is used for two different courses, two sets of learning materials are created. Each set of learning materials combined with the technical structure of the learning system to form a learning module. There are therefore two learning modules, i.e. the PHP learning module and the IT Infrastructure learning module, developed for the two courses. These modules are also described in Chapter 14. The behaviour data gathered from the learning system can then be the input to the process of cognitive trait modelling.

Chapters 15, 16 and 17 present the practical evaluations. The psychometric data obtained from the tools introduced in chapters 10, 11 and 12 are used to make statistical comparisons to the data obtained from cognitive trait modelling.

Finally, chapter 18 presents a summary of this dissertation. It also highlights the major contributions and limitations of this study. Future research directions are also pointed out in chapter 18.

CHAPTER 2

Literature Review

2.1 Introduction

One limitation of web-based interaction is the limited communication bandwidth than traditional face-to-face interaction. The term bandwidth represents the amount of information that can be transferred in a unit of time through any means possible (Forbus, & Feltovich, 2001). In the face-to-face communication mode, if a verbal instruction is not understood, clues can be available to the counterpart through gestures, group dynamics and other local medium. But the clues in the web-based mode are not always so obvious and in many cases not available at all. Therefore, tailoring the information to the right-level for the receiver to understand is a crucial factor for the success of any web-based application.

In web-based educational systems, the type of learning systems that tailor the learning material to meet learners' needs are usually called adaptive learning systems (Karampiperis, and Sampson, 2005; Ketamo, 2003; Kinshuk, and Lin, 2003). Adaptive learning systems can adapt the learning content according to characteristics of learners. They typically aim at providing individualised courses similar to that of the one-to-one teaching from a private tutor. Adaptive learning systems are the environments that cognitive trait model (CTM) could be used. Literature about adaptive learning systems is reviewed in section 2.2 .

In order for adaptive learning systems to provide adaptivity, they have to know about the students. There are many aspects of a student that different learning systems want to know about, including domain knowledge (Nykänen, 2006; Lu, Wu, Wu, Chiou, and Hsu, 2005; Ogata et al., 2000), learning styles (Graf, Lin, and Kinshuk, 2005; Brown et al., 2005), cognitive styles (Tarpin-Bernard and Habieb-Mammar, 2005), emotions (Lyons, Kluender, and Tetsutani, 2005; Fischer, Blommaert and Midden, 2005), preferences (Bontcheva, and Wilks, 2005; Bontcheva, and Wilks, 2005), and so on. The information about an aspect (e.g. domain knowledge) of a student could allow a learning system to tailor its teaching content to suit the needs of the student in term of the particular aspect. The information about students is often stored in so-called student models.

Student models could be static or dynamic. Static student models are created at the beginning of a course: questionnaires and psychometric tests are example of means to create student models. Once static student models are created, they remain static and do not get updated. In the other hand, dynamic student models are created in the process of student's interaction with the learning system. Cognitive trait model is a dynamic student model. Section 2.3 introduces some other different dynamic student models to stand as background for the discussion of cognitive trait model to come.

After learning systems have information about students, what happen than? How to adapt, and what to adapt? Exploration space control (ESC) provides a suitable framework that adaptivity, no matter domain dependent or domain-independent, can be realised (Kashihara et al., 2000). Even though the provision of adaptivity is a step after student modelling, and hence beyond the scope of this study, it is however linked to an important antecedent research of cognitive trait model. ESC and its elements are discussed in sections 2.4.1 and 2.4.2 respectively. A domain independent adaptation framework (Lin, Kinshuk and MaNab, 2005) was developed based on elements of ESC and it is discussed in section 2.4.3 .

2.2 Adaptive Learning Systems

Learning systems, which are implemented on the web, can often be classified as part of hypermedia systems. Addition of adaptivity into hypermedia systems qualifies them into a group of system called adaptive (educational) hypermedia systems (AHSs) (e.g. Karampiperis, and Sampson, 2005). Hypermedia systems are inherently information systems with visual navigational aids that can be used to move through a hyper-linked information space. Hypermedia systems are in themselves good tools for information dissemination – they allow access to great amount of information from different locations at different times. Students are no longer bound to come to a particular space in a particular time (e.g. attending a lecture) in order to access the information. If portable devices could be employed for educational purpose, there is even greater mobility in the learning process (e.g. Chan et al, 2006).

However, static hypermedia systems are often criticised for their direct transplantation of learning materials from traditional media (e.g. text books) to the Internet (Forbus, & Feltovich, 2001). The great amount of information in hypermedia system could also cause cognitive overload on the students (Kinshuk et al., 1999). Adaptive hypermedia systems try to overcome the limitation of static hypermedia system by providing customisation. The terms customisation, personalisation, and adaptation all express a similar goal – to transform the information or learning material to a presentation that best meet the needs of learners (Kinshuk et al., 1999). The adaptive characteristics improve the usability of the hypermedia systems. Without adaptivity, the hypermedia systems would present the same material, with the same set of links, to all learners. It could work well if the intended user group has the same/similar learning characteristics, but it is rarely the case in real learning environments. Examples of adaptive hypermedia systems include HYLITE (Bontcheva, and Wilks, 2005), AHA (De Bra, 2002a), InterSim (Kinshuk et al., 1999) and ELM-ART II (Specht et al., 1997).

Adaptive hypermedia systems, with the ability to change the content according to the student's needs, provide similar situation as if there were many instructors available for each individual student, and therefore "the learner's chances of doing well in this classroom would appear to be significantly better than in a classroom with one instructor because each learner would adapt to the instructor(s) that would facilitate his/her learning style" (Glibert and Han, 1999, p.2). Learning therefore becomes a personalised experience (Kabassi, and Virvou, 2003; Dagger, Wade, and Conlan, 2005).

In order for the adaptive hypermedia systems to provide adaptation, they need student models. The processing to create student model is called student modelling. Student modelling is discussed next.

2.3 Student Modelling

Student modelling situates within a larger research arena called user modelling (UM). There are also commercial interest in knowing about user preferences, needs and characteristics (e.g. Fink and Kobsa, 2000). Student modelling is UM applied in educational context.

Student modelling is the process of creating a representation of student in the learning system. The representation is often called *student model* or student profile. A student model contains information about a particular student. The information about the student is necessary for adaptive learning systems to provide right adaptation; therefore student model is an essential component in any adaptive learning systems (Han et al., 2001). Different student models, however, contain different information about the students. Different emphases in different student models are result of variations in subject domains, in addition to different constraints posed on by different types of student models. In the following sub-sections, several types of student models are examined. It has to be noted that this is not an exhaustive study of all existing student models, but it is believed that the types of student models categorised in this study cater for most of the known student models. This section serves as a background for the discussion of cognitive trait model, which is also a student model, in the coming chapters.

2.3.1 Modelling Competence State

Students' domain competence has to be constantly updated to reflect the progress in the students' understanding of the subject domain. This is often accomplished by recording the pages/concepts visited by the students and the result of the learning from some form of assessment (Bontcheva and Wilks, 2005). Updating or diagnosis is an important task to maintain the currency and correctness of the student model. The following is a list of types of state models:

- overlay student model
- differential student model
- perturbation student model
- constraint-based student model

2.3.1.1 Overlay Student Model

The student's knowledge at any point is assumed to be a subset of expert's knowledge in an overlay student model. The differences between the student's and the expert's set of knowledge are believed to be the student's lack of skills and knowledge, and the instructional objective is to eliminate these differences as much as possible (Bontcheva, and Wilks, 2005; Michaud, and McCoy, 2004; Staff, 2001). Data in the overlay model can either be binary (e.g. Mastered or Not-Mastered) or probabilistic (e.g. any fraction within 0 and 1). Overlay models have been used in ICICLE (Michaud, and McCoy, 2004) to teach grammatical components of freeform English writing, and in the SQL-Tutor (Mitrovic & Olhsson, 1999), which combines the overlay and the constraint-based model to teach database query language (SQL).

An issue with the overlay model is that there is no mechanism to differentiate between the knowledge the student has not yet grasped and the knowledge the student has not yet been exposed (Smith, 1998). Thereby, it is difficult to employ strategies to help students if they have any misconceptions.

2.3.1.2 Differential Student Model

This model is a more structured variant of the overlay model (Friedland, 2001). Differential model separates the entire domain knowledge into learned by the student and not-learned by the student (Staff, 2001). The WEST system (Burton & Brown, 1982; Abdullah, 2003) employed the differential student model.

2.3.1.3 Perturbation Student Model

This model retains the information of what the student has known, and what the student has known incorrectly (Abdullah, 2003). Similar to overlay and differential models, perturbation model records what is being learned; unlike overlay and differential models, perturbation model includes students' misconceptions or errors. The record of errors is sometimes called an error model or a buggy model.

The error model can be created by enumerative or generative process. For enumerative modelling, the system developers analyse the model and determine possible errors students can make or are prone to make (Smith, 1998). An error can either be a primitive error, or a composite error, which is the combination of primitive errors. Enumerative modelling techniques suffer from costly computational requirements while matching the errors, and resource-intensive development cycle.

Neclle is a system using perturbation model (Ogata et al., 2001). Neclle stands for Network-based Communicative Language-Learning Environment. It is a learning system designed to teach Japanese language especially to Chinese speaking students. It employs a communication gap model (CGM) that has difference of meaning in Japanese and Chinese for the same character (sometimes Japanese and Chinese share the same character but different meanings). The student model of the intelligent tutoring system of Virvou et al. (2000), teaching the passive voice of the English grammar to Greek students, is another example of perturbation student model. Its error model is enumerative – hand-coded by experts. It includes the errors that are caused by the interference of the mother tongue and other foreign languages that the students are familiar with.

Lu et al.'s (2005) perturbation model is also enumerative. In a system to teach basic arithmetic to children, they identified 31 types of addition errors, and 51 types of subtraction errors. They have even categorised all the error types into 1) carelessness,

2) systematic and predictable errors, and 3) random errors. It is the second type of errors (systematic and predictable) that Lu et al. (2005) were trying to model.

The inclusion of misconceptions in student models provides the excellent facility and resource to expand the explanation during the feedback to the students. However, misconceptions predefined during system development increase the time-span needed for implementation, and cause computational problems as "the search space involved in constructing and maintaining the student model is greatly expanded, requiring the use of heuristics to prune the search space" (El-Sheikh, 1997).

An alternative to enumerative modelling is generative modelling where the system uses an expert's model, which is a cognitive model, to detect students' errors. No errors or bugs need to be predefined because they can be deducted from the cognitive model. Errors are regarded as failed extrapolation of the concepts learned, and if the general form of the extrapolation errors can be found, then the majority of the errors can be explained (Mayo, 2001).

2.3.1.4 Constraint-based Student Model

Martin's (1999) SQL-Tutor adopted constraint-based model (CBM), which represents both domain and student's knowledge as a set of constraints. Constraints represent basic rules/concepts of the domain. The student model of SQL-Tutor represents a set of constraints that the student has violated (misunderstood), and therefore can be thought as an implicit bug library (Martin, 1999; Abdullah, 2003). This bug library is different from the error model of the perturbation model; the bugs in CBM are defined as the failure to give the right solutions to the question and nothing else, whereas the error model can contain information about errors that are not presented in the domain knowledge model. The CBM only keeps track of the incorrect knowledge via recording the amount of constraints violated, but not the current coverage of the student's correct knowledge, which is redundant in this model, and therefore gains a great improvement in the storage utilisation. Error patterns in the CIRCSIM-Tutor (Evens et al., 2001) serve the similar role as (violated) constraints described by Martin (1999), and the difference between them is only nominal.

2.3.2 Modelling the Process

Process models are oriented towards modelling the problem-solving process the students undertake. A process model represents the students in term of both the knowledge they learned in the domain, and inference procedures. "Such a model would be an executable process model, and could thus predict what the learner will do next, as well as work backwards from learner behavior to generate explanations" (El-Sheikh, 1997). In terms of student learning, Self (1999) commented that the process of construction of knowledge is more important than the knowledge per se. This comment describes very well the purpose of process model and why should process model be differentiated from state models.

The student model ViewGen is in essence a process model (Bontcheva and Wilks, 2005). ViewGen represents students' believes in conceptual graphs. Conceptual graph reasoning algorithms can be applied to find out whether a student has a certain belief from the existing set of believes of that student. The student model constructed by ViewGen can be used to predict the kind of mistakes the student will/is likely to make.

El-Sheikh & Sticklen (1998) described a particular type of process model called the function-based model, or functional model for short. The aim of the functional model is to make use of the known functionalities inside a learning environment to 1) make causal inferences, and 2) provide a reasoning algorithm that can be used to simulate the learning environment for given starting conditions. Each function is subdivided further into a set of behaviours. The entire learning environment can be represented as a hierarchy of functions and behaviours. Causal inferences about students' current competences can be made by the set of functions that they had gone through. For example, if the start condition is called ***a***, and the finish state of a particular task is called ***b***, and let ***C*** represent all the sub-functions and behaviours of the function ***f***, where:

$$f(a) = b$$

It could be inferred that the set of behaviours, ***C***, had been carried out given the function ***f*** was performed successfully. By this inference mechanism, the entire learning environment can be simulated explicitly, and the predictions of both the students' and the tutor's (module) actions can be made.

In the perspective of learning theory, the state modelling approach originates from the theory of behaviourism, which treats the student as a black box capable of producing a certain response when a specific stimulus is given. The instructional goal is to improve the student response in terms of competence or mastery level by the process called conditioning (Mayo, 2001). Testing through questions-and-answers is an effective tool to measure the student performance in the behaviourist instruction. However, the cognitivism claims that learning is not merely the direct transfer of external information into internal knowledge, but is a process of reorganisation of the outside information into an internal representation of the domain (Reisberg, 1997). The internal representation is sometimes called the mental model. The process model is aimed at assisting both the students and tutors to form, understand, and better develop the mental model in order to optimise the effects of learning and teaching.

Both the state model and process model need to be constantly updated to reflect beliefs of the student, no matter whether those beliefs are related to declarative or procedural knowledge. As described by Mayo (2001), the short-term representations of the student model are often very specific, e.g. "the student has given the right answer to question 11", whereas the long-term representations typically contain inferred beliefs, e.g. "the student has mastered Java programming". This inference is also called student model diagnosis. Along the line of student model diagnosis, a distinction can be made about enumerative modelling and generative modelling.

2.3.3 Student Model Diagnosis

The goal of student model diagnosis is provide the learning system the most up-to-date information about the student (Stankov, 1996). The tasks required for diagnosis include collecting and analysing information about students.

Kobsa et al. (1994) categorized three main sources from where the information about students can be obtained:

- **Stereotypes**: The stereotypes categorise users into predefined categories.
- **User supplied preferences**: These are requested explicitly from students.
- **Analysis of user actions**: The actions carried out by users are used to infer the user's preferences, competency level, and so on.

In the following sub-sections, different methods of student model diagnosis are discussed.

2.3.3.1 Stereotypical Modelling

Some student models place students into predefined stereotypical groups (e.g. Michaud, and McCoy, 2004; Tsiriga and Virvou; 2004). This simple stereotype model represents a student's knowledge in a topic-value pair. The value describes only a particular student attribute and is usually the mastery level (novice, intermediate, expert) for the corresponding topic/unit.

Webb et al. (2001) claimed, by modelling the community (stereotype) in commercial context, that "*very substantial increases in purchases are claimed for systems that recommend products to users of retail web sites using models based on purchases by other users*". On the other hand, more focus has been placed on modelling individuals in academic research (Webb et al. 2001).

A more recent trend of using stereotypical model is called default model. When a new student is encountered, there is no historical data that the system could infer on, and the default model is therefore created by the demographic or user-supplied data to cater for this situation.

Study of Tang et al. (2001) characterised users according to their navigational strategies. The characterisation is described as follow:

a. **Serendipitous browser:** Users who avoid the repetition of long invocation sequences.
b. **General purpose browser:** Users who navigate in a probabilistic way. It has also been commented by Eklund and Zeiliger (1996) that users have roughly a one in four chance of repeating a more complex navigation sequence.
c. **Searcher:** Users who infrequently perform the same short navigation sequences, but do perform long navigational sequences often.

In Michaud and McCoy (2004), even though they employed the concept of stereotypes like other studies, but their student model allowed dynamic allocation of students into different stereotypes when student progressed through the course. It can therefore be categorised as a dynamic student model.

2.3.3.2 Coverage Modelling

This is one of the simple methods of diagnosis and is typical in overlay student models (e.g. Bontcheva, and Wilks, 2005; Michaud, and McCoy, 2004). This method measures, in the entire learning space, how much the student has covered, by recording which concept or page had been visited.

2.3.3.3 Performance Modelling

This is similar to the coverage modelling, but the only difference is that the system measures what was learned, by means of tests (e.g. Beck, Jia, and Mostow, 2003; Guzman, and Conejo, 2004). "*Although this is a straight forward method of measuring a student's performance it gives reasonable clues about what type and how much information the learner will need*" (Smith, 1998).

2.3.3.4 Problem-solving State Tracing

This technique compares the problem solving steps of the student to that of the expert's answer (Lu et al., 2005). The student usually does not need to follow every step strictly; alternatives and tolerances can be specified. Systems employing this technique need to have sophisticated problem-solving models, and those problem-solving models are very domain-dependant, thus they are usually used within domains where the problems are well-structured, and where strictly followed de facto standard procedures for problem solving exist. The ProcessMap in Lu et al. (2005), the Reciprocal Tutoring System, RTS, (Wong et al. 2003), the LISP-Tutor (Anderson & Reiser, 1985), and the WEST (Burton & Brown, 1982; Fischer, 2001) are examples of systems that utilise the problem-solving state tracing technique.

2.3.3.5 Path Finding

It is an extension of the problem-solving state tracing. Path finding includes algorithms to find the transition from one state to another. The transition, once found, can be used to predict student actions (Stankov, 1996). Path finding is technically complex as it requires the system to model the student's cognitive process of the problem solving.

2.3.3.6 Skill Tracing

Skill tracing is also called knowledge tracing (Han et al. 2001). This technique is often used in domains where the procedural (know-how) knowledge dominates. In those domains, procedure skill acquisition is the main focus of learning and the skills in such domains are often called rules. The entire domain can be modelled by a set of rules.

As opposed to problem-solving state tracing, which has to model all the states in a problem-solving episode, skill tracing only records the usage of skills demonstrated during the problem-solving process (Smith, 1998). Probabilities can also be used to represent the student's understanding on each rule (Han et al. 2001). Skill tracing has been implemented in the WEST tutoring system (Burton & Brown, 1982).

2.3.3.7 Case-based Reasoning

Case-based reasoning (CBR) is used to perform both student modelling and machine learning (Han et al. 2001). CBR stores two main types of information: information of the students, and information of the cases of problem solving. When a student starts a new session, the system creates a new case. The system can then find similar cases by looking up cases solved successfully by other students with similar attributes to the current student. Those similar cases can be used to predict the student's behaviour and also the result. Interventions or guidance can be planned. In the circumstances where the strategy used by the current student is different from that of the similar cases, and the final answer is proved to be consistent with the expert's, then this case is regarded as an instance of machine learning.

The above discussion explored different types of student models and different means by which the information in the student models is gathered. The information in the student model is used to adapt the learning material and the navigational structure (together form the exploration space).

How a learning system adapts its exploration space is called the *adaptation framework* in this study. It is obvious that there is lack of emphasis and interest in the literature about adaptation framework. An important reason could be that each system is believed to be so different that generality is difficult if not impossible. The differences in the different learning systems result in different domain-dependent and/or systems-dependent student models which in turn result in different adaptation frameworks and strategies.

However, we believe that if there is possibility of domain-independent student models (such as cognitive trait model), there is possibility of domain-independent adaptation framework. It has to be noted that the adaptation framework is sequentially a step after the student modelling process and therefore is not the main focus of this dissertation; our early research has however demonstrated the viability of such domain-independent adaptation framework (Kinshuk, Lin, and Patel, 2003; Kinshuk, and Lin, 2005). It is also one of the sources of inspiration for the study of cognitive trait model. The following section is devoted for the discussion of such adaptation framework.

2.4 Domain-Independent Adaptation Framework based on Exploration Space Control

Cognitive trait model is scoped for hypermedia learning systems and is characterised by its domain-independence/transcendence. The adaptation framework we are seeking needs to be domain-independent and applicable in hypermedia systems as well. Studies about exploration space control (Kashihara et al., 2000) have analysed common features in web-based hypermedia learning systems, and therefore are useful resources for extraction of domain-independent elements of hypermedia systems (Lin, Kinshuk, and McNab, 2005). Exploration space control is briefly introduced in section 2.4.1 , elements that are common in hypermedia systems are discussed in section 2.4.2 , and the adaptation framework is discussed in section 2.4.3 .

2.4.1 Exploration Space Control

Exploration is a self-directed process, and is an effective way of learning. Exploratory learning, which involves searching the information, navigation through the learning space, understanding of domain-related conceptual knowledge and acquiring skills, often requires high cognitive effort of the learner. Exploration Space Control (ESC) is a theoretical framework to support exploratory learning in multimedia web-based educational systems by allowing learners to explore and acquire domain concepts and skills with adequate amount of cognitive load (Kashihara et al., 2000).

ESC attempts to limit the learning space, called exploration space, to maintain the learners' cognitive load at an adequate level depending on their learning approaches and capacities. ESC tries to facilitate adequate learning for a whole spectrum of learning competence by including approaches to cover both extremes - active learning support and step-by-step learning support.

The main concept of ESC is to provide appropriate level of control; to control the available learning space by adaptive navigation, and to control the presentation of the learning content by adaptive presentation. Four types of controls are included: embedding appropriate information, limiting information resources, limiting exploration paths, and limiting information to be presented.

The aim for these different controls is to avoid overloading the cognitive capacity of the learners as this might greatly discourage them and hamper learning process. Careful adjustment of these controls allows a learner to progress in his/her own pace in a way that the learning satisfaction is obtained and thus the learning efficiency and effectiveness ensue. When the learners start to engage in their learning more actively, the levels of controls are gradually reduced. Active learning shows signs of confidence of the learner which is likely the result of increased domain understanding.

However, an important issue needs to be addressed before the different aspects of controls can be implemented - what can be controlled in a web-based learning environment? The four types of controls discussed by Kashihara et al. (2000) are abstract.

In the next section, common elements of web-interfaced learning environment, called exploration space control elements (ESCEs), are elicited and discussed.

2.4.2 Exploration Space Control Elements

Adaptive techniques are grouped into two broad categories: adaptive content and adaptive navigation (Brusilovsky, and Maybury; 2003; Hothi & Hall, 1998; Specht et al., 1997). Same applies to exploration space control elements: content elements and navigational elements (see Table 2-1).

Table 2-1: Exploration space control elements

Nav. Link:	Number Relevance
Content:	Amount (detail) Concreteness Structureness No. Info Resources

There are two ESCEs for the navigation: the number of navigational links and relevance of the links (Table 2-1). Number of links available in the text determines the size of the exploration space. Links can be targeted to either internal or external resources. While the former can be used to provide a preset sequence of presenting learning materials, the latter allows resource sharing and provides opportunities for accidental learning to take place (Reisberg, 1997). Number of links can be controlled by utilizing adaptive techniques such as link removal and link disabling (De Bra, 2002b; De Bra, 1999; Brusilovsky, 2004).

Relevance of links indicates the necessity of the information, as stated in course objectives/requirements, behind the links. Highly relevant links bring the learner to the core information that they need to learn in order to meet the course requirements, whereas less relevant links provide extension or different perspectives to the core information. Kinshuk et al.'s (1999) categorisation of six different types of navigational links can be used to explain the relevance of links (see Table 2-2). Relevance of the links can be controlled by techniques such as link sorting/re-ordering (Brusilovsky, 2004; Hohl et al., 1996).

Table 2-2: Types of link and their relevance to the domain (not to scale)

Types of link	Relevance to the domain
1. Direct successor link	
2. Fine grained link	
3. Glossary link	
4. Problem link	
5. Parallel concept link	
6. Excursion link	

Links with higher relevancy are links to the concepts that are closely related to the core curriculum. Direct successor links are used to provide the main navigational structure across the learning space. The entire series of successor links often represents a predefined sequence of concept presentation usually suggested by the subject matter experts. Fine grained links provide drilled-down explanation of domain concepts, and are often present in topic outline. Both direct successor links and fine grained links are of high relevance to the domain.

Glossary links are used to explain meaning of terms used in the text. Pop-up windows are often used to implement glossary links. Text shown by glossary links usually does not contain other hyperlinks; if it does, they could be in the category of excursion links. Problem links bring the learner to exercises/problems of the related concepts after fulfilment of the learning unit. Both glossary and problem links are regarded as of medium relevance to the domain.

Parallel concept links lead the learner to analogous concepts or different perspectives of current concept for comparative learning. Excursion links lead the learner to an external website that bears some relevance to the current concept. Both parallel concept links and excursion links often target to external websites for such resources for economical and copyright reasons, and they are both regarded as less relevant links and are more of supplementary nature.

There are four ESCEs for content: amount, concreteness, structureness and number of information resources (Table 2-1). Amount/detail of content decides how detailed the knowledge presentation is. The amount of content can be controlled by techniques such as conditional inclusion of fragments, stretch text (De Bra et al., 1999), or explanation variant (Hothi & Hall, 1998).

The concreteness determines the abstract level of the information. The more concrete a piece of information is, the closer to observation it is. Abstraction refers to the opposite of the concreteness and is often represented by generalised theories, rules or models. Explanation variant (Hothi & Hall, 1998) is a suitable technique to replace concrete content instead of abstract one or vice versa for different learners.

The structureness of information indicates the ordering, arrangement, and sequencing of the information presented as a series/set of concepts. Differently structured information content could be better understood by learners with different learning styles. Concepts may or may not be directly or indirectly related to each other with certain sequence. The elaboration theory (Reigeluth, 1992) suggested a structured approach by stating that the instruction should be organized in increasing order of complexity for optimal learning.

The more structured the information is the more orderly fashion it is presented to the learners. Structured information helps the learners in building up their mental models, but on the other hand, limits the freedom of navigation. Adaptive techniques such as information re-ordering or link removal/disabling (Brusilovsky, 2004; Hohl et al., 1996), and map adaptation (Mukherjea, 2000; Benford et al., 2000) can be used to achieve the required structureness of the information space.

The last ESCE for content is information resource (shortened as Info resource). Information could be presented using different media, such as text, audio, visual, and so on. The effect of each media for presenting information is different: "Audio is good to stimulate imagination, video clips for action information, text to convey details whereas diagrams are good to convey ideas" (Kinshuk et al., 1999, p. 2). Besides, each media type has different impact on each individual's learning. If there is more than one media (e.g. a textual explanation and a chart), it could make the information more impressive and easier for future recall. The greater the number of information resources, the more choices the system has for selection to suit the learners' characteristics. Conditional inclusion technique can be used to include different media types depending on the learner's preference (De Bra et al., 1999).

Exploration space control provides a theoretical foundation, rooted in cognitive science, for utilisation of adaptive technologies. The six exploration space control elements (ESCEs) discussed above are a set of domain independent features that can be found in almost all web-interfaced learning systems, and thus provide a level of abstraction that different adaptive techniques can be employed within one theoretical framework - exploration space control (see Figure 2-1).

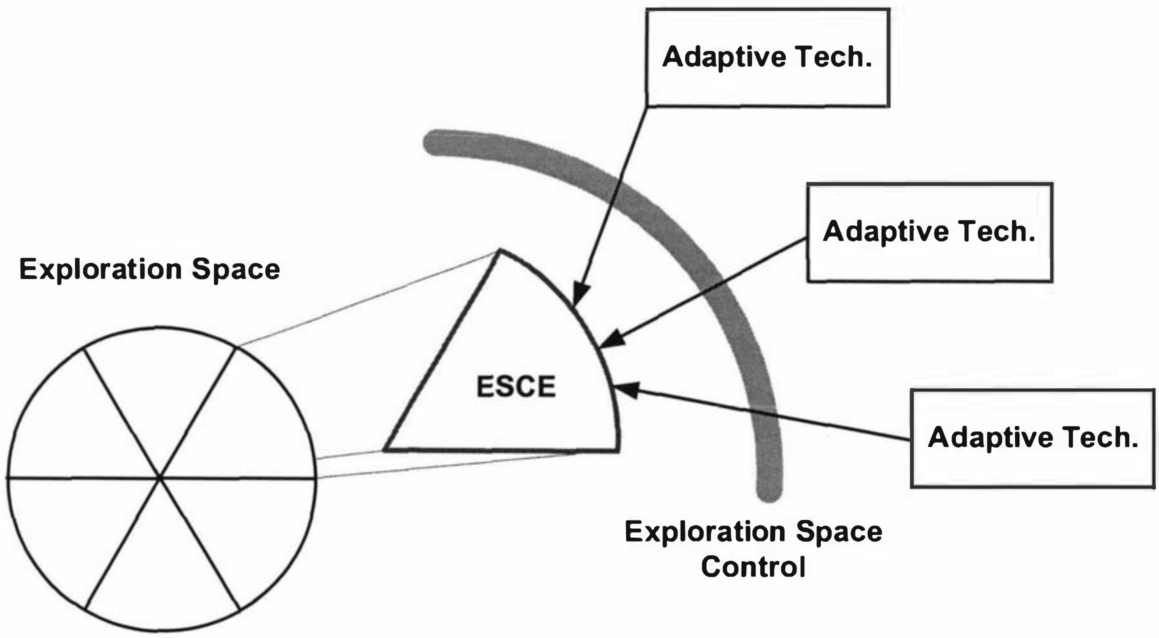

Figure 2-1: ESCEs act as levels of abstraction so that different adaptive techniques can be used according to the theory of exploration space control

There has been a lack of consistency in the development of a general and domain independent framework for adaptation, as most researches on adaptivity are domain dependent (e.g. Ketamo, 2003). Brusilovsky (2004) described them as *closed corpus adaptive hypermedia* because their adaptation framework applies to *only the set of hypermedia documents* in their own system. Domain-dependent is probably even an overstatement.

The value of ESCEs lies in its domain independence which can then be utilised to create domain independent adaptation framework. Such framework should be able to be used in multiple domains without the need to be developed from scratch.

Framework of cognitive adaptation is an exemplary application for ESCEs because of the domain independent nature of cognitive traits. That is, the same cognitive trait, such as working memory capacity, is used in multiple domains. Therefore, if we develop an adaptation framework for working memory capacity, framework should be able to be used in Mathematics, History, Computer Science, and so on. The economy and benefit of such effort are therefore obvious. The next section presents the cognitive adaptation framework.

2.4.3 Domain-Independent Adaptation Framework

Based on exploration space control elements (ESCEs), the cognitive adaptation framework is scoped to web-based hypermedia systems. The adaptation framework matches the ESCEs to different categories of learner's cognitive traits. The category of cognitive trait is binary: high or low. Each category (e.g. low) of each trait (e.g. working memory) is matched to a suggested treatment in the adaptation framework (e.g. reduced the exploration space by removing less relevant links). Please note that the treatment is stated in terms of ESCEs. That is the reason that makes it domain independent.

The cognitive adaptation framework is developed on the basis of literature about the three cognitive traits. In the following sections, literature relevant to each cognitive trait is presented followed by the adaptation framework for the cognitive trait.

2.4.3.1 Adaptation Framework for Working Memory Capacity

Working memory is the cognitive system that allows us to keep active a limited amount of information (roughly, 7 +- 2 items) for a brief period of time (Miller, 1956) to temporarily store the outcomes of intermediate computations during solving a problem and to perform further computations on these temporary outcomes (Baddeley, 1986). The research on working memory (Kearsley, 2001; Huai, 2000) shows that the speed of learning, the memorisation of learned concepts, effectiveness of skills acquisition and many other learning abilities are all affected by the capacity of working memory which is mainly comprised of two components: the limited storage system, and the central execution unit carrying out the cognitive operation efforts.

There are already many guidelines to design learning systems, written by human-computer interaction (HCI) experts, devoted to address the relationship between the storage aspect of the working memory and good interface designs. The effort to facilitate learning with regard to working memory is mainly focused on the instructional design to assist the synchronised operation with the central execution unit by assisting the formation of higher order rules, build up of the mental model and of course not to overload the storage system of the working memory. The working memory is analysed below with respect to learning.

Please note that the description of working memory in this section is only brief and is meant to serve to give a rational for the following adaptation framework. More comprehensive literature review about working memory is available in later chapter of this dissertation.

When the working memory capacity of the learner is low:
The number of paths and the amount of information should decrease to protect the learners from getting lost in the vast amount the information, from overloading the working memory with complex hyperspace structure (Kashihara et al., 2000). The reduced number of paths and amount of information can also allow more time for learner to re-view essential content if necessary.

The relevance of the information should increase so the learners get the important information. The concreteness of the information should increase so the learner can grasp the fundamental rules first and use them to generate higher-order rules as suggested by the structured learning theory (Scandura, 1973).

The structure of the information should stay unchanged. The increase of structure-ness could facilitate the building of mental model and assist future recall of the learned information. But as Huai (2000) indicated, the versatile learners tend to have smaller short-term memory (storage aspect of working memory) than serial learners, and the increase of structure-ness limits their navigational freedom, which is the primary way they learn. So basically, the net effect cancels out and the structure of the information is recommended to stay unchanged.

The number of the information resources should increase, so the learners could choose the media resources that work best along their cognitive styles and allow deeper understanding of the subject domain (Aptitude Treatment Theory: Cronbach and Snow, 1989; Level of Processing Theory: Craik & Lockhart, 1972).

When the working memory capacity of the learner is high:
The number of paths and the amount of information should increase and the relevance of the information should decrease to enlarge the exploration and domain space of the learning process. More knowledge is then available to those learners who can process more higher-orders rules. The higher order rules "account for creative behaviour (Kearsley, 2001, ¶ 1).

The concreteness of the information should decrease to avoid boredom for the learners resulting from too many similar examples. The structure of the information and the number of information resources should stay unchanged because there are no direct and apparent benefits associated.

The above discussion can be formalised as shown in Table 2-3.

Table 2-3: Adaptation Framework for Working Memory

	Path		*Content*			
Level	**Number**	**Relevance**	**Amount**	**Concreteness**	**Structure**	**Info Res**
Poor	-	+	-	+	\	+
Good	\+	\-	+	-	\	\

The symbols used in the formalisation have the following meanings:
"+" → should increase
"-" → should decrease
"\+" → should slightly increase (recommend only), or could increase
"\-" → should slightly decrease (recommend only), or could decrease
"\" → no change recommended

For example, Table 2-3 suggested that the number of path (navigational link) should decrease while the learner's working memory is identified low.

Table 2-3 represents the adaptation framework of working memory capacity. In hypermedia systems, such adaptation framework can be said to be domain-independent. Similar efforts to create adaptation framework for inductive reasoning ability and divergent associative learning are presented in the next two sections.

2.4.3.2 Adaptation Framework for Inductive Reasoning Ability

Induction is to figure out the rules/theories/principles from observed instances of events. William (2001) described it as working opposite of deduction, moving from specific observations to broader generalizations and theories. It is a bottom-up approach and has an open-ended and exploratory nature.

The research on inductive reasoning ability (Heit, 2000; William, 2001) shows that higher the inductive reasoning ability, the easier it is to build up the mental model of the information learned. Mental model, also called cognitive structure, "provides meaning and organization to experiences and allows the individual to go beyond the information given" (Kearsley, 1998, ¶ 1). From the constructivist's point of view, the learner's selection and transformation of information, constructs, hypotheses, and the decision process, all rely on the mental model (Bruner, 1973).

For students who possess better inductive reasoning ability, it is easier for them to recognize a previously known pattern, generalize higher-order rules and as a result, the load on working memory is reduced and learning process is more efficient. For its educational value, there is a need to specify means to support those with lower inductive reasoning ability and to maximize the learning for those who are already good at induction. The following discussion analyses the effect of poor and good inductive reasoning ability on the learning process and presents an adaptation framework for inductive reasoning ability.

When the learner's inductive reasoning ability is poor:
The number of paths should increase to give the learner more opportunity for observation and thus promote induction. The relevance of paths should decrease and the concreteness of the information should increase so the learner can have more diverse observations to promote induction.

The amount of information should increase to give detailed and step-by-step explanation to the learners, so they can see the rules/theories easier. The structure of the information should increase so that it is easier for the learner to build up the mental model and see the sequential relationship of the topics and relationship of concepts. The number of information resources does not need to change because there are no direct and apparent benefits associated.

When the learner's inductive reasoning ability is good:
The number of paths and the amount of the information should decrease to speed up the learning process. The concreteness of the information should decrease to avoid the boredom resulting from too many similar examples. The structure of the information, the number of information resources and relevance of paths do not need to change because there are no direct and apparent benefits associated.

The above discussion can be formalised as shown in Table 2-4.

Table 2-4: Adaptation Framework for Inductive Reasoning

	Path		*Content*			
Level	Number	Relevance	Amount	Concreteness	Structure	Info Res
Poor	\+	\-	+	+	+	\
Good	\-	\	-	\-	\	\

2.4.3.3 Adaptation Framework for Divergent Associative Learning

Divergent associative learning denotes the characteristic of learning that links existing knowledge to the new information to make sense of it and thus the information becomes new knowledge. Quinton (2001, p. 6) pointed out that "we do not learn information as discrete, isolated facts, but instead integrate new information with knowledge we already possess. Our best learning occurs when new material is readily connected with what is often complex and multiple link of association".

"Cognitive psychology suggests that a mental model consists of two major components: knowledge structure and the processes of using this knowledge" (Merrill, 2000, p. 1). Inductive reasoning ability aids in figuring out the pattern of the correct operations on how to use the knowledge structure whereas the divergent associative learning skill assists the build-up and storage of the knowledge structure itself.

In order to assist the association processes during the student's learning, the instruction needs to assist the recall (revisit) of learned information, clearly show the relationships of concepts (new to existing), and facilitate new or creative association/insight formation by providing information of related domain area. The divergent associate learning is analysed below with respect to learning process.

When the learner's divergent associative learning skill is poor:
The number of paths and structure of the information should increase. More hints and information should help the learner to associate one concept to another. The number of information resources should increase. Different information resources (media) should provide different magnitude of understanding of the same concept.

The relevance of the paths should increase to prevent the learner from getting lost in the less-relevant information and create too many useless associations. The amount of information and the concreteness of the information do not need to change because there are no direct and apparent benefits associated.

When the learner's divergent associative learning skill is good:
The number of paths and the structure of the information should decrease so that the learners can navigate more freely and hence enhance the learning speed, and stimulate more associations. The relevance of the paths should decrease to enlarge the information space and hence the available knowledge. The amount of information, the concreteness of information and the number of information resources do not need to change because there are no direct and apparent benefits associated.

The above discussion can be formalised as shown in Table 2-5.

Table 2-5: Adaptation Framework for Divergent Associative Learning

	Path		*Content*			
Level	**Number**	**Relevance**	**Amount**	**Concreteness**	**Structure**	**Info Res**
Poor	+	+	\	\	+	+
Good	\-	-	\	\	\-	\

The relationships between various learner attributes and ESCEs are summarised in Table 2-6.

Table 2-6: Domain Independent Cognitive Adaptation Framework

		Path		Content			
Student Attributes	**Level**	**No**	**Rel**	**Amt**	**Con**	**Str**	**Info**
Work memory capacity	Low	-	+	-	+	\	+
	High	\+	\-	+	-	\	\
Induct reason skill	Poor	\+	\-	+	+	+	\
	Good	\-	\	-	\-	\	\
Assoc learn skill	Poor	+	+	\	\	+	+
	Good	\-	-	\	\	\-	\

(No=Number; Rel=Relevance; Amt=Amount; Con=Concreteness; Str=Structure; Info=Number of Information Resource)

Table 2-6 represent the cognitive adaptation framework that consist the three cognitive traits covered in this study. The development of this adaptation framework is the antecedent of current research about cognitive trait model: that is, we know how to give different treatments to variances of cognitive traits, but how do we know the cognitive traits of students? This brought us to the research question stated in chapter 1. The discussion of this adaptation framework outlines an important motive of this research.

2.5 Summary

Adaptive learning systems can tailor the learning materials to meet the needs of individual learners. An important component in every adaptive learning system is the student model: knowing the students is the pre-requisite of tailored learning material (adaptivity). Depending on different emphases, different student attributes are recorded in student models; there are student models about domain performance (Nykänen, 2006), learning styles (Graf, Lin, and Kinshuk, 2005), cognitive styles (Tarpin-Bernard and Habieb-Mammar, 2005), emotions (Lyons, Kluender, and Tetsutani, 2005), preferences (Bontcheva, and Wilks, 2005), and so on. The majority of student models in current literature are about domain performance. These student models are called performance-based model.

Within performance-based model, different philosophical views about knowledge and different nature of domain knowledge differentiate state-models from process-models. State models are student models that treat knowledge as states and learning is a progress through those states (e.g. Michaud, and McCoy, 2004) whereas process models try to model inference procedures during problem solving (Bontcheva and Wilks, 2005; Mayo, 2001). There are further classification of state models into overlay student model (Michaud, and McCoy, 2004), differential student model (Friedland, 2001), perturbation student model (Ogata et al., 2001), and constraint-based student model (Evens et al., 2001).

Student models are essential for adaptive learning systems. Cognitive trait model is one of the student models. The review of other student models provides a background for the discussion of cognitive trait model to come in later chapters. The discussion of exploration space control and the adaptation framework however presents the antecedent research and also a reason to start the investigation into cognitive trait model.

Exploration space control (ESC) attempts to provide a common theoretical background for web-based adaptation by employing theories from cognitive science and provides supports for both active and passive learners (Kashihara et al., 2000). Exploration space control elements (ESCEs) are a set of domain independent components of web-interfaced systems. ESCEs cover both the navigation and content aspects of web-based systems, and allow the development of cognitive adaptation framework.

In the cognitive adaptation framework, various ESCEs are adapted to different level of cognitive traits. The framework serves as a tactical plan on how the strategies suggested by the ESC theories can be carried out, and provides a practical guideline for developing web-based learning systems to incorporate cognitive support. It has to be pointed out that more research work is needed to provide more robust theoretical basis for the adaptation framework, it is nonetheless worth-noting for its novelty of approach and its generality of potential applications: i.e. it is applicable to a large number of web-based learning systems.

This chapter serves as the background information of cognitive trait model especially on the section of student modelling. It gives an overall view of what are the current focuses of research in student modelling and a sign of the lack of emphasis in the modelling cognitive abilities. Cognitive trait model is designed to modelling cognitive capacities and could be used to be the input of the domain independent adaptation framework in adaptive learning systems. Cognitive trait model will be introduced next.

CHAPTER 3

Cognitive Trait Model

3.1 Introduction

In addition to the new demands imposed by new constraints in the so-called knowledge economy introduced in chapter 1, the need of cognitive support is also reflected in the new trend of teaching and learning. In the field of instructional science nowadays, new and innovative learning practices, such as exploration-based learning, problem-based learning and constructivist learning are getting more and more attention (e.g. Kravcik, Kaibel, Specht, and Terrenghi, 2004; Elissavet, and Economides, 2003; Tam, 2000; Burke, 2001). For these student-oriented learning practices, the role of students has taken more responsibility in the learning process. Teachers are becoming facilitators instead of directors of the learning process.

The ability for a computer assisted learning system to provide cognitive support is thus becoming more important because the cognitive traits are the tools the students have to use to construct their own knowledge or representation of the outside world. They are analogous to the hardware specification of a computer: the execution speed of the central processing unit, the size of the cache, random access memory, and so on. A computer with low hardware specification might take a long time to process a task or it might crash; a student with low cognitive traits might similarly feel a lot of stress to perform a learning task or might eventually give up because of cognitive overload. Without, appropriate cognitive support and tailoring of learning material, some students might be discouraged due to cognitive overload, and some might be bored because of too simplistic learning material that is not adequately matched with their high cognitive abilities.

Two characteristics of CTM that fit the demands of life-long learning are domain-transcendence and persistence. These two characteristics are explored in more detail in this chapter. In this study, we are not claiming CTM to be domain-transcending and persistent in an absolute sense. We mean it in a practical sense. The meaning of practical sense is clarified using a simple scenario in section 3.6 . Section 3.2 starts the discussion about CTM's domain-transcending characteristic. This characteristic is a result of the specific approach adopted in this study. The approach is introduced in section 3.3 . Section 3.4 moves into discussion about the persistent nature of CTM, which in fact depends on the persistent nature of the three cognitive traits. Literature about the persistency and stability of cognitive traits are presented in section 3.4 . An overview of the structure and the components of CTM is then given in section 3.5 . Section 3.6 gives a concluding remark and section 3.7 summarises this chapter.

3.2 Domain Transcending Cognitive Trait Model

One of the characteristics of cognitive trait model (CTM) is domain-transcendence. This characteristic is inherited from the domain-transcending characteristic of the three cognitive traits. Unlike knowledge, such as knowing how a specific gene affects the colour of hair or knowing how to do programming in Java, the three cognitive traits, working memory capacity, inductive reasoning ability and divergent associative learning are not specifically bounded to any domain. When students are learning in biology classes, they could be using working memory as a temporal processing facility; using inductive reasoning to learn the principles of Genetics; and using divergent associative learning to associate what is current learning to other knowledge in Biology, in other sciences or even to prior knowledge about computer programming (such as genetic algorithm). When students are learning about Java programming, History or Mathematics, these three cognitive traits are at work too.

It will be clear in later chapters that inductive reasoning ability and divergent associative learning are influenced to a certain extent by domain knowledge. Is this a contradiction to the claim that they are domain-transcending? The answer could be yes if this question is asked outside the context of this study. However, in this study, the question can be said to be irrelevant. It is because the approach adopted to aggregate and combine different perspectives about cognitive traits – domain knowledge could be treated as one of the perspectives too. More about the approach taken in this study is presented next.

3.3 Approach of Cognitive Trait Model

Often, different theories or perspectives exist for the same object of study, for example Politics, Economy, and Psychology. In this study, the objects of study are the three cognitive traits. Different psychologists had proposed different theories about the cognitive traits. In our view, these different theories are merely different perspectives which could be competing with or supplementary to each other.

In this study, we do not aim to and cannot judge which perspective is the most correct or most useful to adopt. All perspectives, extracted from documentations of valid scientific studies, are believed to bear relevance to their corresponding cognitive traits. Their disagreements, if any, are regarded in this study as differences in viewing the same object from different angles. For example, looking at a person's face from the front could results in a different portrayal (or image) compared with looking at it from the side. The different angles could be amounted to the differences in subjects (age, gender, race, etc.) in experiments, methodology of study or the underlying philosophical beliefs of the researchers. We call this difference the *perspective difference* of cognitive trait.

Furthermore, each individual student is different, too. There is even a special branch of Psychology, called Differential Psychology, dedicated to study individual differences in areas such as personality, motivation, intelligence and ability, interests, values, self-concept, self-efficacy, and self-esteem (Guilford, 1971; Buss and Greiling; 1999; Sternberg and Gardner, 1983). To be precise, a student does not come to a learning environment/system with only his/her knowledge or motivation. The student comes in an entirety including all the aspects of individual difference including knowledge, motivation, intelligence, interest and so on. It is also very difficult, if not impossible, to determine which aspect of these individual differences comes into play to affect students' behaviours. We call this issue the *individual difference* of student in this study. Together with the perspective difference, the individual difference accounts to the second difference.

A student might be highly motivated to learn one day, but the following day the motivation might have been reduced. The use of changing learning motivation during a very short period of time is actually not a good example. Most of the studies in Differential Psychology are interested in individual differences that remain stable and consistent in a longer time frame, for example IQ and personality (Buss and Greiling; 1999). It is also this type (i.e. stable) of individual differences that this study is interested in, instead of the rapid variation of moods or sudden performance fluctuation caused by unusual health or environment conditions.

The two *differences*, perspective and individual, are really two *difficulties* when we are searching for a solution to the research question "how to model cognitive traits". The following two subsections discuss how to treat and resolve these two difficulties.

3.3.1 Perspective Differences

We have mentioned that the term perspective difference denotes the fact that different researchers have different views on the same object of study. A technical term used in this study to represent a perspective of a cognitive trait is *manifestation of trait* (MOT). Greater details of MOTs are discussed in subsequent chapters. For now, it is suffice to know that an MOT is an indication of a cognitive trait. For example, slow comparison speed (an MOT) is an indication of low working memory capacity (a cognitive trait) (Salthouse & Babcock, 1991).

However, there are two possible versions/ways to analyse how these different perspectives are structured with respect to the corresponding cognitive trait. Clear understanding of the distinction of the two versions is essential in understanding the approach taken by this study. These two versions are 1) MOTs are evenly distributed parts of the cognitive trait (see Figure 3-1), and 2) MOTs are not evenly distributed part of the cognitive trait and could overlap with each other (see Figure 3-2).

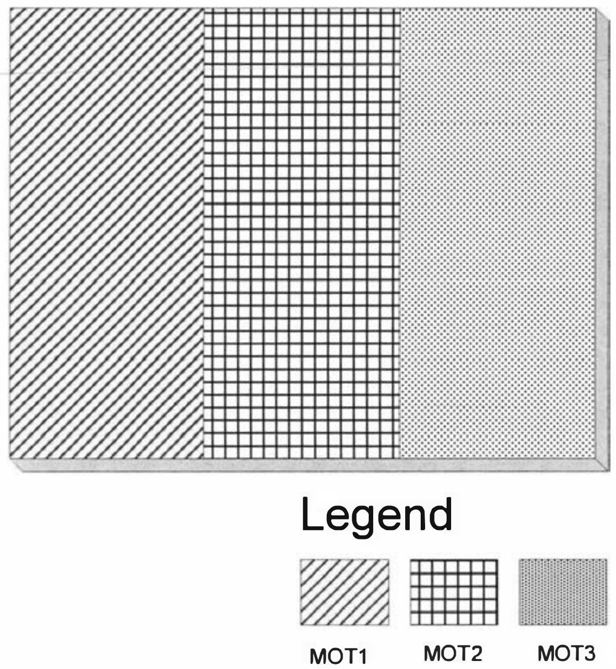

Figure 3-1: Evenly Distributed MOTs

In Figure 3-1, the large 3D rectangular box represents a cognitive trait. Assuming there are three MOTs for the cognitive trait, the three MOTs are evenly distributed inside the cognitive trait and there is no shared area between any of them.

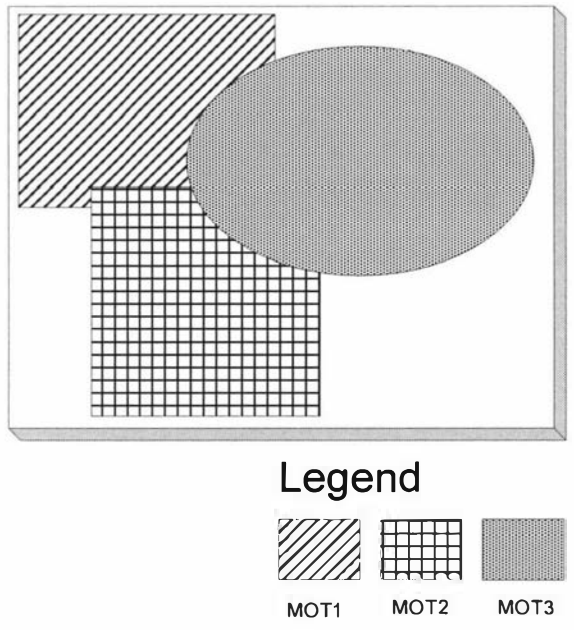

Figure 3-2: MOTs could overlap with each other

The second version allows overlaps and uneven distribution of MOTs. The second version is depicted in Figure 3-2. The three MOTs in Figure 3-2 are allowed to have different shapes and shared area with others.

In terms of graphical models, the evenly distributed version shown in Figure 3-1 can be represented by Figure 3-3A, and the overlapped version shown in Figure 3-2 by Figure 3-3B. The extra hidden layer in Figure 3-3B allows combination of influences from the input layer and can account for the overlapped areas in Figure 3-2.

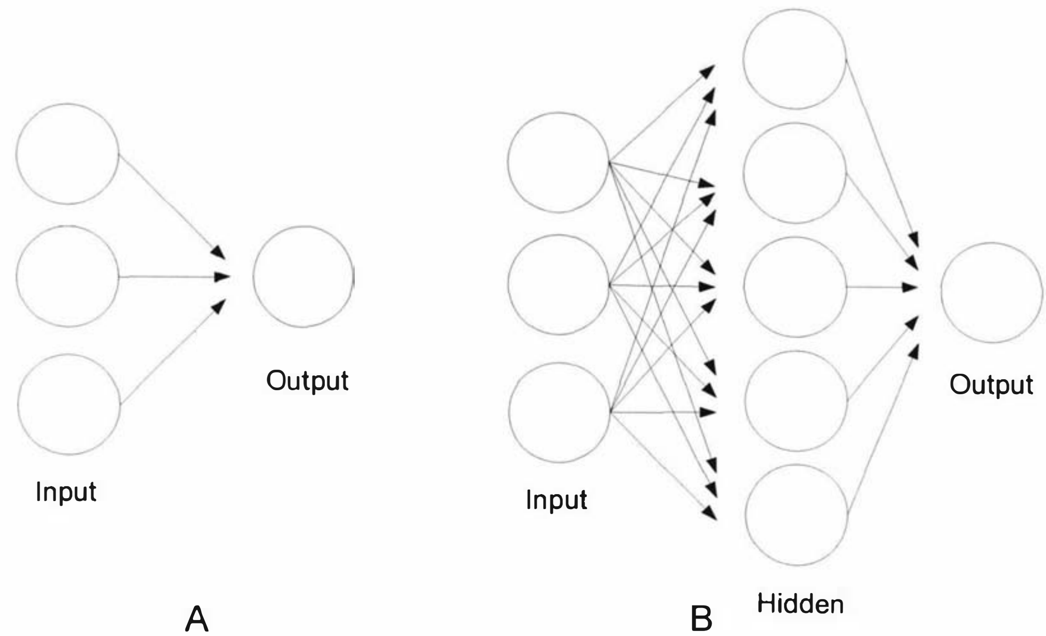

Figure 3-3: Graphic models showing 2 different ways MOTs are structured

The acknowledgement of not being able to clearly discern the relationships of different perspectives rules out the possibility of using the evenly distributed version.

The version shown in Figure 3-2 is potentially more capable to realistically reflect the relationships between different perspectives. The multi-layered graphical model shown in Figure 3-3B is also believed to be more capable of solving complex relationships (Agarwal and Chaudhuri, 1998; Hussain, Yu and Johnson, 1991). Furthermore, if even there is provision for overlap, one MOT does not necessarily overlap to all other MOT. Therefore, the overlapped version is more flexible than the evenly-distributed version. For the reasons above, the overlapped version is selected over the evenly-distributed version in this study.

3.3.2 Individual Differences

No doubt that there are differences in individuals' cognitive traits and how individuals exhibit their cognitive traits. For example, a student might exhibit some MOTs very often and some MOTs very rarely. The MOTs exhibited often are very effective in determining the cognitive traits of the student (therefore said to be *more influential*), other MOTs might not be very effective indicators of the student (therefore *less influential)*. For some students, some MOTs might have a high co-occurrence rate, for other students, they might have other MOTs co-occurring frequently or no co-occurrence at all.

For the individual difference, there are also two different versions: one is the dynamic-degree version (see Figure 3-4) and the other is the dynamic-structure version (see Figure 3-5).

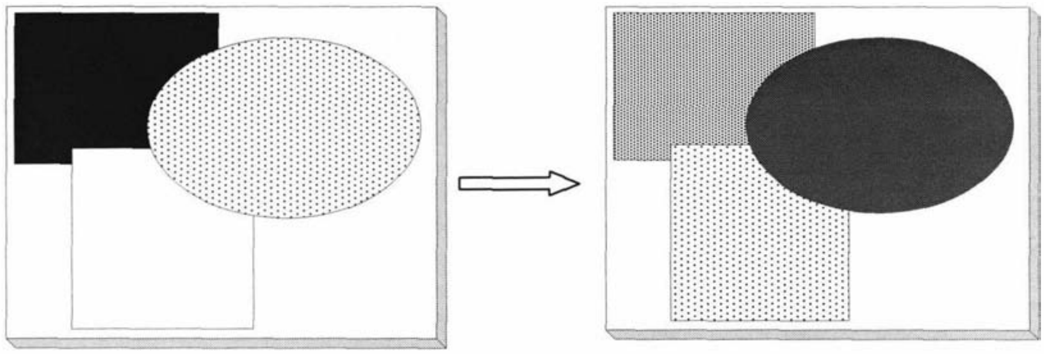

Figure 3-4: Dynamic-degree version of individual difference

In both Figure 3-4 and Figure 3-5, the two 3D boxes represent the same cognitive trait, e.g. working memory capacity, for two different individuals, or they could represent the same individual at two distinct points of time. The 3 different shapes in each 3D box represent 3 different MOTs for the cognitive trait. The different shades represent different degrees of influence.

In Figure 3-4, the structures and relationships of the three MOTs remain the same, but the degrees have changed. This is like saying "more or less". For example, the MOT represented by the oval in Figure 3-4 changes from less influential (lighter shade in left side box) to more influential (darker shade in right side box) in determining the cognitive trait of the student. This dynamic-degree version stresses on the homogeneity, universality and stability of the structures and the relationships of MOTs.

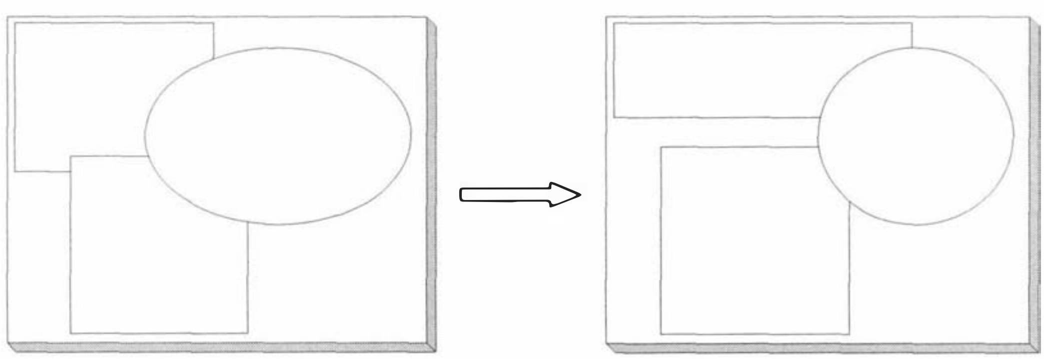

Figure 3-5: Dynamic-structure version of individual difference

In Figure 3-5, different MOTs could change into different shapes and forming different relationships with other MOTs for different individuals or at different points in time for the same individual. This dynamic-structure version stresses on the flexibility and individuality of the structures and relationships of MOTs.

However, it is the dynamic-structure version (shown in Figure 3-5) that was selected in this study. The reason is explained as follows. An MOT, for example, linear navigational pattern, might be very applicable in determining the cognitive trait (working memory) of one student but not applicable to another student. This could be:

1. a result of differences in experimental subjects when the theory was constructed: for example, a conclusion derived from study involving primary school children might not be applicable to a male engineering student in a tertiary institution.
2. caused by statistical incompleteness (type I error): while a research concludes that its statistics shows that subjects tend to behave in a certain way in a certain condition, it is actually saying that more than a certain percentage of subjects (e.g. 95% or 97%) who participated in the study behaved in the said way in the said condition. What about the other 5% or 3% of subjects in the study? What about other people who did not participate in the study? It is possible that there are types of people for whom the conclusion does not hold true.

It needs to be pointed out that the size of the shapes in the dynamic-structure version (Figure 3-5) can be construed as the degree of influence of the MOT over the cognitive trait. As very large shape in Figure 3-5 could be construed as one of the input node in Figure 3-3 with very large weight: its activation has a great degree of influence on the output of the entire cognitive trait Furthermore, in the dynamic-structure version:

1. if it needs to, a relationship between 2 shapes (MOTs) in the dynamic-structure version could remain same across individuals as some psychologists believed the structural in-variance of cognitive abilities (Schaie, Willis, Jay, & Chipuer, 1989).
2. if it needs to, an MOT could remain its shape and size as some researchers pointed out regarding the stability of the cognitive traits (Park, et al., 1999; Waters and Caplan, 1996).

It is obvious that the dynamic-structure version is more encompassing and more continuous as per results of researches pointed out above. It is therefore more plausible to assume the dynamic-structure version than the dynamic-degree version.

The choice of dynamic-structure version can also be justified theoretically. In chapter 1, we mentioned the two different versions of relativistic empiricism. The first version is held by humanist and it means the truth lies in the immediate human experience and is relative to each perceiver (Leahey, 1996). The second version is the position of this research and it refers to the use of student behaviours to infer about the degree of truth different theories about cognitive trait have on different students. The degree of truth is believed to be relative to each student. There is no contradiction about these two different versions. On the contrary, we can point out a causal relationship between these two different versions by using Vernon's (1979) definition of intelligence.

"Intelligence A is the basic potentiality of the organism, whether animal or human, to learn and to adapt to its environment...Intelligence A is determined by the genes but is mediated mainly by the complexity and plasticity of the central nervous system...Intelligence B is the level of ability that a person actually shows in behaviour---cleverness, the efficiency and complexity of perceptions, learning, thinking, and problem solving. This is *not* genetic...Rather, it is the product of the interplay between genetic potentiality and environmental stimulation...I have suggested that we should a third usage to Hebb's Intelligence A and B, namely Intelligence C, which stands for the score or IQ obtained from a particular test (Vernon, 1979, pp. 10)."

The important point is about Vernon's (1979) definition of Intelligence B. It is a product of learning – it entails that certain cognitive abilities is shaped/caused by learning. In chapter 1, we have also discussed about two definitions of relativistic empiricism. The first is a general version stated that each individual construes "truth" differently (Leahey, 1997). The second version is of this study and pointed out that although each different theory of a cognitive trait holds a certain degree of truth about the cognitive traits of students, the degree of truth is relative to each student. There is no contradiction between these two versions. In fact, they can be linked together using Vernon's (1979) work.

If this definition of the first version of relativistic empiricism and Vernon's (1979) definition of Intelligence are right and the second version of relative empiricism should logically happen. That is, if we learn from our experience, which is defined to be relative in the first version, then the relative experience causes different learning. Different learning in turn develops different cognitive abilities that are defined in version 2. The difference in cognitive ability will certainly reflect different degrees of truth for theories of cognitive trait and therefore supports the dynamic-structure version than the dynamic-degree version shown in Figure 3-5.

3.4 Persistent Cognitive Trait Model

The term "persistent" is used to indicate that the cognitive trait model (CTM) is quite stable over a long period of time. The terms "persistent" and "stable" used here does not mean "no change", but rather "gradual or slight change". For a student taking a course from ages between 18 to 21, there could be no obvious change in the cognitive traits. But there may be a gradual change from age 18 to age 80. Three cognitive traits are analysed in this study. Regarding to their "persistency", each of the cognitive traits is studied separately in the following subsections.

3.4.1 Persistency of Working Memory

Recent researches have suggested that working memory (WM) deficiency is the cause of schizophrenia (Aleman et al., 1999; Park, et al., 1999). Park et al. (1999) studied working memory function in relation to clinical symptoms of schizophrenia over the period of 4 months. They found that there was no change in WM scores after the 4 months period for normal subjects; for schizophrenia patients, even though there were slight improvements in the WM score, there were still a significant correlation of WM scores between the first test and the test after 4 months.

Waters and Caplan (1996) also did a longitudinal study for a period of 3 months and obtained a test-retest reliability of 0.65 and 0.66 for two of the WM tests they used.

Waters and Caplan had also reported a similar study done by Tirre and Pena in 1992 with a test-retest reliability of 0.727 of WM tests.

Salthouse and Babcock's (1991) study involving 460 adults between 18 and 87 years of age found that 1) the working memory score has a negative correlation to age and 2) the change of working memory score with respect to age difference was only gradual.

Even though it is hard to find longitudinal studies about the stability of working memory that span across decades, the stability of WM is often assumed for adults before "old age". There is an implicit assumption about the persistency of WM in Salthouse and Babcock (1991) study: instead of comparing WM difference for every year of age, they used decades. Laumann's (1999) study, which compared younger adults and older adults on their performance with respect to working memory capacity, inductive reasoning ability, pair-associative learning and vocabulary tests, used a range of 16-26 as younger adults and 61-90 as older adults. Again, the trace of WM persistency assumption can be found in Laumann's (1999) study.

3.4.2 Persistency of Inductive Reasoning Ability

Schaie and Parham (1977) had noted that actually observed age decrement did not reliably appear for primary mental abilities, for which the speed of response was not critical, until the age after sixty, and the decrement was of relatively limited magnitude. They used Thurston's seven primary abilities, namely Verbal Meaning, Space, Inductive Reasoning, Number, Word Fluency, Intellectual Ability and Educational Aptitude. Study of Schaie and Parham (1977) involved measurements data of 2,151 subjects from the first test and repeated measurement data for 723 subjects. They found that reliable age-related changes (with the exception of the highly speeded Word Fluency measure) cannot be observed prior to age 67.

In Schaie and Willis's (1986) 14-years longitudinal study of 229 older adults (with mean age 72.8 years), 107 subjects (46.7% of sample) were classified as having remained stable on inductive reasoning ability (the stable subjects) and 122 were classified to have declined inductive reasoning ability (the decline subjects). Definition of decline was 1 standard error (SE) of measurement or greater. Within the 107 stable subjects, 37.8% had declined, but not greater than 1 SE whereas the other 63.2% of the stable subject did not have any significant decline in inductive reasoning ability. Although the actual stable subjects account for only 29.51% (46.7% * 63.2%) of the total number of subject, given the advanced age of the subjects (mean age 72.8) in which decline of cognitive ability is believed to be rapid (Schaie and Parham, 1977), inductive reasoning ability is still quite stable.

3.4.3 Persistency of Divergent Associative Learning

Divergent thinking is a cognitive style (Bahar and Hansell, 2000; Hudson, 1966; Kolb, 1984). Cognitive styles are "ways individuals react to different situations and they include stable attitudes, preferences, or habitual strategies that distinguish the individual styles of perceiving, remembering, thinking and problem solving" (Bahar and Hansell, 2000, p350). The conception of a style, in and of itself, implies long term stability. The stability has been reported as extending "not only over weeks and months, but over years" (Bahar and Hansell, 2000, p350).

Divergent associative learning (DAL) is believed to inherit the stability of divergent thinking because the difference between DAL and divergent thinking is not in the process but is in the end product: DAL produces associations, and divergent thinking produces new ideas.

Associative learning is the other part of DAL. The deficiency in associative learning in old age is believed to be largely due to perceptual speed (Salthouse, 1996). Perceptual speed is highly related to working memory. Dunlosky, Hertzog, and Powell-Moman's (2005) findings suggest that the deficiency of associative learning is closely related to the deficiencies in encoding and decoding which happen in working memory. Associative learning is therefore believed to share the stable and persistent characteristic of working memory. Divergent associative learning is therefore believed to be persistent because of its two persistent constituents – divergent thinking and associative learning.

3.5 Structural Overview of Cognitive Trait Model

Cognitive trait model (CTM), a student model that profiles students according to their cognitive traits, could be structured as shown in Figure 3-6 (Lin, Kinshuk, & Patel, 2003). Different components are identified according to functions necessitated by:

1) the target system (i.e. hypermedia-based learning environment): the Interface Listener Component and Action History Component;
2) the adopted approach to aggregate different perspectives and therefore treat the *perspective difference* of CTM: the MOT Detector Component; and
3) the aim to cater for *individual difference*: the Individualised Trait Networks Component.

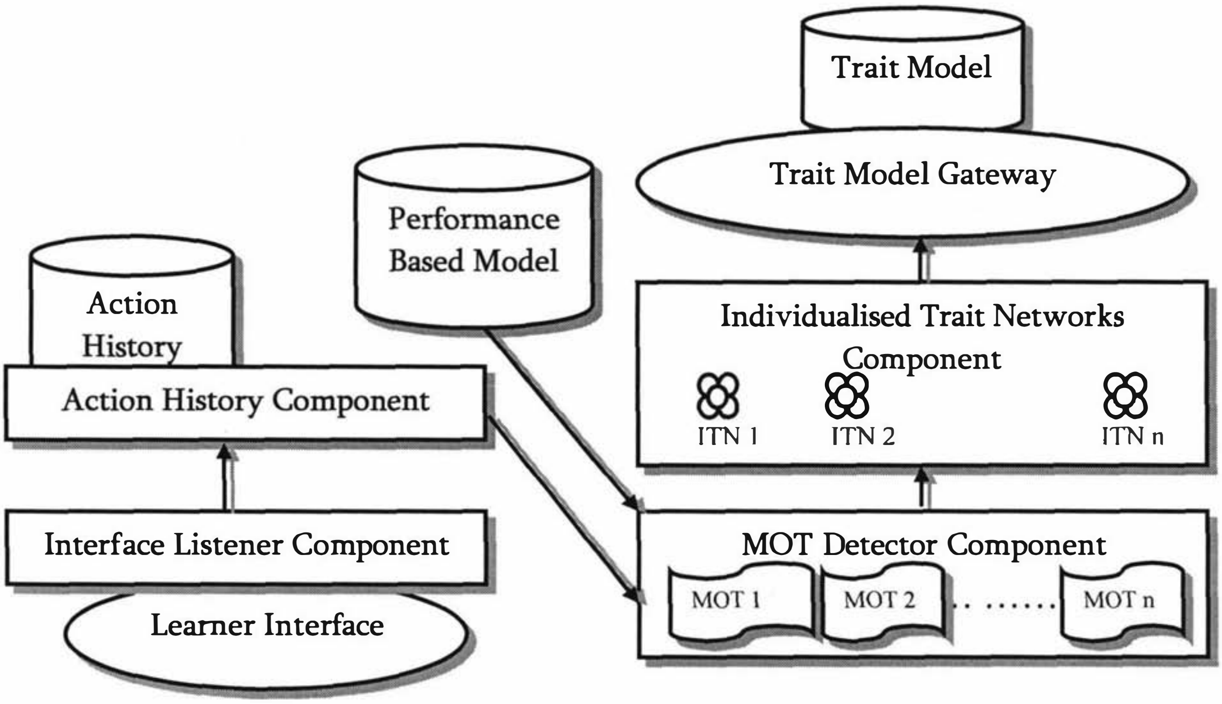

Figure 3-6: Structure Overview of Cognitive Trait Model

The learner interface provides a presentation of the learning system to the learners for all possible interactions. In web-based systems, the learner interface is generally implemented inside a web browser. Due to the stateless nature of the HTTP protocol used by web browsers, it is necessary to embed a mechanism that can monitor events created by a learner's interactions within the learning system. The mechanism is represented by the Interface Listener Component in Figure 3-6. Series of learner actions are then passed on to the Action History Component and are stored in Action History.

CTM is complimentary to the performance-based student models that already exist in learning systems. Learning systems can use the information in CTM to provide cognitive-trait based adaptation (Beck, Jia, and Mostow, 2003; Guzman, and Conejo, 2004). Performance-based student models represent learners' domain competence and model the problem-solving process that the learners undertake. Learning systems can provide domain-based adaptation using the information in performance-based models. Performance-based models can also provide information regarding a learner's knowledge background in a domain which can also be used to infer the learner's cognitive traits. Relationship between domain knowledge background and cognitive traits is discussed in later chapters.

Certain learner behaviours, called manifestations of trait (MOTs) in this study, can be used to infer cognitive traits of learners. Information gathered by performance-based models, such as passing or failing a unit, can be useful for detecting MOTs of some cognitive traits, and therefore is used as a source by the MOT Detector Component. Each MOT is a piece of an interaction pattern that manifests certain learner cognitive trait (e.g. low inductive reasoning ability). The MOT Detector Component detects those MOTs among the series of actions recorded in the Action History Component.

Chapter 6, 7 and 8 are dedicated to the discussions of MOTs of the three cognitive traits.

The Individualised Trait Network (ITN) Component in Figure 3-6 assigns each detected MOT to one of the ITNs. Each ITN represents one cognitive trait and has a number of weighted nodes in itself. The number of nodes depends on the number of MOTs of the cognitive trait the ITN is representing. The weights of nodes get updated after each learning session, similar to how a neural network updates itself and learns (Bar-Yam, 1999). Each ITN is an instance of a type of network called multiple portrayal network which is discussed in detail in chapter 5. The mechanism used in ITN is also explained in more depth in chapter 5. The results of executions of each ITN are then saved in the Trait Model via the Trait Model Gateway.

Technically, the Trait Model, the Action History, and maybe the Performance-based Model are databases. The Action History Component and the Trait Model Gateway are interfaces between the actual program logic and the databases. These two interfaces allow rapid system adoption for educational institutions that may use different types of databases. The Performance-based Model in Figure 3-6 is an abstracted database from the actual performance-based model in the learning system. Different kinds of performance-based models have different forms of implementation and may need different plug-ins or application program interface (commonly known as API) to communicate with. The abstracted Performance-based Model works to simplify the logic in the MOT Detector Component.

3.6 Conclusion

It has to be clearly understood that CTM is not meant to replace performance-based student models but to complement. Performance-based student models record dynamic student-specific and domain-specific data and can be used to provide performance-based adaptivity, whereas CTM stores cognitive traits of students and can be used to provide adaptivity based on students' cognitive traits. Both types of adaptivity can be used alone or they could be used in conjunction with each other to provide even more holistic adaptivity. The overall structure of CTM shown in Figure 3-6 includes also an abstracted performance-based student model in the learning system – it shows how CTM and performance-based student model can work together.

This study is not claiming CTM to be domain-independent in an absolute sense because the approach adopted in this study includes different factors that influence cognitive traits. As discussed in chapters 7 and 8, domain knowledge happens to be an influencing factor for both inductive reasoning ability and divergent associative learning. Domain knowledge is taken as one of the MOTs for both inductive reasoning and divergent associative learning. Once a student moves from one course to another, the domain knowledge MOT can just be reset to "low" again assuming "low domain knowledge" is the motivation why the student wishes to enrol in the new course.

With these two characteristics of domain-transcendence and persistence, the role of CTM is no longer just a traditional student model passively sitting in the server waiting to get expired when the student finishes the course. *CTM becomes more of a learning companion*. It enables the student to carry the CTM around in a portable media or stored in a location on the Internet that could be accessed by a universal resource identifier (URI). The information of a student can then travel with the student to different educational institutions, and different learning environments (classroom, computer laboratory, Internet Café, field-trip, and so on).

CTM could also take on the "*personal consultant role*". Once there is a CTM developed for a student, if a student enrols in a new course of study, the CTM can be made available to the new learning management system which could then provide the right level of adaptivity to the student right from the beginning of the course. The learning management systems could consult the CTM of the student if they (or their designers) want to offer learning material adapted to the student's cognitive traits and wish the student to have satisfactory learning experience.

The student's behaviours and actions in the new course can again feedback and update the CTM which will be ready once more for future study. So if the CTM is first developed for a student when the student is 20 years old, as long as the student keeps updating the CTM, the CTM would still be able to be representative for the student's cognitive trait when the student is 60 years old. This is also a reason that this study is not claiming the persistence of CTM in an absolute sense – persistence of cognitive trait in several years is practical enough.

3.7 Summary

The aim of this study is the development of cognitive trait model (CTM). CTM allows learning systems to provide fine-tuned system adaptivity to support the cognitive processes of students during learning.

The domain-transcending characteristic of CTM is made available because of the all-inclusive approach adopted by this study, that is different perspectives are all included. Domain knowledge is taken as one of the influencing factors of cognitive traits. The persistent characteristic of CTM can be claimed due to the persistency in the three constituent cognitive traits.

The domain-transcending and persistent characteristics of CTM make it a student model very suitable for life-long learning. The need of CTM is further stressed by the popularity of student-oriented theories and practices in educational systems nowadays.

MOT Detector Component and Individualised Trait Network Component in Figure 3-6 are the two components in cognitive trait model that require special attention. These two components are each discussed in the following two chapters in detail.

CHAPTER 4

Semantic Relation Analysis

4.1 Introduction

Semantic relation analysis is a method used to analysis student behaviours in the MOT Detector Component in cognitive trait model. The idea of semantic web allows the analysis of student behaviours using the semantic relations. Semantic web is emerging as a powerful paradigm for managing web content in the ways that are meaningful to computers (Berners-Lee, 2003; Berners-Lee, Hendler, and Lassila, 2001). In order to allow computers to make sense out of the content, metadata of web content needs to be created in a standardised format. Technological tools to append semantics to content include Resource Description Framework – RDF (W3C, 1999a), and RDF schema (W3C, 1999b). RDF uses eXtensible Markup Language (XML) and Universal Resource Identifier (URI) to provide machine understandable format so that automated processing of Web resources would be possible. RDF schema is a language to define kinds of, and properties of resources being described by the RDF that instantiates the schema.

Ontology, according to Berners-Lee's (2003) Semantic Web Stack, is a level higher than RDF Schema and therefore is capable of containing richer semantic information than RDF Schema. According to Cristea (2004), ontologies *"are constructed from structured vocabularies and their meanings, together with explicit, expressive and well-defined semantics"*, and ontologies makes knowledge reusable by featuring classes, instances, relationships of classes, properties of classes, functions of classes, and constraints and rules to use classes.

With wider adoption of semantic web, a great opportunity is arising: cognitive trait modelling by the semantic relationships. Activities of learners on the web have been recognised as a source to provide information about the learners (Loeber, and Cristea, 2003; Mullier, 2000). Traversal of the web pages can therefore be represented as a series of activations of relationships that exist between the traversed pages. If certain pattern of occurrences of relationships can yield information about the learner (or software agent), be it preference, characteristics, cognitive capacity or goal, interpretations can then be made.

This chapter introduces a novel approach called *semantic relation analysis* (SRA) for analysing learner's navigational pattern among learning objects in subject domain. Based on the learner's behaviour/action patterns, this approach is capable of performing domain-independent analysis. Revisiting the structural overview of cognitive trait model (see Figure 4-1), semantic relation analysis happens in the MOT Detector Component. SRA is used to analyse learners' online behaviours in order to find indications (MOTs) of cognitive traits.

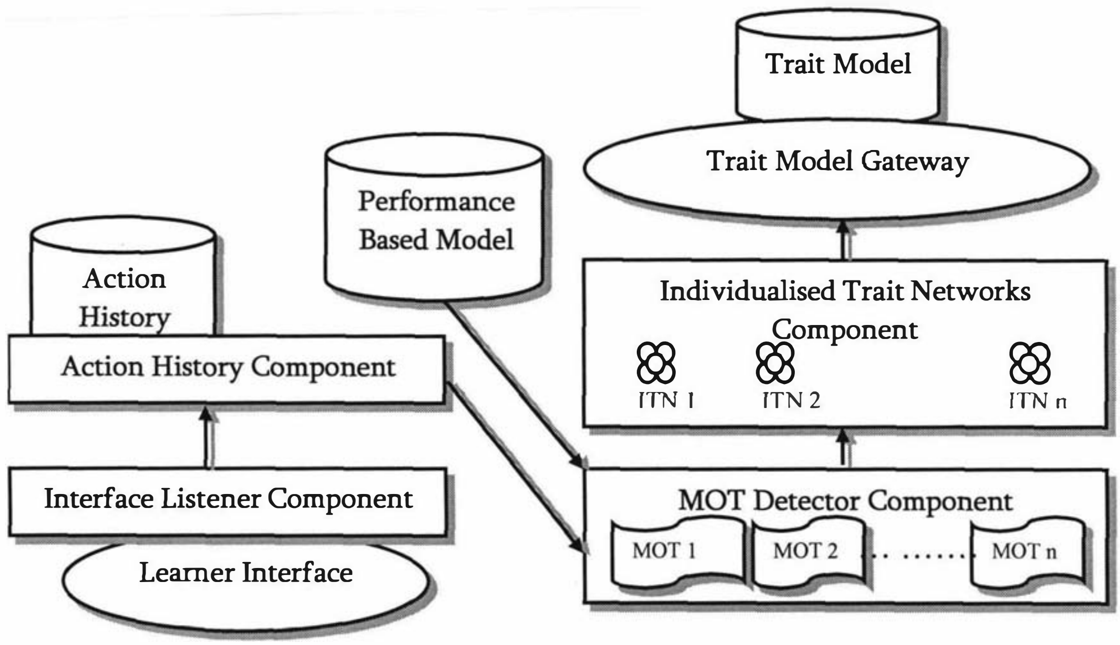

Figure 4-1: Structure Overview of Cognitive Trait Model

Because learning object relations are the basic unit of analysis in SRA, this chapter starts with a discussion of learning object relations in section 4.2 . Then, an overview of existing approaches of navigational pattern analysis is presented in section 4.3 . Section 4.5 then discusses semantic relation analysis. Finally, section 4.5 gives a conclusion and summary of this chapter.

4.2 Learning Object Relations

A learning object in a learning context may relate to other learning objects in the same context or outside the current learning context. In hypermedia learning environments, relationships of learning objects could be instantiated as links and they provide means of navigation in the learning system. If all learning objects are thought to be nodes in the hyperspace of learning, then their relations are the connections from node to node.

In every learning system, learning objects relate to learning objects differently. For example, two learning objects (say B1 and B2) may be related to another learning object (say B) by an "IsPartOf" relation, whereas learning object B may be related to each learning object B1 and B2 by a "HasPart" relation. There are many types of relations among learning objects, and they can be put into categories such as IsPartOf and HasPart. LTSC (2002) has defined 12 different types of categories based on Dublin Core which is a set of metadata used in digital libraries for describing digital objects, collection management and exchange of metadata (http://dublincore.org/).

Categorisation of relations enables semantic relation analysis to be domain-independent, which is the most important advantage of content-less navigational pattern analysis over content-based analysis. In addition, semantic relation analysis still contains some semantic information about the relation of the learning objects, which makes it possible to perform analysis that combines the strengths of content-base and content-less analysis.

By LTSC's (2002) definition, any single relation must be directional and binary (learning object A to learning object B), as illustrated in Figure 4-2.

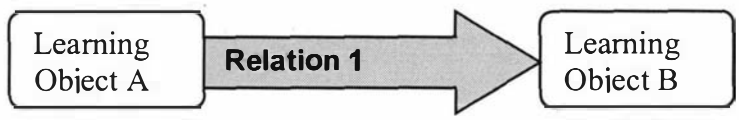

Figure 4-2: Direction of relation

However, every learning object can have more than one relation (see Figure 4-3).

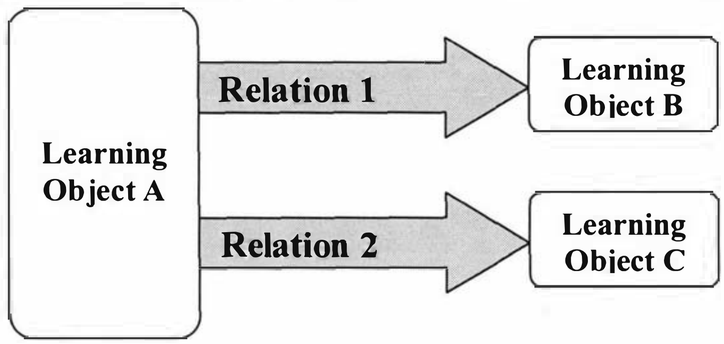

Figure 4-3: Multiplicity of relations

Relations are abstractions of hyperlinks and they can also be categorised. As stated above, the LTSC's (2002) definition is the basis for relations that are used in this work. The intention is to be as "conforming" as possible to LOM standard and maximise semantic interoperability, so that there will be only extensions of the LOM's relations, not replacement of them. In the description of learning objects' relations, LTSC (2002) proposed that relations are those that a learning object may have towards other learning objects, and relations include IsPartOf, HasPart, IsVersionOf, HasVersion, IsFormatOf, HasFormat, References, IsReferencedBy, IsBasedOn, IsBasisFor, Requires, and IsRequiredBy.

Study on adaptive multimedia had already identified and categorised different types of links used in web-based learning systems, and these links are therefore used more frequently in the context of discussing and developing learning environments (Kinshuk et al., 1999). When considering the expansion of the existing set of relations to satisfy the need for more descriptive relations, the types of links provided by Kinshuk et al. (1999) can be identified as follows:

- Direct successor links – They are the links that lead to the successive domain concept/unit after the learning task in current concept/unit is fulfilled.
- Parallel concept links – They are the links that lead to the analogous concepts that are related to the domain concepts. Comparison and contrast are available through those links for those who wish to increase their knowledge in width.

- Fine-grained links – They are the links that lead to detailed explanation of the current concept. They provide and preserve finer granularity of domain concepts, more accurate and more specific information to those who really need in-depth understanding.
- Glossary links – They are the links that lead to the definitions of domain concepts/terms.
- Excursion links – They are the links that lead to related learning that is usually outside of the current context. They are the sources where learners can find other related knowledge of their interests, and also create the possibility for accidental learning to take place (Reisberg, 1997).
- Problem links – They are the links that lead to problems/exercises of the unit.

IsPartOf and HasPart define learning object's hierarchical relationship. IsVersionOf and HasVersion describe that one learning object is an instantiation of another one. IsFormatOf and HasFormat are used to specify the format information that a learning object contains of another one. Referential relationships are catered by References and IsReferencedBy. IsBasedOn and IsBasisFor relations describe that a learning object is fundamental to another and finally, Requires and IsRequiredBy point out the prerequisite relationships.

These relations proposed by LTSC (2000) are based on Dublin Core and provide a thorough coverage of relationships among data. A notable similarity exists between the LOM's relations and the links described in Kinshuk et al.'s (1999) types of link. The comparison is discussed below.

The direct successor link can be expressed by the IsBasedOn and IsBasisFor relations because the succeeding is based on its successor. The IsPartOf and HasPart relations' hierarchical nature best suit the definition of the fine-grained link. The glossary link can be substituted by the References and the IsReferencedBy relations. Any other learning objects particularly designed for referential purposes can use those relations, and therefore glossary links are only a subset of References and IsReferencedBy relations.

The other three types of link are not addressed by those of LTSC's (2002) relations – they are parallel concept link, problem link, and excursion link. These three types of link are not covered by LOM's terminology and needed further explication. Parallel concept links lead to analogous concepts that are related to the current concepts in focus. Parallel concept links occur frequently in comparative studies and in explanations of a theory or principle's applications. An example of parallel concept could be the cause of raining and the formation of dew on the window. This type of link (relation) between learning objects occurs frequently in educational context because the ability to create analogies and to be able to utilise theories for practical purpose are highly valued (Holland et al., 1987). Therefore, one relation is named "Parallels" as an extension of the current LOM's set of relations (LTSC, 2002).

Problems/questions provide evaluation for the learning – a problem link points to an evaluation unit of the learning topic. An evaluation unit is expected to be a learning object in this discussion and will be called an evaluative learning object. Therefore, there are two new types of relations required for this purpose: Evaluates and EvaluatedBy.

Excursion links occur frequently in web-based systems. Excursion links lead to other learning objects, which are usually outside of the current learning context/curriculum, but are related to the current learning object. Reisberg (1997) pointed out that excursion links provide chances for accidental learning to take place, and therefore may lead to a much wider learning experience. This type of relation is rare in traditional learning media (books or videotapes) due to the limitations of traditional media which is perhaps the reason that it is not considered as necessary in Dublin Core's specification and subsequently in LOM. Considering that Wiley (2000) deliberately defined learning object to be Internet-based, there is an obvious need to include this new relation in order to provide more descriptive relations of Internet-based learning objects. The new relations are named here as ExcursionTo and IsExcursionOf.

A learner's interactions with the learning environment are represented by the sequence of activation of learning object relations. Semantic relation analysis is used to discover information about the learners, and more particularly it is used to discover information about the learner's cognitive traits (e.g. working memory capacity). In chapter 6, 7, and 8, examples are given showing how to use semantic relation analysis to detect those learner behaviour patterns that indicates learners cognitive traits (the behaviour patterns are called MOTs in this study).

4.3 Existing Navigational Pattern Analysis Methods

The navigational behaviours of learners are seen by many researchers as an important parameter for understanding aspects of the users (Loeber, and Cristea, 2003, Mullier, 1999; Sun, and Ching, 1995), and hence valuable resources for the construction of student models. There are two most dominant navigational pattern analysis methods in the literature: *content-less navigational pattern analysis* and *content-based navigational pattern analysis*. Each of them is described in detail next.

4.3.1 Content-less Navigational Pattern Analysis

In content-less navigational pattern analysis (Mullier, 1999), every web page is treated as a node in the hyperspace, and every node is treated equally regardless of its content. Relationships between the nodes are not defined. The focus is on the navigational behaviours, and certain navigational pattern may indicate certain type of navigational approach, which can reveal what the learners are actually doing. Content-less analysis method can identify activities such as scanning, browsing, searching, exploring, and wandering (Mullier, 1999). The most important advantage of content-less navigational analysis is its domain-independence, which makes it reusable across different domains and systems.

However, its domain-independence makes it inaccurate in specific situations; following is an example to illustrate this point. While frequently revisiting a particular node may give impression that the learner's working memory capacity is not sufficient enough to allow the learner to proceed on the course smoothly, but if the frequently revisited node is a reference node (e.g. a periodic table or a list of function names and their parameters) then it is perfectly sensible that every (or nearly all) learners need to revisit the node frequently. Content-less analysis would not be able to differentiate a reference node from an ordinary node. Inaccuracy is the main disadvantage of content-less analysis.

4.3.2 Content-based Navigational Pattern Analysis

The other approach is called content-based navigational analysis (Mullier, 1999). It is the primary analysis method for performance-based student models (e.g. Lu et al., 2005; Mitrovic and Ohlsson, 1999; Staff, 2001) which record learners' progresses and grades in subject domains. The contextualised semantic information of every node is recorded by the learning system and by the learner's progress based on the semantic information in the concept map or ontology of the domain. The learning system then makes inferences about the learners (their interests, skill levels, and so on), and stores these inferences in a student model. Mullier (1999) pointed out that the most serious drawback of the content-based approach is that it is totally domain-dependant, which means that similar efforts of analysis have to be carried out for every new domain or course. If domain ontology is modified, inference rules may need to be laboriously re-written as well.

Given that web pages in the learning system are treated as learning objects, information about the relationship of learning objects is becoming more widely available with the popularity of semantic web, especially in subject domains where ontologies already exist (Lee, Ye, and Wang; 2005). The semantic relationship can become a great source of navigational pattern analysis.

4.4 Semantic Relation Analysis

Semantic relation analysis (SRA) is developed in this study by adopting the advantages from both content-less and content-based analysis methods. Learning object relations are used as the basic units of analysis. Because the learning object relations are not directly dependent on any domain, SRA is therefore domain-independent. Let's use an example to illustrate semantic relation analysis.

In chapter 6, we will see that "reverse navigation" is an indicator of working memory capacity. Constant reverse navigation can be interpreted as the inability to hold on to information just perceived, and therefore a sign of low working memory. Assuming the learning object relations IsBasisFor and IsBasedOn are used to link two sequentially related learning objects, then we can use IsBasedOn to represent "reverse navigation". That is, the activation of the IsBasedOn relation denotes that the learner has reversely navigated back to a previously learned page and therefore manifested a sign of low working memory.

Why use learning object relations when we can just use a script to detect whether the "Back Button" of the browser is pressed? The reason is because learning object relations give us more semantic information about the two pages involved in a navigation so that we can avoid misjudgements such as mistakenly thought a re-visit to a reference page (e.g. periodic table) as a "reverse navigation because of low working memory".

The above is only one of the examples of using SRA to analyse student behaviours. In the discussion of MOTs of cognitive trait in chapters 6, 7 and 8, more uses of SRA can be seen.

4.5 Discussion and Summary

Semantic relation analysis was made possible by the endeavours to append more semantics in the web, i.e. the trends to employ semantic web instead of tradition WWW. Existing standardisation of learning objects, such as LOM, provides a well-structured basis for applying semantic relation analysis in learning context. The discussion in this chapter offers examples of how the extendibility of LOM standard (LTSC, 2002) could be utilised to cater for the features of current technologies. Parallel concept links, problem links, and excursion links are very commonly used nowadays in web-based learning systems (Kinshuk et al., 1999); the existing Relations in LOM (LTSC, 2002) are not sufficient to cover them. Thus Parallels, Evaluates/EvaluatedBy and ExcursionTo/IsExcursionOf are developed as extension of LOM's relations. There are total 15 relationships used in this study:

1. EvaluatedBy
2. Evaluates
3. ExcursesTo
4. IsExcursionOf
5. HasPart
6. IsPartOf
7. IsBasisFor
8. IsBasedOn
9. References
10. IsReferencedBy
11. Requires
12. IsRequiredBy
13. HasExample
14. IsExampleOf
15. Parallels

The semantic relation analysis has the advantage of domain-independence that is similar to that of the content-less navigational pattern analysis. However, it has more semantic information than what the content-less navigational pattern analysis could offer and thus is more or less free of the inaccuracy problem embedded in the content-less navigational pattern analysis. Because of its domain-independence, once an analysis task is done, it is possible to reuse the results in new domains without having to carry out the same analysis task again.

In chapters 6, 7, and 8, demonstrations are given about how to apply semantic relation analysis in cognitive trait modelling. It is also believed to be a potential method to obtain information about learners or users should there be more semantic information added into the Internet and therefore it is also listed as one of the future research possibilities in chapter 18.

It has been pointed out that the semantic relation analysis is mainly used in the MOT Detector Component (see Figure 4-1). After detection of MOT, the results are sent to the Individualised Trait Network Component which is an implementation of multiple portrayal network. Multiple portrayal network is discussed next.

CHAPTER 5

Multiple Portrayal Network[1]

5.1 Introduction

Cognitive trait model (CTM) is a student model that profiles the learner's cognitive traits. Working memory capacity, inductive reasoning ability and divergent associative learning are cognitive traits investigated in this study. By using the profiles created by CTM, adaptive computer-supported learning environments can adapt the content to suit individual learner's needs based on his/her cognitive traits (Lin, Kinshuk & Patel, 2003).

With the aim to accurately profile learners' cognitive traits, extensive amount of literature studies on cognitive traits were carried out. Taking working memory as an example, cognitive scientists developed different theories and perspectives for working memory capacity: Baddeley (1992) decomposed working memory into its components and studied it structurally; Salthouse and Babcock (1992) and Daneman and Carpenter (1980) viewed working memory as a process; and Atkinson and Shiffrin (1968) defined working memory functionally as the gateway allowing information to be transferred to the long-term memory. Some researchers developed models about working memory capacity whereas others studied it experimentally. An empirical study by Huai (2000) showed that students with holistic learning style (prefer the big picture view) have significantly smaller working memory than students with serial learning style (highly capable to follow and remember sequentially fixed information). All these different theories/experiment-results provide different views to the same entity: working memory capacity. The different views on working memory capacity are analogous to different portrayals of the same physical object. When viewing a physical object from different angles, it results in different portrayals (images).

In discussing different intelligence theories, Sternberg (1990) contended that different "metaphors of mind" guide different theories about human intelligence. In Sternberg (1990), geographic, computational, biological, epistemological, anthropological, sociological, and systems metaphors are listed. Different metaphors provide different views to intelligence and lead to different research programmes, different questions, and different answers. Baer (1993, p95) asserted that "the theories deriving from different metaphors provide different glimpses of the 'true' nature of intelligence". Sternberg (1990) therefore argued that theories based on different metaphors can

[1] The discussion of this chapter include concepts called manifestation of traits (MOTs) which are fully discussed in chapters 6, 7, and 8. For some readers, it might be benefit if they read chapter 6 before commence reading this chapter. Simulation and validation of the work introduced in this chapter is presented in chapter 9. Interested readers can go to chapter 9 to find out more of it.

provide one another important insights, and *theories arising from diverse approaches might be profitably combined to build more inclusive theories.*

Although, differences, even we are told to value them in a democracy, become problem statements for those who try to understand the cognitive traits. In this study, we propose a mechanism, called *multiple portrayal network* (MPN) that is capable of representing an entity that the relationships of its portrayals are difficult to know. MPN is also able to evolve itself based on the behaviours of individual learners in order to provide more accurate profile of the learner.

In order to present the works about MPN, the overall structure of CTM is briefly revisited in next section to serve as the background information regarding where MPN fits into current study. Detailed description of MPN is then presented. Theoretically, MPN is also one type of machine learning; its relation to other machine learning techniques, especially to artificial neural network, is also briefly mentioned. Finally, we conclude this chapter by a discussion of the benefits and limitations of MPN.

5.2 Cognitive Trait Model and MPN

Figure 5-1 shows the overall structure of cognitive trait model (CTM). The Individualised Trait Networks Component in Figure 5-1 contains one to many Individualised Trait Networks (ITNs). Each ITN represents one cognitive trait. After the MOT Detector Component finishes detection of MOTs, it sends the result to the Individualised Trait Networks Component.

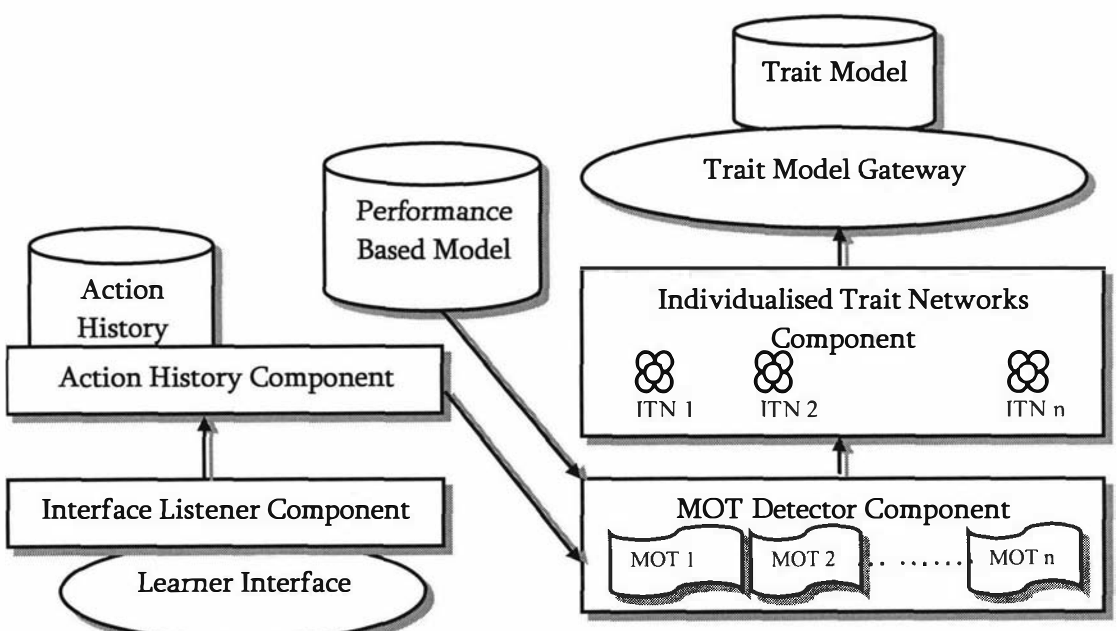

Figure 5-1: Structure Overview of Cognitive Trait Model

Each node in an ITN corresponds to one MOT (e.g. non-linear navigational pattern) of the cognitive trait that the ITN represents (e.g. working memory). The major function of any ITN is to calculate the value that represents the corresponding cognitive trait.

Once a particular MOT is detected from the learner's actions, the corresponding node is activated. The result of the execution of an ITN determines how the nodes in the ITN should be updated. The results of the execution of the ITNs are then sent to the Trait Model Gateway, which is responsible for all the transactions to the Trait Model.

Each ITN in the Individualised Trait Networks Component is an instance of a type of network we called *multiple portrayal network* (MPN). ITN is the name of MPN used in cognitive trait model whereas MPN is the general name of this type of network that is not bounded to a single application. Undeniably, MPN is resulted from the investigation of cognitive trait model, but the intention is to generalise it to make it usable in other applications as well. Cognitive trait model can then be taken as one of its example application – the term MPN is used hereafter in this chapter.

5.3 Multiple Portrayal Network

Multiple portrayal network (MPN) is a network representation of an *entity* of which the constituents are nodes N. $N = \{n_0 \ldots n_n\}$ Each node n_i is a *partial portrayal of the entity*. The overall value of the entity, O, is determined by its constituent nodes. Each node n_i contains a numerical value called *weight* w_i which determines the node's influence over the overall value O of the entity. Figure 5-2 depicts an example of MPN consisting of three nodes.

Figure 5-2: Example of a 3-node MPN

As shown in Figure 5-3, each node consists of a pair of attributes: l (stands for low) and h (stands for high). The pair shares the weight w of the node – if one attribute's value increases, then the other decreases. Therefore, the values of the two attributes are metaphorically similar to the two ends of a scale (see Figure 5-2). Values of attributes are therefore best represented by percentage, for example when l is 40%, h should be 60%. Each of the two attributes in a node represents one of the dichotomic properties of the node, i.e. they are opposite to each other. For example, if one attribute represents linear navigation, the other should represent non-linear navigation.

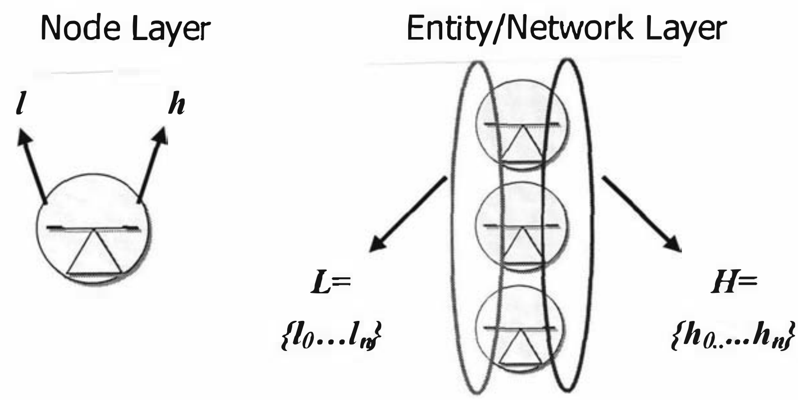

Figure 5-3: Two-layered view of dichotomic property of node and entity

The attributes in all nodes *N* can be split into two groups: *L* and *H*. *L* and *H* each represent one of the dichotomic properties of the entity, for example *L* for low working memory capacity, and *H* for high working memory capacity. It is therefore a 2-layered (Node Layer + Entity Layer) representation of an entity which is dichotomic in nature (see Figure 5-3).

Activation of any attribute is independent to other attributes including the other attribute in the same node. Only activated attributes affect the result of the execution of the MPN. Feedback at the end of an execution is used to change the percentage value of attributes. A node is labelled activated in an execution if at least one of its attributes (i.e. *h* or *l* of the node) is activated. For each of the groups, *L* and *H*, the weight of activated node multiplied by the attribute (in percentage) of the group are summed by a method call *Inclusion Resolution* which will be explained in detail later in this chapter. The group with higher sum is labelled the winning group, and the group with lower sum is labelled the losing group. The percentage values of the attributes in the winning group are increased, and that of the losing group are reduced. By this method, the portrayal of the entity can gradually move towards an accurate representation of the entity.

The dichotomic nature of nodes is an important characteristic of the network. As the two attributes in one node represent opposite nature of a node, if both attributes of the node are activated in an execution, a *contradiction* occurs. For example, if certain part of the behaviour log of a student indicates that the student is able to perform simultaneous task (an indicator of high working memory) and certain part of the behaviour log indicates the lack of ability to perform simultaneous task (an indicator of low working memory capacity), this is a contradiction.

A contradiction implies that the underlying theory represented by the node is not a suitable portrayal of the represented by the entity of the particular student. That is, the theoretical background of using "the ability to perform simultaneous task" to infer working memory capacity is not very suitable for the particular student. This does not imply the theory is wrong, but it indicates that there are certain aspects this student that makes the theory not applicable. This is the *individual difference* that we have discussed in chapter 3. A contradiction therefore means that the node's influence (its weight) to the overall value of the entity should be decreased. This is based on the principle of non-compromise (Minsky, 1986), and therefore is named as *non-compromising rule.*

The non-compromising rule overrides the attributes' rights to either increase or decrease their values from being in a winning or losing group. The weight of a node labelled contradictory is decreased (see Figure 5-4). The non-compromising rule enables the MPN to gradually adapt itself by removing none-representative node of the entity and move towards a more accurate portrayal of the entity. In the application of MPN in cognitive trait model, the non-compromising rule allows the MPN to evolve into an individualised network representation for only the student it represents. This individualisation is of particular importance because the aggregated effect caused by summing of bias in inferential statistics employed by different cognitive researchers has not yet been thoroughly clarified (Lin, Kinshuk & Patel, 2003). It is therefore an important requirement for the CTM to evolve in order to represent each different individual.

In the context of cognitive trait model, an MPN starts up by incorporating all the different portrayals and allows the learner's actions to gradually guide the MPN's evolution. The inappropriate portrayals are automatically faded out (represented by reduced node size in Figure 5-4) and only the representative ones remain.

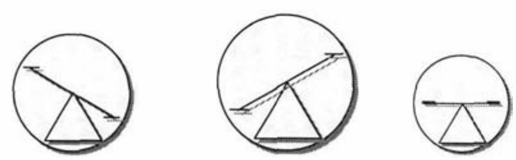

Figure 5-4: Tilt of scale shows the changed percentages of attributes, and different size of circle shows the changed weights of nodes

In order to create an accurate representation of an entity, an important question needs to be considered: if different nodes represent different portrayals of an entity, could they overlap with each other, and what kinds of relationship are possible among them?

5.3.1 Types of Relationships between Nodes

There are several possible relationships between any two of the nodes. The first one is inclusion: one of the two nodes completely includes the other node (Figure 5-5a). This is an extension of the overlap: node A completely overlaps with node B, but the reverse is not true.

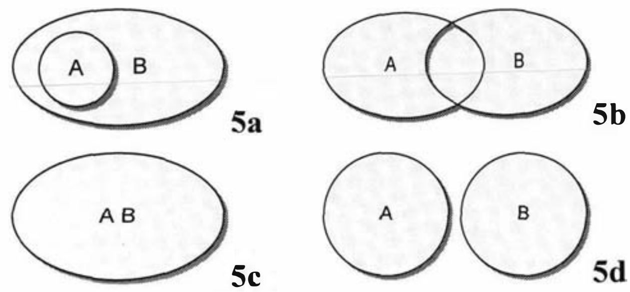

Figure 5-5: Different relationships of nodes: (a)inclusion, (b)overlap, (c)equivalent, and (d)independent

Two nodes of an MPN could also overlap with each other (Figure 5-5b). The overlap is the correlated occurrence of the two MOTs. In the view of Minsky (1986), each mental agent in the higher level of hierarchy may share with other higher level agents some lower level agencies. For example, the GET agent and the FIND agent both need the SEE agent to accomplish their tasks. An agent in Minsky's (1986) view is a set of mental functions to complete a task: the GET agent gets an object; the FIND agent finds an object; and both the GET and FIND agent need to use the SEE agent to see objects in order do their tasks. Similarly, any two nodes in an MPN, representing two different MOTs of the same cognitive trait, might share some common elements.

Figure 5-5c shows that two nodes are equivalent to each other. The equivalency is defined by their identical occurrence, i.e. the co-occurrence rate is 100%. This is most likely due to 1) different terminologies used to mean the same construct, 2) researches in different contexts interpreting the same construct differently.

However, any two nodes could also exist independent of each other (see Figure 5-5d). This type of relationship happening to all the nodes is unlikely because different nodes are different aspect of the same entity. The underlying core of the entity is very likely to bring some correlations to its nodes. However, it is still possible that two nodes are totally independent to each other theoretically.

5.3.2 Inclusion Resolution

Except the independent relationship, all other relationships may create misrepresentations of the entity if there is no mechanism to resolve the relationships of nodes. Inclusion of one node, say node A, in another, say node B, would cause a bias – the weight of node A is doubly represented. If node B includes node A, then the activation of node A must also activate node B, therefore giving credit to the weight of node A is totally unnecessary. Overlaps and equivalency of nodes indicate the same problem, too. Therefore, an Inclusion Resolution mechanism is proposed to solve this problem.

The Inclusion Resolution mechanism works by first identifying the *Included* and the *Inclusive* Node. Please refer to Figure 5-6, the Included Node is graphically represented as a smaller region (node A) whereas the Inclusive Node is the larger region (node B). Mathematically speaking, the Included Node is the one whose conditional probability, with regard to the other, is larger, and vice versa for the Inclusive Node. The $P(A|B)$, read as the probability of A given B, is $2 / (2 + 5) = 2 / 7$, and P(B|A) is 2 / (2 + 8) = 2 / 10 = 1 / 5. P(A|B) is greater than P(B|A) and thus A is the Included Node, and B is the Inclusive Node.

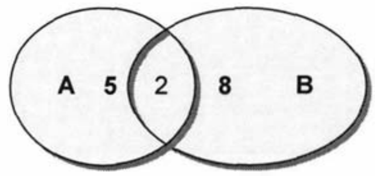

Figure 5-6: Node A is Included Node and B is Inclusive Node

The weight of the Included Node should remove the included region. The included region is 2 in Figure 5-6, and thus the proportion that A should be reduced is 2 / 5. The distinction of the Included and the Inclusive Node is vital as it is the key to distinguish which node should be reduced. But why not the Inclusive reduced? Figure 5-7a and Figure 5-7b show the reason.

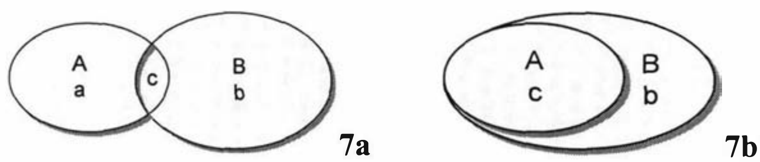

Figure 5-7: Demonstration of why the weight of included node should be reduced

In Figure 5-7a, there are two nodes (nodes A and B), and three regions (regions a, b, and c). From the graphical size, node A is the Included, and node B is the Inclusive. Nodes A and B overlap in the region c, and because node A is the Included Node, region c should be taken out from the total region of node A, and leave node B unaffected. Thus, the total weight, of node A is now a / (a + c).

Figure 5-7b showed that node A is completely included in node B, region a has now disappeared, thus the weight of node A is now 0 / (0 + c) which is equal to 0 and is compliant to the previous discussion that the completely Included Node should not be given any credit.

5.4 Application of Multiple-Portrayal Network in Cognitive Trait Model

As discussed previously, different researchers try to look at cognitive traits differently. It is analogous to different observers perceiving different portrayals of an object from different angles. In detailed discussion about cognitive traits in chapters 6, 7, and 8, there are number of manifestations of trait (MOTs) for each cognitive trait. MOTs come from different theoretical perspectives of the cognitive traits, similar to different portrayals of the same object.

In close scrutiny, each of the MOTs holds certain degree of truth about the corresponding cognitive trait. Taking any one of them and discarding the rest means taking a great risk of losing the accuracy desired. With the regarded difficulty to understand the mysteriousness of the mind (Blackmore, 2003, p.36), not a single MOT could include a complete and all-embracing description of how working memory works. Due to this difficulty, MPN provides a viable solution.

In MPN, an entity/network represents a cognitive trait, such as working memory capacity, and each of the MOTs is represented by a node in the entity. Each of the two attributes of a node represents either low or high working memory capacity. When a cognitive trait model is just initiated, it could contain several instances of MPN each representing one cognitive trait. A cognitive trait has same number of nodes as the number of MOTs it has. For example, if there are three MOTs for working memory capacity, the MPN instance for working memory capacity will be initiated with three nodes like Figure 5-1. After several learning sessions, the MPN will be changed according to the learner's behaviours, for example it could become like Figure 5-3. The tilt in the scales shows the student's tendency towards having either low or high working memory capacity, and the decreased size of nodes indicates that contradictions were detected in the nodes. The contradiction implies that the theories (about working memory) the particular node stands for do not represent the working memory of the student that well.

The ability to handle unclear and complex relationships between nodes is of particular importance to cognitive trait model. This ability is termed *Complex-Relationship* (CR) *Manageability* in this study. Researchers examined the same entity, that is cognitive trait, and there is no proof to show that there is no overlap, or other relationships, between their theories. If all the different theories are indeed not related to each other, the mechanism of Inclusion Resolution mechanism can still accommodate them as having independent relationships. Otherwise, the proposed Inclusion Resolution mechanism has potential to handle aggregation of MOTs nonlinearly and achieve the desired CR-Manageability.

5.5 Multiple-Portrayal Network as Machine Learning

The idea of MPN was inspired by machine learning. Its weighted node structure is similar to that of an artificial neural network, ANN, (e.g. Bar-Yam, 1997). However, there is a significant difference between MPN and ANN. In this section, a brief conceptual introduction to ANN is presented. MPN is then compared to ANN. Finally, discussion is directed to categories of machine learning that MPN fits to in order to shed some light on where MPN situate in the larger context of machine learning.

5.5.1 Artificial Neural Network

An artificial neural network (ANN) is an information processing system that comprises of multiple interconnected processing nodes (Stergiou, and Siganos, 1996). The nodes in ANN are often called neurons because of the analogy of ANN to human brain. The neurons in ANN are weighted, i.e. they each have a value, called weight, attached to it. The weight of a neuron acts as a modifier of the output of the neuron. For example, if a neuron has weight equals to 0.5, then whatever the neuron will output will need to be multiple by 0.5. The modification of neurons' weights accounts for the ANN's learning.

Similar to a human brain, an ANN learns by examples. It can learn for example how to mimic an OR function by using the data in Table 5-1:

Input A	Input B	Output
0	0	0
0	1	1
1	0	1
1	1	1

Table 5-1: Truth Table of OR

In each training session, each pair of Input A and Input B in Table 5-1 are used as inputs to the ANN, and the Output as learning-guides to the ANN – they guide the ANN to modify the weights on its neurons. Using a simple ANN with 2 input neurons and 1 output neurons, Smith (1996) showed that the ANN learned the OR function after 8 training sessions.

Smith (1996) pointed out that ANN is particularly useful where:

1. an algorithmic solution cannot be formulated;
2. a lots of example data can be gathered; and
3. structure of the data needs to be extracted.

ANN is often applied to solve complex problems where algorithmic solutions cannot be formulated and the hidden structure of the data needs to be extracted (Smith, 1996). Pattern recognition (handwriting, voice, or face) is an area where ANN is extensively employed (e.g. Pentland, & Choudhury, 2000; Wu et al., 1991).

5.5.2 Multiple Portrayal Network and Artificial Neural Network

Both multiple portrayal network (MPN) and artificial neural network (ANN) used weighted nodes. Both types of network are self-adaptive – they can both learn from experience (data). However, there exit three major differences between MPN and ANN, namely training, connections of nodes, and types of end representation.

1. Training: An ANN needs to be trained using example data before it can be used; whereas an MPN is used and trained at the same time. At the first glance, it may appear that the approach of ANN (training before use) is more reliable. But the reliability of MPN is derived from the fact that the essences of what its nodes represent (the different perspectives of cognitive traits) are supposedly already scientifically validated by the researchers who put forth their theories.
2. Connections of nodes: Initially, there are predefined and existing connections between nodes (neurons) in ANN. These connections might be strengthened or weakened during the ANN's learning process. There are however no existing connections between nodes in MPN. Only if a node co-occurs with other nodes, the co-occurrences are then used to build the connections between nodes.

3. Types of end representation: An ANN aims to represent a function which takes inputs and will generate outputs. For example an OR function takes 2 inputs to generate 1 output. An MPN aims to aggregate different perspectives of an entity to give an accurate representation of the entity. For example, an MPN for the working memory capacity of an individual aims to represent the working memory of the individual taking into account different perspectives/theories of working memory.

This comparison is not meant to see which of MPN or ANN is better. It is used to point out some differentiating features of the two.

5.5.3 Machine Learning and MPN

In terms of machine learning, mechanism of MPN can be categorised in both reinforcement learning (Ghahramani, 2004; Sutton and Barto, 1999) and learning-to-learn (Baxter, 2000). In reinforcement learning, the environment gives reward or punishment to actions taken by a mechanism. The goal of the learning is to maximize reward or minimize punishment (Sutton and Barto, 1999). In terms of MPN in CTM, decision is made based on the weight of activated nodes – reward or punishment is also given only to activated nodes.

In learning-to-learn, a mechanism learns its own inductive bias, which refers to additional assumptions that the mechanism is used to predict correct outputs for situations that have not been encountered so far, based on its previous experience. Since it is not necessary to train MPN before using it, certain risk has to be acknowledged for the fact that the predictive power of MPN solely rely on the inductive bias. Typically, the inductive bias is supplied through the skills and insights of the expert manually (Baxter, 2000). However, the aforesaid risk is remedied by the fact that such bias in MPN (used in CTM) is trivialised because of the fact that the various research results and theories about human cognition used in this study are presupposed to have been validated.

MPN resembles what has been described as a learning-to-learn mechanism (Baxter, 2000) without the requirement of pre-training. Pre-training is typical in learning-to-learn mechanisms. MPN differs from learning-to-learn on its theory-originated instead of human-originated inductive bias. Future research could be conducted to examine MPN's relationship with other learning-to-learn mechanisms.

Similar to the employment of conditional probability in the Inclusion Resolution mechanism, Bayesian network also uses conditional probability to perform inferences (MacKay, 2003). Theoretically speaking, there should not be a great amount of dependency in terms of depth – for example A is dependent on B which is again dependent on C, and so on. The reason is because the studies of a cognitive trait are about the same cognitive trait, e.g. working memory; they are not about sub-elements, sub-sub elements and sub-sub-sub elements of working memory which will result in dependency in depth. Bayesian network is suitable to study the dependency in depth issue (MacKay, 2003). We therefore do not think that we need Bayesian network in this study.

5.6 Summary and Discussion

Multiple portrayal network (MPN) is a network structure suitable for representation of an entity that has multiple portrayals. Such entities are quite common in cognitive science in which different researchers examined a cognitive entity, for example working memory, from different perspectives and came up with different theories for the entity. Each of the portrayals of the entity usually does not provide a consensus and complete model for the entity; relationships between portrayals are often unclear or unknown. MPN provides an Inclusion Resolution mechanism to circumvent this issue and allows nonlinear aggregation of portrayals.

By using the non-compromising rule, MPN in cognitive trait model allows the learner's behaviours to shape the MPN and to determine which theory(ies) is good representative to the learner's working memory and which one is not. In other words, an instance of MPN will gradually grow towards an individualised network that represents only its user (the learner). It therefore will provide excellent resources for researchers in whichever field MPN is applied, to examine how different theories affect different users to which degree, and how different theories relate to each other.

It is worthwhile to note that the dichotomy of attributes is needed when MPN is applied in cognitive trait model, however it is not compulsory. With the mechanism of Inclusion Resolution, MPN can still achieve the CR-Manageability and the representation of an entity that includes multiple portrayals. The validation of this claim is presented in chapter 9.

The author would like to point out again that MPN is generalised from the use of ITN in this study. The generalised description of MPN presented in this chapter is hoped to be of sufficiently detailed that it can be used elsewhere too. ITN can be seen as an example application of MPN.

The portrayals, i.e. the MOTs, are extracted from the literature reviews about the characteristics of cognitive traits. In the next three chapters, each cognitive trait will be looked at individually. The MOTs will also be listed in the next three chapters.

CHAPTER 6

Working Memory Capacity

6.1 Introduction

Working memory (WM), previously also known as short-term memory (STM), denotes the memory capable of transient preservation of information. WM is functionally different from the memory that stores historical information which is often termed as long-term memory (LTM). Richards-Ward (1996) called the storage aspect of WM as Short Term Store to firstly emphasise its storing function, and secondly to avoid confusion about STM and WM. The latter point is believed to be unnecessary anymore as STM is believed to be the storage component of WM (Engle et al., 1999). The relationship between WM and STM is clarified in the section 6.2 .

The significance of WM as key aspect to understand human cognition can be seen from the large number of documented research, ranging from some of the earlier works such as Miller (1956), Atkinson and Shiffrin (1968), and Baddeley and Hitch (1974), to more recent investigations and debates such as Bayliss, Jarrold, Gunn, and Baddeley (2003), Bunting, Conway, and Heitz (2004), Kane and Engle (2003), and Logie, Maylor, Sala, and Smith (2004). This great body of research works offers also a great variety of perspectives on the nature of WM. Section 6.3 explores some of the characteristics of WM from research literature.

From the known characteristics of WM, manifestation of WM can be derived. Section 6.4 lists manifestations of WM. Manifestations of WM remain at an abstract level. Some of the manifestations can be translated into implementation patterns.

Different from manifestations, implementation patterns are system-definable and system-dependent. Section 6.5 presents implementation patterns obtained from translation of manifestations of WM. The translation criteria are based on characteristics of hypermedia-based learning systems designed for conceptual learning as opposed to learning procedures. We used the term “target-systems” to mean such systems. The system described in chapter 14 is an example of target-system. Section 6.6 provides a summary of this chapter.

6.2 Short Term Memory and Working Memory

The idea of short term memory (STM) emerged in the debate in cognitive psychology about a different memory system than the long term memory (LTM) (Schacter, 2000). An important trigger of this debate was the fact that amnesic patients revealed intact abilities to remember immediate short string of digits despite of having difficulties in long term retention of these digits. Miller (1956, 1994) called this memory system the short term memory (STM) and found that individuals were capable of remembering 5 to 9 (7+-2) chunks of digit(s) in the STM.

The view with solo emphasis on the storing aspect of the transient memory was quickly discredited by:

1. evidences showing the tests result of STM correlated poorly with performance on higher level tasks such as reading comprehension (Turner and Engle, 1989); and
2. evidences showing that simple maintenance in STM was a very poor way of learning (Baddeley and Hitch, 1974).

More and more researchers saw that working memory also includes a processing component (Baddeley and Hitch, 1974; Daneman and Carpenter, 1980; Baddeley, 1992; Salthouse et al., 1989).

At the time of their writing, Engle, Tuholski, Laughlin, and Conway (1999) pointed out three different views regarding the relationship between STM and WM:

1. STM is equivalent to WM.
2. WM is a subset of STM.
3. STM is a subset of WM.

In order to study the relationship of WM and STM, Engle et al. (1999) used eleven memory tasks and two general fluid intelligence tests in their study. Their analysis showed that:

1. STM and WM reflect separate but highly related constructs; and
2. WM has a strong connection to intelligence whereas STM does not.

By taking out the common variance of STM from WM, Engle et al. (1999) found that the residual (of WM) was highly correlated to the fluid intelligence score. It could be interpreted that the part of WM, which is uncommon to STM, is related to the fluid intelligence. Engle et al. (1999) therefore argued that WM consists of a storage component, namely the STM, and a processing component, which is called the Central Executive (Baddeley and Hitch, 1974). The STM is not connected to fluid intelligence whereas the Central Executive is.

6.3 Characteristics of Working Memory Capacity

Relevant literature of different perspectives of working memory is presented in this section.

6.3.1 Structure of Working Memory Capacity

With recognition of a processing component in working memory (WM), Baddeley (1992) studied the structural aspect of working memory and tried to understand it by decomposing WM into its sub-components. The structure of working memory was described as a control-slave system comprised of the Central Executive (controlling and processing component), Phonological Loop (slave component for verbal information), and a Visual-Spatial Sketch-Pad (slave component for graphical information). The Central Executive takes the role of monitoring and controlling the output of the two slave systems and selecting what is relevant for potential processing. The term "potential" is used here because not all processing are consciously-directed. Metaphors used for working memory include "blackboard of the mind" (Reddy, 1980), "mental sketch-pad" (Baddeley, 1986), and "on-line memory" (Goldman-Rakic, 1987). Although these metaphors capture the essential idea of the transient storage capacity of working memory, they still suggestively emphasise the role of the storage functionality of the working memory. The Central Executive, which is conceptualised as very active and responsible for the selection, initiation, and termination of processing routines (e.g., selecting, encoding, storing, and retrieving), is still the least understood aspect of the working memory (Baddeley, 1986).

6.3.2 Working Memory as Operation

Baddeley (1986, 1992) studied working memory (WM) with emphasis on its structure; others took a more pragmatic approach and focused on the operational aspect of working memory (e.g. Salthouse et al., 1989; Daneman, & Carpenter, 1980).

Salthouse et al. (1989) proposed that working memory consists of (1) a storage capacity sensitive to the number of items presented, and (2) an operational capacity sensitive to the number of operations performed on items. Daneman and Carpenter (1980) espoused the same view.

Salthouse et al. (1989) found that young adults have higher operational capacity than older adults especially among the highly capable participants. Little or no difference was reported on the storage capacity across the age differences. Therefore, Salthouse et al. (1989) concluded, at that time, that it was the operational capacity that causes age-related WM decline. A further study of the operational efficiency of WM showed that it was not the operational capacity (number of operations allowed) that affected the efficiency of WM, but it was actually the speed of execution (e.g. comparison speed) that determined the performance of the overall system of WM (Salthouse & Babcock, 1991).

Daneman and Carpenter (1980) also agreed that the speed of execution was the main factor contributing to individual difference in WM and WM related performances. However, they put forwards an explanation of how quantitative differences in WM capacity (storage) could influence the qualitative differences (the execution speed). They speculated that larger the storage capacity of WM, easier it is for chunking concepts and relations into higher order units. The higher order (abstract) units in turn have positive influence on the execution speed.

The emphasis on the execution speed of the processing component in WM had already broken away from pure structuralism and turned towards functionalism. There are however, more functionalist views on WM. Atkinson and Shiffrin (1968) is an example.

6.3.3 Working Memory as Function

In addition to the storage capacity, Atkinson and Shiffrin (1968) defined WM functionally as the gateway allowing information to be transferred to the long-term memory (LTM). This definition stresses the ability to channel the incoming isolated information (as received by our senses) to the semantically networked structure in the LTM. This involves a great degree of cognitive efforts such as interpretation, translation, association, memorisation, and so on. This functionality is comparable to the Central Execution unit mentioned above and essentially it transforms and transfers the messages from the short-term storage system into the long-term one. The transformation process invokes the formation of rules (data with operational application) from pure data (in the form of incoming messages) and the transferring process filters what rules and data are to be stored for long-term and what are to be discarded.

From this point of view, efficient WM contributes to better memorising into and retrieval from LTM, and vice versa for poor WM.

6.3.4 Working Memory and Age

Several studies have shown that age-related performance of young children and old adults, compared with young adults, can be characterised by the inability to retain information in WM while simultaneously processing other information (Laumann 1999; Case, 1995; Verhaeghen & Salthouse, 1997; Salthouse & Babcock, 1991; Kausler, 1991). Deficiencies in WM capacity result in different performances in a variety of tasks and can be seen in the difference in the score of WM test (Laumann 1999). Examples of tasks affected include natural language use (comprehension, production, etc.), recognition of declarative memory, skill acquisition, new vocabulary learning and so on (Byrne, 1996).

Campbell and Charness (1990) also reported age-related difference in WM performance. They used arithmetic operations that required the participants to perform long sequence of calculations involving seven steps. Older adults committed more errors and responded slower than younger adults. Age-related differences in error rates were greatest at the stages where the loads on WM were high. The loads on WM were particularly higher in later steps of the sequence of calculations than in earlier steps (Campbell and Charness, 1990).

6.3.5 Working Memory and Navigational Pattern

An empirical study by Huai (2000) showed that students with holistic learning style also have a significantly smaller short-term memory but have remarkably higher learning effect in the long run, whereas the students with serial learning style (highly capable to follow and remember sequentially fixed information) have better short-term memory but poorer learning result in the long run.

This point shows the intricate relationship between humans' inbuilt abilities and how different learning styles are adopted to circumvent any deficiencies in those abilities.

The navigational strategies adopted by serial learners are linear whereas holists sometimes do better by jumping directly to complex concepts (Felder, 1988).

6.3.6 Working Memory and the Fan Effect

Fan effect is a name given to the observed phenomena that the time required to verify a proposition encoded in long-term memory increases with the number of total propositions committed to long term memory (Anderson 1983a, 1983b). A proposition is a statement in the form like "The LAWYER is in the PARK". The fan-effect experimental procedure was described in Cantor and Engle (1993). Participants, who involved in fan-effect experiments, are presented and required to learn simple propositions (statements). The number of other propositions sharing the same concepts (LAWYER and PARK) is experimentally manipulated, and is called the fan-size of the proposition. For example, if there are large numbers of propositions that have the term "PARK", then the fan-sizes of these propositions are said to be large.

A verification test is then given. "The LAWYER is in the BANK?" is an example of questions in the verification test. Test result of Cantor and Engle (1993) showed that response time and error rate were greater for propositions with greater fan-sizes than propositions with smaller fan-sizes. This phenomenon is called the *fan effect*.

The fan effect seems contradictory at the first sight: experts, who have greater number of propositions (knowledge) in a domain, should be faster in verifying a proposition than novices whereas novices should spend longer time during the verification test. It appears that the experimentally-observed fan effect is inconsistent to the generally-expected expert/novice performance. Cantor and Engle (1993) used the mental-model concept to explain this contradiction.

Experts have already had elaborated links between the propositions and thus an integrated mental model representation. The integrated mental model has the information of all the propositions. It serves as a single unit of access during the verification test. Because accessing one mental model is faster than accessing a set of propositions individually, experts can therefore perform the verification task faster than novices. Therefore, in experts, no fan effect or negative fan effect appears (Cantor and Engle, 1993)

Cantor and Engle (1993) also point out that the constituent propositions must be closely related in order for the mental model to emerge. By using causal- and/or temporal-relationship, propositions can be combined into a single theme and therefore an integrated mental model. When proportions are unrelated, it is difficult for the development of a mental model, and therefore fan effect can still be observed.

One important concept during the discussion of fan effect, which is generally related to long-term memory, is activation (Anderson 1983a, 1983b). Activation of one concept causes automatic activation of associated concepts and the total amount of activation is limited. In other words, the greater number of associations activated, the lower their activation levels will be. That is, the more associations to share the limited amount of activations, the less each association can get. Only when the activation level exceeds a certain threshold, a concept can surface to consciousness.

Even though not directly connected, the concept of activation described by Anderson (1983a, 1983b) is in accordance with the findings of Mednick (1962). In a study asking participants to do free-association, Mednick found that the greater associative response rate correlated to lower total number of associations. For example, a participant might answer "chair, study, dinner, wood, etc." very quickly when the target associative object is "table", the total number of items this participant answered is smaller than others who give answer slower. More details about Mednick's study are presented in chapter 8 along with associative divergent learning

Based on the Anderson's (1983a, 1983b) concept of activation, Cantor and Engle (1993) hypothesized that the individual difference in total amount of activation could be related to individual difference in work memory (WM) task. This is because of the attention-switching feature in WM task.

In the WM task called OSPAN (e.g. Turner & Engle, 1989; OSPAN is described in more detail in the chapter 10 about Web-OSPAN), a participant is first required to solve an arithmetic operation (e.g. Is 3 x 5 = 12), then presented a word to be remembered (e.g. Tree). Attention has to be switched from the operation task to the memory task. After seeing the word, another arithmetic operation is presented, followed by another word to be remembered. Cantor and Engle (1993) viewed that when the participants were working on the operation, the word did not receive any attention (low activation level) and therefore needed to be re-activated when it needed to be written down. Therefore, Cantor and Engle (1993) argued that the amount of available activations in LTM determined the capacity of WM.

Based on the equivalence of available activations in LTM and WM, Cantor and Engle (1993) further hypothesized that high WM participants should be more capable of integrating the propositions into a mental model than low WM participants, therefore negative fan-effect should be observed in high WM participants whereas fan-effect should be observed in low WM participants.

In an experimental study using fan-effect material that varied in thematic relatedness (how easy the propositions were integrated into a mental model), Cantor and Engle (1993) were able to demonstrate the correlations between high WM and negative fan-effect, and low WM and fan-effect.

6.3.7 Working Memory and Attentional Control

Attention control has been mentioned as a function of the Central Executive in WM (Baddeley, 1992). Engle et al. (1999) viewed WM as the content of short-term memory plus the limited-capacity controlled-attention processes associated with the Central Executive. Goode, Goddard, and Pascual-Leone (2002) also adopted the view of capacity plus attentional control view of WM, but they focused more on the inhabitation aspect of attentional control, i.e. the ability to ignore irrelevance or distraction.

Kane and Engle (2003) used a task, called the Stroop task, to show the relationship of attention control and WM. The Stroop task requires the participants to read out the colour of the text while at the same time, the text is also a name of a colour. If the colour of the text and the name of the colour in the text match, it is called a congruent trial, and otherwise it is called an incongruent trial. In the task, the goal of the participants is to 1) read out the colour of the text and 2) ignore the word. However, the task is designed in such a way that congruent trials outnumbered the incongruent trials. So it is easy for the participants to forget to keep attention on the second goal and just rely on the text to answer. Kane and Engle (2003) showed that the high WM participants made fewer errors and responded faster in the Stroop task than their low WM counterparts. This result demonstrated that the high WM participants were more able to control their attention than the low WM participants.

Logie et al. (2004) used the term perspective memory to refer to goal maintenance. One is said to have good perspective memory if one can resist distraction and forgetting of one's goal. In consistence with the study of Kane and Engle (2003), Logie et al. found high WM correlated to high perspective memory and low WM correlated to low perspective memory. Logie et al. also showed that the failure of perspective memory (i.e. forgetting the intention to do things) in old age is due to inefficiency in WM.

6.3.8 Working Memory and Interference

Bunting, Conway and Heitz (2004) argued against Cantor and Engle's (1993) proposal to equate working memory to the total amount of available activation in long term memory. By replicating the experiment of Cantor and Engle (1993) in addition to three more experiments with varying degrees of interference (e.g. multiple persons in same location, or same person in multiple locations), Bunting et al. (2004) showed and asserted that the ability to resist interference, not the limited amount of activation, was the critical determinant of individual differences in the fan effect. Interference showed a higher detrimental effect on low WM participants than on high WM participants.

The interference-resistance view of WM had also been reported in earlier studies. As new items enter into working memory, other items become harder to access, and the cognitive system becomes less efficient. This is called the displacement or interference (Byrne, 1996; Baddeley, 1986). Less tolerance of displacement or interference indicates sign of low working memory capacity.

6.3.9 Working Memory and Domain/Task Specificity

An important question is whether WM capacity is domain dependent or domain independent. Most of the evidences gathered indicate the latter.

Daneman and Carpenter (1980) speculated that the individual difference in reading comprehension should be attributed to the difference in efficiency of processing component in WM, in particular the difference of efficiency in processing textual information. Daneman and Carpenter devised a test of WM called the *reading span task*. In the reading span task, participants read groups of sentences aloud while simultaneously trying to remember the last word of each sentence. They argued that measure of working memory capacity (in this case, the score of reading span task) is task-specific (i.e. to reading task) because 1) the processing and storage components in working memory compete for limited resource, 2) good readers have better reading strategies that lead to less requirement on processing and hence more resources are available for the storage component (to remember the last word in each of the sentences). Daneman and Carpenter had indeed found high correlation between the score of reading span task and reading comprehension.

However, Turner and Engle (1989) had a different view on the results of Daneman and Carpenter's (1980) study. Turner and Engle hypothesized that people who were good readers had high WM capacity regardless of the task being performed. The high WM capacity should allow good readers more resources for storage regardless of whether they had better reading strategies or not. Turner and Engle (1989) used three span tasks: 1) reading span task similar to that Daneman and Carpenter (1980) had used, 2) a sentence digit task that required the participants to remember a digit after each sentence, 3) an operation word task that required the participants to solve arithmetic operations followed by a word-to-be-remembered at the end of each operation, along with a reading comprehension test to conduct an experiment. They found that good readers can remember more words and digits than poor readers regardless of whether the background task is reading sentences or solve arithmetic operations. They concluded that they had demonstrated the task independent characteristic of WM.

Stated in the previous discussion about the fan effect, the development of higher order presentation, such as mental model, can ease the load on WM and thus increase its efficiency (Cantor and Engle, 1993). This could easily lead to the confusion that WM is dependant on the expertise/experience in a task or a domain. However, the development of the higher-order presentation is not the function of WM, and is likely to be resulted from the exercise of inductive reasoning ability or other mental abilities. WM is merely instrumental during the work of those mental abilities. As it will be pointed out later in chapter 7, WM is one of the contributing factors to the ability to use induction. Therefore, this study maintains the domain-independent view on WM.

6.3.10 Working Memory and Reading Comprehension

Reading comprehension is one of the important factors that bring the change of the focus from short term memory to working memory capacity. Tests for short term memory were found to correlate poorly with higher order cognitive functions (Turner & Engle, 1989). Reading comprehension is the instance of the higher cognitive functions that WM related to in a positive way in researches like Turner & Engle (1989), Engle et al. (1999), Daneman, & Carpenter (1980), Bunting et al. (2004), Cantor and Engle (1993), and Bayliss et al. (2003).

Beacham, Szumko, and Alty (2003) also used deficiency of WM to describe dyslexia. Dyslexia refers to impaired ability to read. It is therefore not hard to see the usefulness of using reading comprehension as an indicator of WM capacity.

6.3.11 Working Memory and Field-(in)dependence

Field dependence/independence (FDI) is one of the cognitive styles which are defined as "tendencies that are consistently displayed by individuals to adopt a particular type of information processing strategy" (Ford and Chen, 2000, p283). Field-independent individuals are highly analytic and operate with an internal frame of reference whereas field-dependent individuals process information globally and operate with a relatively external frame of reference (Ford and Chen, 2000). Goode, Goddard, and Pascual-Leone (2002) saw field-independent individuals as those who can extract useful information out of its context (e.g. a rule, a theory or a descriptive model) whereas field-dependent individuals have more reliance on the context.

Field-dependent learners prefer concrete material, whereas field-independent learners prefer to learn abstract material (Ford and Chen, 2000; Davis, 1991). An association can be found between field-(in)dependency and WM capacity in structural learning theory (Scandura, 1973). Structural learning theory postulates that the information is learned as rules. In order to identify and learn low-order (fundamental) rules, representative problem samples of the low-order rules have to be presented and the corresponding solutions need to be made available to learners prior to that of the high-order (advanced) rules. The number of representative problem samples should increase for learners with low WM capacity so that they can grasp low-order rules first and use them to develop high-order rules (Kinshuk and Lin, 2005).

Miyake, Witzki, and Emerson (2001) used a hidden figure test, which had simple figure hidden in more complex pattern, to measure FDI. The hidden figure tests were administered with additional tasks to tap the visual-spatial sketchpad and the Central Executive of WM. Miyake, Witzki, and Emerson (2001) found that while visual-spatial sketchpad and the central executive were occupied by the additional tasks, performance of the hidden figure test dropped (that is showing more field dependent characteristics). This study again provides support to the links between high WM and field-independence and low WM and field dependence.

6.4 Manifestations of Working Memory Capacity

Each of the points mentioned when discussing characteristics of working memory (WM) gives indication about the student's working memory capacity (WMC). Each of the indication is called a Manifestation Of cognitive Trait (MOT); WM discussed in this chapter is one of the cognitive traits.

An MOT is formally defined as an indication of the cognitive trait. It has to be stressed that an MOT is an indication only, not the entire representation of the trait. In chapter 5, analogy is made between an MOT of a cognitive trait and a portrayal – an MOT shows only one perspective about the cognitive trait as a portrayal shows only one view about an object.

An MOT can be a single observable student action (e.g. comparison speed) or it can be a complex pattern comprised of a long sequence of observable student actions (e.g. frequently revisiting learned materials). An MOT can also be a student's attribute (e.g.

age). The discussion of the characteristics of WM can be summarised into various MOTs as shown in Table 6-1.

Table 6-1 : MOTs of Working Memory Capacity

	Low Working Memory Capacity	High Working Memory Capacity
1.	non-linear navigational pattern	linear navigational pattern
2.	low comparison speed	high comparison speed
3.	unable to retrieve information effectively from long-term memory	able to retrieve information from long-term memory effectively
4.	unable to complete long sequence of calculation or procedural	able to complete long sequence of calculation or procedural
5.	poor reading comprehension	good reading comprehension
6.	lower interference resistance	higher interference resistance
7.	older age	younger age
8.	greater fan effect	lesser fan effect
9.	poor attentional control	better attentional control
10.	field dependent	field independent
11.	greater Stroop error	less Stroop error

It is possible that there are contradictions among the MOTs observed from the same student. For example, a student may be young adult (manifests HWMC) and may still be using constantly reversed navigation (manifests LWMC). This is perfectly acceptable because a cognitive trait, such as WM, can be decomposed further into a group of sub-components or could be studied (looked at) from a number of different perspectives. Each perspective has its focus and method of explaining why this particular cognitive trait works in a certain way. For example, Atkinson and Shiffrin (1968) defined working memory functionally, whereas Baddeley (1986, 1992) defined it structurally. The Multiple-Portrayal Network discussed in chapter 5 is an example of possible mechanisms to resolve the relationship among the manifestations.

In the next section, an attempt is given to translate MOTs of Table 6-1 into the terms more useable in hypermedia-based learning systems. However, some of the MOTs in the table are not readily observable in a hypermedia-based learning system. These non-translated MOTs are also discussed at the end of section 6.5 .

6.5 Implementation Patterns

The manifestations of trait (MOTs) discussed previously are extracted from the literature based on the characteristics of working memory (WM) capacity. They provide a very general guideline for analysing learners' behaviours in order to infer their WM capacity. However, sentences like "low comparison speed" are too general to be useful in terms of implementation in the target-systems. Therefore, more detailed account of those MOTs is considered in this section.

Some of the MOTs listed in Table 6-1 involve patterns of student behaviours that could be tracked and matched from the log of the students' interactions with the learning system. However, in order to bring those patterns a step closer to implementation level but, at the same time, maintain their domain independence, careful considerations have to be taken. It is decided that the MOTs can be translated in terms of learning objects, properties, and relations of learning objects which can then be implemented domain-independently. The translations of MOTs are called implementation patterns (IPs). The IPs for the MOTs listed in Table 6-1 are discussed in detail in the next section.

6.5.1 Implementation Pattern for Navigational Linearity

Linear navigation implies that the learner is traversing the learning space in a way that was originally designed to be the main route. In web-based learning environment, learning space is the possible hyperspace a learner can explore. In many learning environments, it is the Next Button that guides the learner on the intended route designed by the curriculum designers. In terms of link type, it is the direct successor link (Kinshuk et al., 1999), and in terms of relations, it belongs to the IsBasisFor relation. IsBasedOn relation indicates the relation with opposite direction to the direct successor (IsBasisFor) link. The linearity can be represented as follows:

In a single session, for all learning objects in a set of all visited learning objects, the implementation pattern of the linearity can be represented by the following equation:

LM = (No(B) / ISBASISFOR(V)) / (No(E) / EXCURSIONTO(V))

Where

LM is the measure of linearity
W is the set of all visited learning objects.
V is a learning object in the set of **W**.
No() returns the number of items in a set
ISBASISFOR (V) returns the set of learning objects that V has IsBasisFor relations with.
B is the subset of **ISBASISFOR(V)** where for every item **bi** in **B**, **(bi $\not\subset$ W)**
$\not\subset$ means not in the set of.
EXCURSIONTO(V) returns the set of learning object that **V** has ExcursionTo relations with.
E is the subset of **EXCURSIONTO(V)** where for every item **ei** in **E**, **(ei $\subset$ W)**
$\subset$ means in the set of.

In order to explain the linearity of a navigational path, consider the following illustrations (Figure 6-1)

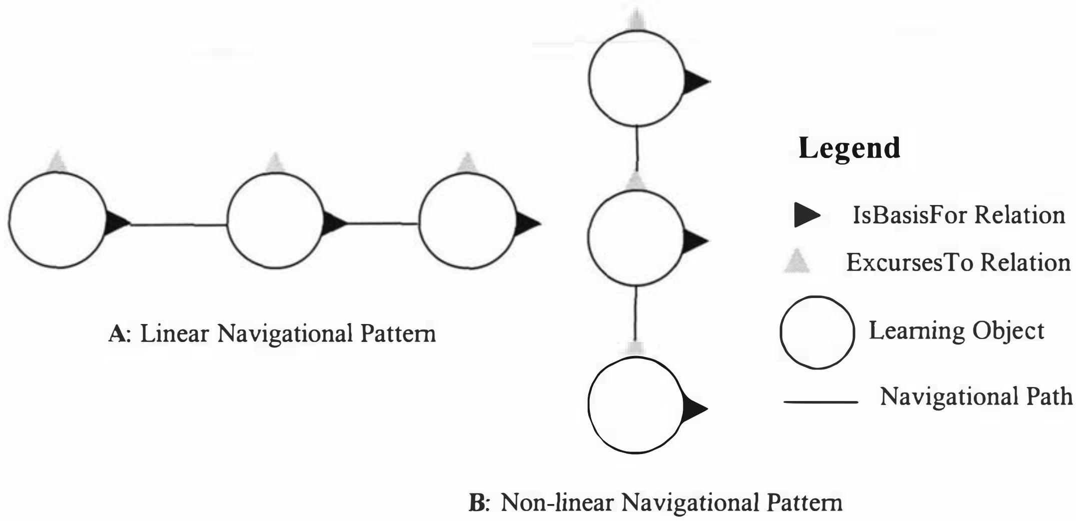

Figure 6-1: Linearity of Navigational Pattern

Figure 6-1.A shows a completely linear navigational pattern, where only the IsBasisFor relations (direct successor links) are involved, and none of the excursion links are travelled. Figure 6-1.B shows a completely non-linear navigational pattern, where none of the IsBasisFor relation is present but only the ExcursionTo relations are present

However in reality, it is quite possible to have a mixture of linear and non-linear navigational patterns in any session of learning interaction. Therefore, the linearity measure is designed for, as its name suggests, the purpose of measuring linearity of navigation.

In the equation of linearity measure:

LM = (No(B) / ISBASISFOR(V)) / (No(E) / EXCURSIONTO(V))

the **No(B) / ISBASISFOR(V)** accounts for the ratio of IsBasisFor relations visited in the session. It represents the ratio of learning objects (a set) that V has IsBasisFor relations with (**No(B)**) and not visited in a session (where for every item **bi** in **B**, (**bi** $\not\subset$ **W**), $\not\subset$ means not in the set of), to the total number of learning object that V has IsBasisFor relations with (**ISBASISFOR(V)**). On the other hand, (**No(E)** / **EXCURSIONTO(V)**) is for the ratio of ExcursionTo relations. It represents the ratio of learning objects (a set) that V has ExcursionTo relations with (**No(E)**) and visited in a session (where for every item **ei** in **E**, (**ei** $\subset$ **W**), $\subset$ means in the set of), to the total number of learning object that V has ExcursionTo relations with (**EXCURSIONTO(V)**). A ratio of the ratio of the qualified IsBasisFor relations to the ratio of qualified ExcursionTo relations is again taken for the final value of the linearity measure.

The reason of taking the ratio instead of the total number is this: there is no fixed number of IsBasisFor or ExcursionTo relations in any learning objects, and the linearity measure could be easily biased because one of the types of relations

(IsBasisFor or ExcursionTo) can just outnumber the other types in a single learning object.

Exception could arise if there is no excursion in a unit. In this case, this implementation pattern should be automatically deactivated.

6.5.2 Implementation Pattern for the Limited Capacity Nature of Working Memory

Even though limited nature of WM capacity is not listed in Table 6-1, this is an agreed point of view for all research works of WM quoted. Applying this limited capacity nature to students' behaviour in learning systems, a "constant reverse navigation" pattern of behaviour could be expected. In web-based systems, there is typically a pre-defined navigational path. Often than not there exist the "Next" and "Back" links. Even without the preset "Next" and "Back" links, there are still the "Forward" and "Backward" buttons in all major types of web browsers to meet the need of "going back to make sure again".

While most likely, the materials just read on previous page should still be fresh and available in working memory, or highly activated in long-term memory in Anderson's (1983a) term. The constant need to navigate backwards could be a sign of working memory deficiency. Figure 6-2 shows an example of constant reverse navigation.

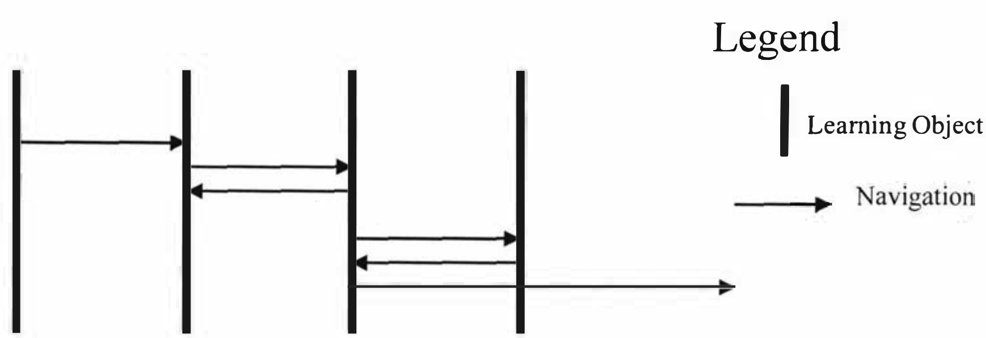

Figure 6-2: Constant Reverse Navigation

It must be noted that for the detection of this pattern, learning object has to be understood than just treated as an equal node to every other node. For example, if a learning object is designed as a reference material such as the Periodic Table in Chemistry, then it is perfectly sensible that a learner needs to come back to this particular learning object often. That is a very serious limitation of content-less browsing pattern analysis and that is why the semantic information about learning object relations needs to be taken into consideration. More discussion along this line is available in the chapter 4 on Semantic Relation Analysis.

Implementation pattern for reverse navigation can be represented as follows:

In a session of learner's interaction, a certain number of ordered pairs (R) exist that represents a navigational action and at least one of the items in the pair is re-visited.

R = (fromLearningObject, toLearningObject)

where ***fromLearningObject*** *represents the source of the navigational action and* ***toLearningObject*** *the destination.*

The phrase "a certain number of **R**" will be discussed in more details below. This implementation pattern looks at each navigational action in a session. It could be easily understood conceptually if all visited learning objects are arranged in a sequential manner according to the time stamp on them.

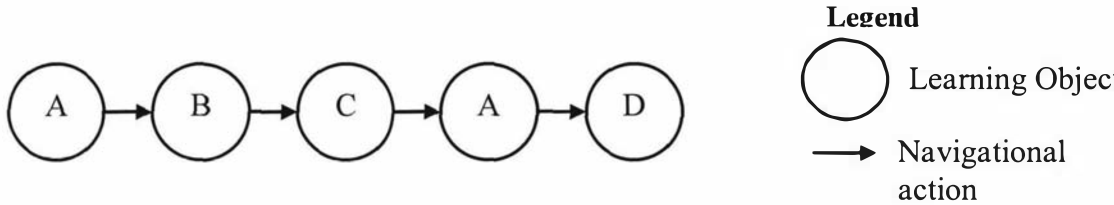

Figure 6-3: Representation of a navigational sequence

In Figure 6-3, there are following ordered pairs of navigation: (A, B), (B, C), (C, A), (A, D). Also, there is a pair that qualifies the description of **R**, that is (C, A) in which A is already visited.

However, how many **R** will be needed for it to become "frequent"? Let us assume that each learning object represents a concept in a learning topic, and each learning object is presented in a single web page. This assumption allows us to claim that each page will only be viewed once because of the following conditions:

- CTM is only designed to be used in an adaptive learning system.
- In an adaptive learning system, the information presented in a page should have already been tailored to the interacting learner.

Therefore, it is likely that if any of the reverse navigations, **R**, should occur, the working memory capacity of the learner is actually lower than what the system believes, and the belief of the system needs to be changed.

6.5.3 Implementation Pattern for Excursions

Ability to resist interference can also give indication to the WM capacity of a learner. Learners can take excursions to obtain side information during a course of learning. Excursions bring less-relevant (side) information to the student, and therefore broaden the learning experience, and create opportunities for accidental learning. But excursions also bring distractions to the learner. Any distraction would affect the processing and working of the working memory, which has limited capacity by its nature (Resiberg, 1997).

The implementation pattern for side information is therefore straightforward:

For every learning object vi in V, if vi has any ***ExcursionTo*** *relation, and if any of its* ***ExcursionTo*** *relations are activated, and*

For LWMC:
if Pass(vi) = false.

For HWMC:
if Pass(vi) = true.

Where

- **vi** is a learning object in **V.**
- **V** is the set of all visited learning objects in a session.
- **Pass (learning object)** return true if the learner passes evaluation of learning object, returns false if failed, or returns Null for not evaluated.

In order to detect this implementation pattern, every activation of the ExcursionTo relation is recorded. And if the learner fails a particular learning unit in which at least one of the ExcursionTo relations in one of the learning objects belongs to this unit is recorded, this pattern is caught.

This is because, in an adaptive learning environment, the main course of learning is adapted (presentation and navigation) to the learner, but the excursions are not (because as the name "excursion" says, they are typically outside of the system). It is quite often that the excursions bring the learners to other web sites for which the curriculum designer has no control of. Therefore, it can be assumed that if the learner has not been to any excursions at all during a course, s/he should be able to pass the course since this course is adapted to his/her individual ability. The distractions from the excursions are accounted for the failure of the learner whose working memory capacity is just not enough to handle the distractions.

By the recommendations of the formalisation of Exploration Space Control (Lin, 2002), for those who possess lower working memory capacity, excursion links should be avoided. It is not sensible to present too much information to the learner who cannot handle it.

6.5.4 Implementation Pattern for Simultaneous Tasks

The ability of attentional control is an MOT of WM (Table 6-1). The setup of working memory span tasks, no matter Daneman and Carpenter's (1980) reading span task or Turner & Engle's (1989) operation word span, require participants to perform a primary task (memory) and a secondary task (sentence reading or operation solving) simultaneously. Simultaneous tasks have to compete for the limited resource of working memory; therefore it provides indications for working memory's capacity.

Simultaneous tasks in a curriculum do not need to be deliberately designed, but they could happen due to learner's wandering away from the current task, performing something else, and then coming back later to the current task. For example, Student

S is half way through reading Paragraph P when he/she encounters Vocabulary V. Student S needs to browse through the Internet and find out the definition and other related information of V. At the time S is searching and reading information about V, S has to try to relate and fit what is found into the context of P in order to understand V and P. This simple scenario is an example of simultaneous tasks. During the action of relating V to P, Student S may need to rehearse V constantly, and review briefly P in order to see the contextual meaning of V. Therefore, the nature of the pattern of simultaneous tasks could, but not limited to, be accidental.

However, one has to be clear about the definition of tasks. In a learning space constructed by learning objects, tasks can be defined by learning objects:

A task is an interaction between a learner and one or more learning objects. And, a task has its boundary.

Boundary is the important structural element that gives tasks their forms. In order to impose structures into learning objects, hierarchical information of learning object has to be used. In Figure 6-4, assuming learning object A and E are different topics, the navigation from B to C is considered to be within the same task (learning A), but the navigation from C to F is considered to be inter-task due to the reason that C and F are not in the same topic. In this example, it is clear that hierarchical boundary can be used to determine tasks' boundary.

But hierarchical boundary is not the only limit. More research on learner's perception of what is a task is required to list all possible types of task boundaries, and this is beyond the scope of current project.

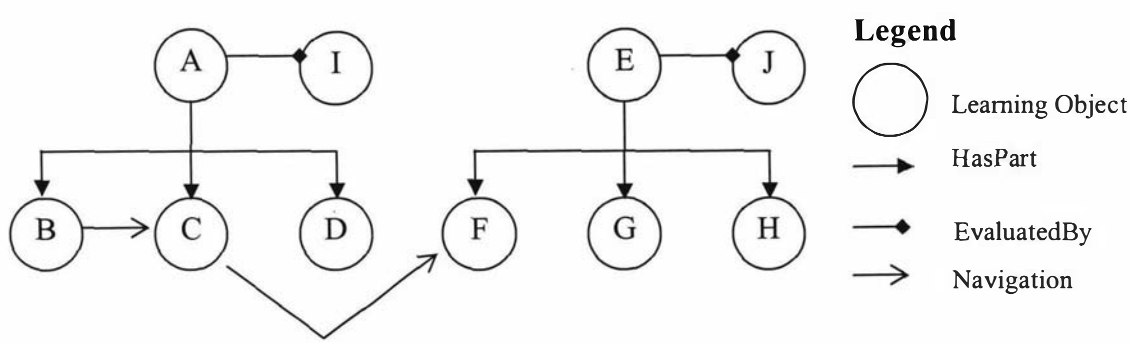

Figure 6-4: Boundary of Tasks

Please note that in Figure 6-4, if the learner did not come back to topic A afterwards, it has to be assumed that the learner has wandered off topic A and therefore no simultaneous tasks were detected. It could be the case that the learner finds topic A to be not useful to him/her at this moment and decides to proceed on topic E first. So a complete pattern for simultaneous tasks in Figure 6-4 could be (B, C, F, G, H, J, D, I). In that pattern, learner jumps from topic A to topic E, finishes topic E (including the evaluation), and then comes back to topic A, and finishes topic A (including the evaluation). If the learner fails at least one of the evaluations (either I or J), it indicates that his/her working memory capacity could not afford to do both tasks (learning topic A and learning topic E) simultaneously. And if the learner passes both evaluations, it indicates the learner has high working memory capacity. Without completing both topics A and E, this pattern is not activated.

The implementation pattern for simultaneous tasks could therefore be represented as follows:

For LWMC:
For **V** and **U**, **Overlaps (V, U)** = true, and **Pass (U)** = false.

For HWMC:
For **V** and **U**, **Overlaps (V, U)** = true, and **Pass (U)** = true.

Where
- **V** and **U** are two learning objects
- **Overlaps (V, U)** returns true if items in V overlap temporally with items in U.
- **Pass (learning object)** return true if the learner passes evaluation of learning object, returns false if failed, or returns Null for not evaluated.

In a technical view, if a learner visits **V,** then **U** and then **V,** then **Overlaps (V, U)** will return true. The tasks of learning **V** and learning **U** overlap. Theoretically speaking, we could use the **Pass** function to check both **V** and **U** to finding whether the simultaneous task had affected the learning on both **V** and **U**. But because of the way that our **Overlaps** function is defined, the learning object **V** is visited twice and the learning object U is visited once. We wish to see whether performing simultaneous tasks has negative impact on learners with lower WMC. Visiting **V** twice could have an improved learning result on **V.** Performance on **V** could therefore be better than other learning objects that are only visited once. We therefore use the **Pass** function to check the performance on **U**.

6.5.5 Implementation Pattern for Retrieval of Information from Long-Term Memory

It has been discussed that working memory capacity is one of the factors that affect the retrieval of information from long-term memory (LTM). Forgetting may be the general term used for the failure of information retrieval from LTM. Many learning theories address the issue of forgetting, for example, according to Ausubel's (1963) Subsumption theory, forgetting occurs because certain details get integrated and lose their individual identity, and Guthrie's (1938) Contiguity theory said that forgetting is due to the interference; stimuli is associated with new responses. However, the focus here is the method of how to identify the forgetting phenomenon.

Previous discussion on manifestation of traits concluded that "being able to retrieve information from LTM effectively manifests HWMC", and "being unable to retrieve information from LTM effectively manifests LWMC", and this relates to being able to recall and being unable to recall learned information respectively. However, it is only meaningful to detect the pattern for "being unable to retrieve information from

LTM effectively" because the learner is expected to recall what s/he had already learned.

The implementation pattern could be expressed as follows:

For LWMC:

*For all **vi** in V, if **vi** is visited in a previous session, and **Pass(vi)**=true, and **Reference(vi)**=false*

Where

- **V** is the set of all visited learning object
- **vi** is a learning object in V
- **Pass (learning object)** returns true if the learner passes evaluation of learning object, return false if failed, or return Null for not evaluated.
- **Reference (learning object)** returns true if learning object is a referential learning object, returns false if not.

This implementation pattern checks that if learning object A has been visited in any previous session, and A is learned (by **Pass(vi)**=true), and it has been visited again indicating that the learner is unable to recall and has to look up A. Please note that **vi** must not be a referential learning object for this pattern to be detected; looking up referential learning object does not indicates LWMC.

Five implementation patterns are discussed so far, they are summarised in Table 6-2.

Table 6-2 : Implementation Patterns of Working Memory Capacity

	Low Working Memory Capacity	High Working Memory Capacity
1.	non-linear navigational pattern	linear navigational pattern
2.	constant reverse navigation	rare (or none) reverse navigation
3.	unable to learn excursions	able to learn from excursion
4.	unable to perform simultaneous task	able to perform simultaneous task
5.	inefficient retrieval from long term memory	efficient retrieval from long term memory

There are, however, still more MOTs that are not suitable for translation into IPs. They are discussed next.

6.5.6 Other MOTs That are not Translated

Eight manifestations of traits (MOTs) of WM are not translated into implementation patterns (IPs). They are age, comparison speed, ability to comprehend highly demanding text/concepts, fan effect, Stroop effect, ability to resist interference, ability to complete long sequence of calculation, and field-(in)dependence. They all could be used to infer about WM capacity. The reasons that they are not translated are given below.

Although age affects the capacity of working memory and is easy to detect if a learner profile is present, unlike other patterns that are reoccurring and contribute to the formation of the Individualised Trait Network (ITN), age can only provide a once-off influence on the overall score. Without the reoccurring characteristics, it is therefore not suitable to be included as an IP in the CTM. An IP gives constant influence to overall ITN. If age is included as an IP, it is going to have a lasting effect which will likely to have all younger adults having high WM and older adults having low WM. Initially, it seems to be a biased decision to include age in CTM; however, age indeed exerts a constant influence on one's WM capacity and the influence of age on WM is not deniable according to literature.

One method to include age is to have the starting score of WM adjusted to the age. This adjustment, without doubt, also has a lasting effect if all other manifestations are not found in a student, i.e. the student will always remain in high or low WM group depends on the age alone. This effect is in accordance to literature's finding that younger adults have high WM and old adults have low WM. However, if other MOTs (IPs to be more specific) in the low WM group have more occurrences, then the value of WM is going to drop. It is also possible that some young adults have low WM and vice versa for old adults.

Comparison speed is another MOT that was not translated. Measuring it requires expensive overheads during the development of learning systems. In order to measure speed (learning or comparison), it requires another set of metadata about what is the average/expected duration of learning for all learning objects. More research is required to determine whether the benefit is worthy for the overhead incurred. There are also too many variables that need to be considered if the time needs to be measured in a web-based systems. Students could be doing other things when they are using the systems. Therefore, measurement of speed as yet is not included in CTM.

In order to be able to detect the ability to comprehend highly demanding text or difficult concepts, each learning object would need to be rated. The rating process requires a systematic categorisation and is beyond the scope of this work.

The fan effect and the Stroop effect, even though could be taken as signs of working memory as the literature has shown, they require certain experimental setup. For example, materials need to be presented as propositions and only a limited number of propositions can be presented in order to show fan effect; the attributes of learning materials (e.g. colour names) have to contradict to the leaning materials themselves (e.g. colour name) in order to observe the Stroop effect. Those conditions are not common in learning systems, and therefore the two effects are not translated.

Ability to complete long sequence of calculation is an MOT of WM listed in Table 6-1. In order to detect this pattern, a very different approach is required, and it involves insights from the process model. The discussion of student model involves explanation of process models. Process models are usually used in a closed system where the primary focus of learning is a particular set of procedures. The process models are capable of closely observing each of the learner's actions/steps and making adaptive assistances. Thus, if the CTM is used to supplement a process model, each learning object would have to be considered as a procedure or skill. Since the process model would certainly be capable of detecting such pattern (missing step), it can directly input this information into the Individualised Trait Network (ITN).

Field dependence or independence (FDI) is the last MOT in Table 6-1 that is not translated into an IP in this study. Although Ford and Chen (2000) had tried to generalise some behaviour patterns for FDI cognitive styles, there were still discrepancy in the two different tools used to measure FDI, namely Group Embedded Figures Test (GEFT) and Cognitive Styles Analysis (CSA). Therefore, more evidence is needed for the validity of their generalisation.

The reason is that FDI is considered to be more closely related to inductive reasoning from its description (Ford and Chen, 2000). It is therefore discussed in more detail with the discussion of working memory's contribution to inductive reasoning in chapter 7 on inductive reasoning ability.

6.6 Summary

In this chapter, characteristics of working memory (WM) are investigated in detail. The investigation includes literature about WM from many different perspectives. Some of them, such as the structural, operational, and functional views represent different schools or systems of psychology as discussed in chapter 1. From the study of characteristics of WM, eleven potentially useful indicators of WM are found. They are the manifestations of traits (MOTs) of WM and are listed in Table 6-1.

MOTs in Table 6-1 reside in an abstract layer, and they are intended to be so. The MOTs could be implemented in different forms of learning environments whether these environments are web-based, standalone, text-based, multimedia. The MOTs can also be implemented differently for different domain types, may it be a domain primarily teaching conceptual knowledge or procedural skills.

Implementations patterns (IPs), discussed in this chapter, are translations of MOTs. Five out of eleven MOTs are translated into IPs. They are listed in Table 6-2. The IPs are ready to be implemented into programming codes or scripts in the web-based system.

Working memory is one of the cognitive traits among the three investigated in this study. In a similar format to this chapter, the following two chapters cover the other two cognitive traits, namely inductive reasoning ability and divergent associative learning.

CHAPTER 7

Inductive Reasoning Ability

7.1 Introduction

The term induction is derived from the Latin rendering of Aristotle's *epagoge,* which is a process for moving to a generalisation from its specific instances (Rescher, 1980). Merriam-Webster online dictionary defined induction as an "inference of a generalized conclusion from particular instances". In many aspects, induction is itself a process of generalisation. With respect to learning, Bransford et al. (2000) pointed out that generalisations could aid the transferability of learning. Transferability of learning refers to the ability to apply learned knowledge to new situations. Generalisation can result in (mathematical) models, or global hypothesis, that can then be applied to a variety of contexts in an efficient manner (Harvery et al., 2000).

Inductive reasoning (IR) refers to the processing of induction in human reasoning. Inductive reasoning is one of the important characteristics of human intelligence: Thurston regarded inductive reasoning as one of the seven primary mental abilities that are accounted for intelligent behaviours (Selst, 2003). Rescher (1980) defined induction as an ampliative methodology of inquiry – a methodology designed to provide information-in-hand transcending answers to our questions regarding factual matters. Pallegrino and Glaster (1982) noted that the inductive reasoning ability (IRA) can be extracted in most aptitude and intelligent tests and is the best predictor for academic performance. Harverty et al. (2000, p.250) cited several other researches that viewed IR as a significant factor for problem solving, concept learning, mathematics learning, and development of expertise. Heller, Heller, Henderson, Kuo, & Yerushalmi's (2001) research showed that IRA is a necessary ability for extracting the knowledge of problem solving in Physics.

Due to the common association between inductive reasoning and deductive reasoning, section 7.2 presents a brief comparison of them. The comparison serves to differentiate induction from deduction and to stress the importance of inductive reasoning in knowledge generation and acquisition.

One of the aims of this study is to find means to model student's IRA, and understanding the characteristics of IRA is the starting point. Relevant researches in many fields, including cognitive science, psychometrics, and machine learning, have been examined in section 7.3 . Working memory capacity (Holland, et al., 1987; Lin, Kinshuk, & Patel, 2003), the ability to learn from analogy (Holland et al., 1987), hypothesis generation, and domain knowledge (Hulshof, 2001; Harverty et al., 2000) are all found to bear influence on human inductive reasoning process. They constitute the manifestations of trait (MOTs) of IRA discussed in section 7.4 .

MOTs are translated into implementation patterns (IPs) in section 7.5 . Exhibition of the IPs during students' interaction with the learning systems can give indication of the IRA of the students. Four MOTs are not translated into IPs; the reasons are given in section 7.5 . Section 7.6 then provides a summary of this chapter.

7.2 Induction and Deduction

Many people distinguish inductive reasoning from deductive reasoning (Skyrms, 1996). They are two basic ways of reasoning and argument. Comparing the differences between induction and deduction could give better ideas about the nature of inductive reasoning.

Induction is recognised as a method that moves from the particular (instances) to the general (rule) whereas deduction moves from the general to the particular (Skyrms, 1996; Arthur, 1994).

In induction, common characteristics of the particulars are generalised into rules or models that can be used in future and in other contexts. The rules, once worked, are believed to have higher probability of working again in same or similar situations in the future. For example, if a certain herb H had always successfully relieved toothache in the past, it is quite natural to assume that H has high probability of successfully relieving toothache next time. The inductive argument can be stated as Argument 7-1:

H had always successfully relieved toothache. *(premise)*
H had not failed in relieving toothache.

(therefore)

H can relive toothache next time *(conclusion)*

Argument 7-1: An example of induction

Given that the premises are true, the conclusion can be said to be quite likely to be true. The likelihood is called the inductive strength of the argument. "An argument is inductively strong if and only if it is improbable that its conclusion is false while its premises are true, and it is not deductively valid. The degree of inductive strength depends on how improbable it is that the conclusion is false while the premises are true" (Skyrms, 1996, p7).

Deduction, on the other hand, uses a different direction of argument: a direction from the rule to the particular. **Argument 7-2** is an example of deductive argument:

There are only three reasons that the water boiler fails to boil water: no electricity, the switch is broken, or the element is broken. *(premises)*
Now, the boiler fails to boil water.
The electricity is there.
The switch is in good working condition.

(therefore)

The element is broken. *(conclusion)*

Argument 7-2: An example of deduction

Given that the premises are true in **Argument 7-2**, the conclusion can only be either valid (100%) or invalid (0%). In the case of **Argument 7-2**, it is quite obvious that the conclusion is a valid one given that the premises are true.

Unlike a deductive argument, the conclusion arrived by inductive argument lacks the certainty, and can only be believed to be a workable one. However, deductive argument makes no advancement of knowledge as Skyrms (1996, p8) stated that "if an argument is deductively valid, its conclusion makes no factual claim that is not, at least implicitly, made by its premises".

It is noted by psychologists that humans are only moderately good at deduction and only make moderate use of it, whereas humans are superb at performing inductive reasoning (Arthur, 1994). The advantage of induction over deduction is that it allows the possibility to discover new knowledge based on existing knowledge (Skyrms, 1996). Many great scientific discoveries were made possible by obvious inductive reasoning of researchers (Holland et al., 1987). Skyrms (1996, p8) pointed out that "if an argument is inductively strong, its conclusion makes factual claims that go beyond the factual information given in the premises".

But why is inductive reasoning preferred to rational deductive reasoning? If, as Platonism suggests, humans are rational, should deductive reasoning not be the default mode of thinking? Arthur (1994, p.406) answered these questions by stating:

> "The obvious one (reason) is that beyond certain complicatedness, our logical apparatus ceases to cope -- our rationality is bounded. The other (reason) is that in interactive situations of complication, agents cannot rely upon the other agents they are dealing with to behave under perfect rationality, and so they are forced to guess their behaviour. This lands them in a world of subjective beliefs, and subjective beliefs about subjective beliefs. Objective, well-defined, shared assumptions then cease to apply. In turn, rational, deductive reasoning -- deriving a conclusion by perfect logical processes from well-defined premises -- itself cannot apply. The problem becomes ill-defined".

Klauer, Meiser, and Naumer, (2000) also pointed out that an important error occur during formal logical thinking is because of the required processing surpass the limited capacity of working memory. The problem of insufficient working memory capacity leads to biased formal logical thinking.

Arthur (1994), however, did not think that deductive reasoning was given up totally when the problem faced was overwhelmingly complicated. Instead, he thought that hypotheses were formed through inductive reasoning, but tested by deductive reasoning. Therefore, there is element of deductive reasoning in an apparently inductive reasoning process in many circumstances – deduction is used as part of a problem solution which may seems apparently inductive. The embedded deduction is called *deduction-in-induction* in this study. As discussed later in this chapter, inductive reasoning quite often does need the help of theoretically guided deduction-in-induction. Hypothesis testing and hypothesis formation are both part of the inductive reasoning process and need the deduction-in-induction (Harverty et al., 2000).

The previous discussion presented a general conception of what inductive reasoning is and how different it is to deductive reasoning. In order to be able to profile a student's inductive reasoning in the cognitive trait model, it is necessary to examine situations where manifestations of inductive reasoning can be observed. Large amount of studies are available in current literature about inductive reasoning. Detailed discussion about the nature and characteristics of inductive reasoning is presented in next section.

7.3 Characteristics of Inductive Reasoning

Zhu and Simon (1987) proposed a three steps division of inductive reasoning. They placed the emphasis on transfer of learning from one context to the other. The three steps are:

1. recognise the similarities and differences of the parameters in the current and experienced contexts;
2. recognise and match pattern of current context to experienced context(s); and
3. recognise/create the theory/method that can be applied to solve the problem.

Point (1) requires information filtering, encoding and classification. In the early stage of an inductive reasoning task, one needs to see what the attributes relevant to the task at hand are. Selected attributes are then encoded to form a meaningful group of which classifications or categories can be created. From selection of attributes to classification creation, it is an iterative process. In situations where a number of meaningful classifications are expected, for example when solving a well-defined problem, the meaningfulness of classification is already a sufficient condition for one to stop this iteration. On the other hand, if one is not confident with what classifications to come up with, for example exploration of a novel domain, one may need to extend this iterative process to include hypothesis testing.

The pattern finding in point (2) is the detection of co-variation from a stack of samples or past experiences (Holland et al., 1987). Heller et al. (2001) believed that learners' attainments of problem solving skills in physics came from reflective practices to extract knowledge from previous experiences of working on other problems or from sample problem solutions. That is, patterns found in previous experiences are used again to solve new problems.

Point (3) corresponds to the hypothesis generation activity (Harverty et al., 2000). Hypothesis generation differs from mere guessing in an important way - having a rationale behind the hypothesis. The rationale of the hypothesis is primarily derived from the observed pattern. Without the activity to confirm the hypothesis, the hypothesis can never be proved or disproved, and therefore forms a loose cognitive structure that is deemed as the source of "fundamental attribution error" (Holland et al., 1987, p222), and is accountable for wrong judgements at later time when this knowledge structure is used as a basis of induction.

Harverty et al. (2000) studied inductive reasoning with respect to mathematical problem solving, in particular function finding. In their study, participants were given a set of data that were said to relate to a function. The task of the participants was to find the function. Harverty et al. (2000) observed three main activities that lead to successful inductive reasoning. The three observed activities were:

- data gathering, which includes activities of data collection, organisation, and representation;
- pattern finding, which includes activities of investigation and analysis of the data collected; and
- hypothesis generation, which includes activities of constructing, proposing, and testing hypothesis.

Hypothesis generation uses the data from data gathering and patterns found, but the sequence of the three activities is not just one-way. The activities of hypothesis can also incur new insight for data gathering and pattern finding. Result of any of the three activity can feedback to any other two activities.

Klauer (1996) studied inductive reasoning using psychometric tests, which included series-completion problems, Raven matrices, classification problem, and analogy problems. Klauer summarised and classified the tasks of inductive reasoning into the following:

- generalisation: detecting similarity of attributes
- discrimination: detecting differences of attributes
- cross classify: detecting similarity and differences in attributes
- recognise relationships: detecting similarity of relationships
- differentiate relationships: detecting differences in relationships
- system construction: detecting similarity and differences in relationships

Although similar to Harverty et al.'s (2000) findings, Klauer's (1996) classification of steps (tasks) in inductive reasoning raised an important point – inductive reasoning lead to an understanding of a system. Relationship recognition and differentiation can only exist in a systematic understanding. A system contains units, attributes of units, and relationships between units. Holland, Holyoak, Nisbett, and Thagard's (1987) *adaptive default hierarchy* offers a similar systematic view of understanding obtained by the exercise of induction.

Holland et al. (1987) proposed a rule-based mental model, called adaptive default hierarchy, as a framework to explain human inductive reasoning behaviour. The adaptive default hierarchy postulates that there is a general default set of rules for every mental model, such as a permission mental model has the following rule: "if X is true then Y is allowed". For example, a Chocolate-Permission mental model for a child could be like this: "if Mom says I cannot have chocolate, then I am not allowed to have the chocolate". The framework is adaptive because it allows exceptions to exist within a mental model to form sub mental models. Sub mental model could be created under the Chocolate-Permission mental model such as "if Mom says I cannot have chocolate, and Dad is present and does not confirm her, then I am allowed to have the chocolate". With respect to the additional sub mental model, the original Chocolate-Permission mental model becomes a super mental model.

So instead of overthrowing the super mental models when exceptions occur, sub mental models are created to cater for the exceptions. The sub mental model can have further sub mental models. The super and sub mental models thus form a hierarchy of mental models. The mental models in the higher level of the hierarchy are usually more general, and in the lower levels more specific. The number of rules in the higher level is less than the ones in the lower level.

Both Klauer's (1996) and Holland et al.'s (1987) views indicate that inductive reasoning is capable of creating systematic views. It is Holland et al.'s (1987) adaptive default hierarchy that has further details with respect to how exceptions are incorporated.

Researchers, such as Klauer (1996), Harverty et al. (2000), and Zhu and Simon (1987), studied inductive reasoning using the atomist approach – they broke the object of study down into smaller components. This break-and-tackle approach is itself a good strategy of inductive reasoning (Harverty et al., 2000). Even though the methodological approach of this study is not purely atomistic, atomistic view is nonetheless beneficial to the course of finding manifestations of inductive reasoning. Therefore, by summarising the abovementioned researches, common steps/sub-tasks of inductive reasoning are listed below:

- relevance filtering: finding out what are the potentially critical attributes to consider
- pattern matching: finding out commonality, spotting regularity
- hypothesis generation: constructing potential rule or model of explanation
- testing: testing and validating the generated hypothesis

The meaning of the term "step" used here does not necessarily be bound to meaning of an element in a predefined sequence of occurrence. Relevance filtering, pattern matching and hypothesis generation (including hypothesis testing) are discussed in more details as they are in themselves manifestations of trait (MOTs) of inductive reasoning. Discussion about background knowledge, problem solving strategies, analogical reasoning, systematic thinking, and classification ability are also presented below because literature suggests that they are all relevant to certain aspects of inductive reasoning.

7.3.1 Inductive Reasoning and Data Relevance

One important step in the early stages of inductive reasoning is data gathering (Harverty et al., 2000). Data gathering includes activities such as collecting relevant and potentially useful data, organise, and present the data into a form (e.g. tabulated) or a state (e.g. summed) where inductive reasoning can be facilitated. The efficiency of inductive reasoning is greatly enhanced if relevant data could be found and used (Wexler, 1999). Without the ability to pinpoint which piece of data really is relevant, or maybe in situations where no information can be drawn to judge the relevancy of data, it would then has to rely on what is called "systematic thinking" to go through each piece of data or combinations of data to test out their relevancy. Systematic thinking although is useful, but would be more time consuming. Systematic thinking is also identified and discussed as one of the MOTs of inductive reasoning later in the chapter.

The feeling of "some thing could be relevant", is not merely a hunch from nowhere, but involves a broader sense of the overall task comprehension (knowing what needs to be done), and possibly also previous experience(s) with something similar. Previous experience (background knowledge) is addressed separately as one of the MOTs of inductive reasoning later in this chapter.

Furthermore, the "ability to filter data relevance" also includes a construct essential to inductive reasoning, namely classification (Sternberg, 1977). A class provides a meaningful container where items with similar attributes can be grouped together. The meaning associated with different classes can be used to determine the relevance of data (attributes of data). Again, classification is itself discussed as one of the MOTs of inductive reasoning later in this chapter.

Although the ability to filter data relevance includes three other MOTs (systematic thinking, background knowledge, and classification), it is still considered as an MOT. The reason is that what we are looking for are potential indicators of inductive reasoning ability, not exclusive, atomistic components of inductive reasoning. We believe that the ability to filter data relevance is as good an indicator as the other three MOTs. It has to be acknowledged that there could be complex relationship between the MOT of the ability to filter data relevance and the other three MOTs, but the all-inclusive approach discussed in chapter 3 and the resulting multiple portrayal network mechanism discussed in chapter 5 are geared to resolve this type of complex relationship.

An example of the relationship between relevance filtering ability and inductive reasoning can be seen from Schank and Neaman's (2001) description of how students use the Return of the Wolf which is a virtual educational emulation of a wild-life park. In the Return of the Wolf, students are given a task to find out why the wolf population is decreasing in a virtual national park. The students can wonder around the virtual national park and collect information by talking to the virtual characters in the park. The program deliberately sets up a trap which provides misleadingly relevant data to the students. Many students did not judge the relevance of the misleading information and induced wrong conclusions. It shows that when irrelevant data is used as the basis of induction, the desired result cannot be obtained.

Another line of study about data relevance and inductive reasoning can be found in study of machine learning (Ross, 2000; Costa, 2000). Algorithms are devised to perform induction as a method of machine learning. An example of such algorithm is the ID3 algorithm (Ross, 2000). ID3 takes in a set of data organised in attribute/value pairs (e.g. colour=yellow; size=large) describing a situation (e.g. whether a fruit is safe to eat). ID3 creates a decision tree considering each attribute as a node and its possible values as the forward branches of the node. The resulting decision tree can often reduce the large data set into a smaller set of rules where it is easier to see the relationships between the attributes and certainly much easier to remember than the data set.

Ross (2000) pointed out that if one irrelevant attribute is brought into computation by the inductive machine learning algorithms, such as ID3, erroneous or dramatically different result might be found. Even though it is not likely that humans and machines process classification tasks, such as the safety of fruit eating example, exactly the same, partial resemblance however is possible.

7.3.2 Inductive Reasoning, Pattern Matching and Working Memory

Transferability of learning is regarded as an important part on how people develop competencies (Bransford et al., 2000). Transferability refers to the ability to apply the problem solving skills, which can contain only conceptual knowledge obtain from case studies or procedural knowledge obtained from previous hand-on exercises, into a novel context. Previous procedural knowledge does not guarantee the ability to solve a problem in a novel context, nor does mere understanding of concepts. Thus curriculum with focus on transferability tries to provide as much contexts of the problems/case studies as possible in order to increase the success rate of transferring problem solving knowledge to new contexts. A student could then create a set of different mental models, which are all related to the concept at scrutiny, from the set of different contexts. Environmental variables in the contexts are encoded to differentiate one mental model from the other.

Often transferability is used as a measure of the quality of learning (Bransford et al., 2000). For the assessment of the transferability to be fair, a "new" context must differ from any previously experienced contexts, but the differences can neither be 0% nor 100% – there must be similarities between the learned contexts and assessment context. It is up to the student to induce which learned mental model to apply to current task at hand. Selecting an appropriate mental model to apply requires pattern matching – matching the environmental variables.

Pattern matching in turn requires comparisons. Comparison as a cognitive process is known to be highly related to working memory capacity, and is positively proportional to working memory capacity (Salthouse & Babcock, 1991). It is therefore logical to hypothesise that higher working memory capacity lays the foundation to higher performance in pattern matching and therefore should correlate to higher inductive reasoning ability.

Some researchers viewed working memory as the amount of activation in long term memory (Anderson 1983a, 1983b; Cantor and Engle, 1993). In this view, (knowledge) units have to be activated in order to be conscious of; otherwise they remain in sub- or un-consciousness. For comparison and pattern matching to occur, the necessary units need to be activated. From this theoretical view, higher working memory means greater number of activations could occur at any given moment. Greater number of activations implies more units could be conscious of and thus worked on (compared). This facilitates both:

1. comparison speed: greater amount of data can be processed in a given moment.
2. pattern matching accuracy: more environmental variables between two contexts can be compared in a given moment; the more similar the

relevant variables between the two contexts are, the higher is the possibility that the learned knowledge can be applied to the new context.

Therefore, the view of working memory as amount of available activation (Anderson 1983a, 1983b; Cantor and Engle, 1993) also supports our hypothesis that high working memory capacity leads to high performance of pattern matching which is in turn an essential step of inductive reasoning (Harverty et al, 2000; Klauer, 1996; Zhu and Simon, 1987).

Another line of relevant research comes from Dougherty and Hunter (2003). They studied the relationship between hypothesis generation, probability judgement and working memory. They hypothesised that "individual differences in working memory capacity are fundamental to probability judgment by limiting the number of alternative hypotheses that can be maintained in the focus of attention" (Dougherty and Hunter, 2003, p.263). In other words, the higher the working memory capacity, the more hypotheses could be evaluated at a given moment, and therefore the higher the accuracy of the inference/decision. Their experimental result supported their claim.

Still another piece of evidence suggesting that the inductive reasoning ability related to working memory capacity is the fact that external representation (what the learners see) can indeed influence one's internal cognitive processes. Wexler (1999) gave an example of rearranging the card in one's hand renders the relation of the cards more perceptually salient. It brings up the point that cognitive capacity of human being is limited in nature. One important factor of being able to perform generalisation, as a form of induction, is to remember the particulars and their attributes. The remembering certainly has to take up the available working memory capacity if external representation in any form is not available.

7.3.3 Inductive Reasoning and Hypothesis Generation

Hypothesis formation and testing are essential steps for induction no matter if the hypothesis is local or global. "Local" and "global" denote how mature a hypothesis is and they are discussed in section 7.3.5 . Dougherty and Hunter (2003, p263) stated "one is unlikely to consider causes or hypotheses that are not initially generated". They further pointed out that hypothesis generation is important in many tasks that require decision making because of its role as a logical precursor of hypothesis evaluation.

Hypothesis, once formed, can then be proved or disapproved to become part of legitimate knowledge. In either way, it contributes directly to the overall knowledge building in the learning process.

Hypothesis primarily exists only as a mental construct in students when they are reading or exploring to learn. It then poses a great problem for any online learning system to detect the formation of hypothesis since there is no explicit way to examine what is happening in a student's mind. However, once the student had constructed a hypothesis, the student will need to confirm it, no matter whether the result of confirmation is positive or negative. According to Popper, a philosopher of science, the primary function of scientific laws and theories is prediction (cited by Holland et al. 1987, p328).

Without the action to confirm, the hypothesis is literally of no use – it cannot be used to predict. Thus, it is logical to say that the lack confirmation a hypothesis is equivalent to no hypothesis at all.

7.3.4 Inductive Reasoning and Background Knowledge

Hulshof (2001) noted that prior domain knowledge (DK) also bears influence on the inductive behaviour of the learner in addition to the general intellectual ability to make induction. The latter is referred as generic knowledge (GK) that is the domain independent knowledge to systematise and relate objects of observation. Hulshof (2001) cited the Klahr and Dunbar's SDDS (Scientific Discovery as Dual Search) theory, which postulated that the discovery activities can be located in either of the two spaces, i.e. hypothesis space and experiment space, and used these two spaces to describe and analyse the discovery behaviours of the learner. Hulshof (2001) further correlated the predicted behaviours of the learner with different levels of generic knowledge and domain knowledge, both in terms of high and low, to the two spaces stated in the SDDS theory. The categorisation is shown in Table 7-1.

Table 7-1: Learner Categorisation

Generic Knowledge / Domain Knowledge	High (HGK)	Low (LGK)
High (HDK)	Start with Hypothesis Space, only goes into Experiment Space to test the validity of hypothesis.	Constant switching between Hypothesis Space and Experiment Space
Low (LDK)	Start with Experiment Space and gradually into Hypothesis space	Stay and Struggle in the Experiment Space

In a discovery task aimed at inducing a problem solution, a learner of HGK/HDK starts by searching hypothesis space because the learner had understanding of the variables in the problem domain. What the learner is focusing on is the selection or creation of a hypothesis that can be applied in the problem at hand. The learner only goes to the experiment space to validate the hypothesis. Learning effect is best for this kind of learner.

Learner of LGK/HDK may start by searching the hypothesis space because of the high stack of relevant domain knowledge. But due to the lack of systematic approach, the learner would fail to discover the right relationship among the objects and hence select or create the right hypothesis to apply. The learner would be forced to search on the experiment space and go back and forth between the two spaces until the solution is found.

Learner of HGK/LDK would typically start with experiment space due to the lack of understanding of the domain variables. But the learner could gradually discover the working patterns of the variables and start to work in the hypothesis space and will gradually become a learner of HGK/HDK.

Learner of LGK/LDK would start with experiment space. Due to the lack of understanding about the domain and the inability to discover systematic patterns, the learner might struggle and remain in the experiment space. Learning effect of the discovery task is hence the worst for this kind of learner.

The learning efficiency of the discovery task decreases from HGK/HDK - HGK/LDK - LGK/HDK - LGK/LDK (Hulshof, 2001).

Heit (2000) showed that one form of inductive reasoning, the diversity-based reasoning, is demonstrated less by children than by adults, but further comparison of American adults and Itzaj (name of Mayan people in Guatemala) adults showed that diversity-based reasoning depends not only on processing but on knowledge. The result corresponds well to the view point of Hulshof (2001) that the efficiency of the HGK/HDK combination is greater than that of the HGK/LDK.

To sum, both Hulshof (2001) and Heit (2000) showed that domain knowledge plays an important role during inductive reasoning.

7.3.5 Inductive Reasoning and Problem Solving Strategies

Harverty et al. (2000) observed the behaviours of the subjects in their experiment of mathematical function finding. They noted that subjects who successfully completed the task employed common solution strategies. In the experiment, subjects were asked to find a mathematical formula (in terms of y and x) given a set of data of the formula. One solution strategy is local hypothesis strategy. In local hypothesis strategy, subjects formed a local hypothesis from a single instance of data and tested if the local hypothesis work for other data instance as well. They may have to generate many local hypothesises before they can find one working for another piece of instance, but this strategy is useful in finding the elements of the global hypothesis (solution).

The action of finding one local hypothesis and testing if it works for other data instances is actually a process of pattern finding. A mathematical formula is constructed by its elements which are algebraic expressions translated from observed patterns, and a certain pattern of behaviour of the formula can be defined by an element of the formula; for example, $(x-3)$ is an element of the formula $y = (x-3)(x/2)$. Finding both the elements and the relationship of the elements can lead to the complete formula.

Another strategy that the subjects employed to successfully solve the problem was called the pursuit strategy (Harverty et al., 2000). In pursuit strategy, subjects found a pattern expressed in quantity(ies), Q, besides the original quantities (x and y). The subjects then tried to understand the formula using Q, and decided whether Q is worthy or not for the pursuit. If the formula can be understood in Q, then the subject tried to translate Q in terms of x and perform the test on the global hypothesis to see if the corresponding y value can be found correctly for each x value. Harverty et al. (2000) found that the pursuit strategy is the most popular one. It worked by finding intermediate quantity(ies), Q, so that the behaviour of the formula can be understood in an easier way than its original quantities. Q is supposed to be easier to be understood than y, and therefore the pursuit strategy transforms a complex process into many simpler ones. By finding the right Qs and combine them together correctly, an algebraic equivalent expression of the formula can be achieved. The Qs are analogous to the puzzle pieces for the formula (Harverty et al., 2000).

7.3.6 Inductive Reasoning and Analogy

Use of analogy also plays an important role for inductive reasoning. Researchers of instructional technology had long recognised the important value of using analogies or parallel concepts to prop understanding of important concepts. Among them, Kinshuk, Oppermann, Patel, and Kashihara (1999) had identified parallel concept link as one of the major six types of navigational links in web-based educational systems.

Holland et al. (1987) pointed out that analogous thinking enables one to view a novel situation using familiar concepts, and showed that many great scientific discoveries could be attributed to the use of analogy as a basis for induction. The wave nature of light was discovered by drawing analogy to the wave of liquid for observed properties such as reflection, and diffraction. Analogy, in Holland et al.'s view, provides an already-structured framework which allows the information available in the new context to be filled in. Subsequently, the information could possibly be made sense of because the structural information about the framework and the information of how operations can change the problem state are readily available from the analogy (the framework). The learning or problem-solving process could therefore be greatly facilitated. Metaphors, according to their perspective, serve the similar role.

7.3.7 Inductive Reasoning and Systematic Thinking

The ability to systematically enumerate all possibilities is considered an important ability to aid the process of transforming local hypothesis to global hypothesis. It is hereafter called the systematic thinking. The systematic thinking differs from mere guessing because it provides a guided list for systematic elimination and therefore increases the efficiency of eliminative strategy.

It has to be pointed out that there are not many existing literature about systematic thinking. It is therefore treated as a construct of this study and is discussed in great details in chapter 11.

7.3.8 Inductive Reasoning and Classification

Sternberg (1977) listed three components of inductive reasoning: classification, rule generation and rule testing. Analogies, series completions, and classifications are three parts of inductive reasoning tests used by Sternberg (1983).

Classification is used to extract the higher order concept from stimuli. van de Vijver (2002) used the set of four letters CDEF as an example of classification. The set is in the following three classifications: four consecutive letters in the alphabet, a group with one vowel, and a group with three consonants. The more classifications one can find from one stimulus, the more chance the classifications are going to overlap with the classifications induced from other stimulus and therefore higher possibility of solving the inductive reasoning problem.

The ID3 algorithm mentioned in the discussion about data-relevance in section 7.3.1 is primarily a classification algorithm (Ross, 2000). Other machine learning mechanisms, such as case-based reasoning and evolutionary computation, are all essentially classification tasks (Costa, 2000; Chen, et al., 1998). They are all labelled inductive machine learning techniques. These studies about machine learning also lend support to the potential contribution of classification ability in inductive reasoning.

7.4 Manifestations of Inductive Reasoning Ability

Based on the above discussion, certain behaviours of the learners, called the manifestations of trait (MOTs), can be used to indicate their inductive reasoning ability (IRA). They are listed in Table 7-2.

Table 7-2: MOTs of Inductive Reasoning Ability

	Low Inductive Reasoning Ability	High Inductive Reasoning Ability
1.	poor at generalisation	good at generalisation
2.	poor data relevance filtering	good data relevance filtering
3.	low working memory capacity	high working memory capacity
4.	no activities to confirm hypothesises	activities to confirm hypothesises
5.	poor background knowledge	good background knowledge
6.	unable to utilise pursuit strategy	able to utilise pursuit strategy
7.	unable to utilise local hypothesis strategy	able to utilise local hypothesis strategy
8.	inability to learn from analogy	able to learn from analogy
9.	poor systematic thinking	good systematic thinking
10.	low classification ability	high classification ability

The MOTs in Table 7-2 are still a step too abstract to be used directly in learning systems. The next section provides translation of MOTs into implementation patterns.

7.5 Implementation Patterns

The ten MOTs listed in Table 7-2 give general indications of students' inductive reasoning ability. Some of the MOTs are not suitable in specific contexts, for example, the uses of local hypothesis strategy and pursuit strategy are applicable in a problem solving procedure and not suitable in a learning system that emphasises on conceptual knowledge. In this study, five MOTs are translated into implementation patterns, and five are not. They are discussed in more detail in this section.

7.5.1 Implementation Pattern for Generalisation from Example

Generalisation skill denotes the ability to abstract consistent patterns from row phenomena. The generalised pattern is assumed to be applicable to other similar situations by human's intuitive assumption about the systematic-ness of the world. The assumption of nature's systematic-ness may be wrong as some argued, but it obviously contributes to many great scientific discoveries (Skyrms, 1996).

The observed row phenomena are often examples or case studies trying to demonstrate some underlying principle in a more memorable way, i.e. in adequate context. The measure of this skill is determined by whether the student can generalise the principles correctly from the presented examples or not. The relations of learning object required are HasExample, and IsExampleOf. Therefore, MOT of generalisation has the following implementation pattern:

HasExample (O) → ... → Pass (O)

*Where **O** is a learning object,*
→ means followed by,
***HasExample (O)** is the activation of the HasExample relation of **O**,*
***Pass (O)** is the function to determine whether **O** is passed after the evaluation,*
***...** indicates other relations that is not take into account for this manifest.*

The function Pass(O) evaluates whether the student has correctly answered the questions in the evaluation unit that contains learning object O. If Pass(O) is true, it indicates higher generalisation skill and hence higher inductive reasoning ability, and vice versa if Pass(O) is false.

7.5.2 Implementation Pattern for Learning from Analogy

Inducing and hence understanding theories could be facilitated by use of analogies (Holland et al., 1987). Analogy presents to a student an alternative angle to look at current problem. The alternative provides a certain degree of familiarity from already-learned knowledge to make solving the present problem easier. Analogous concept to the current concept at hand could be implemented by parallel concept links (Kinshuk et al, 1999).

Example of a parallel concept to the concept of how sound waves travel in air could link to an explanation of how waves travel in water. By first seeing the already-familiar analogy of water wave and then being presented with the new concept of sound wave, the student certainly has higher possibility to induce and learn the properties of sound wave. The MOT of ability to learn from analogy could be translated into the following implementation pattern:

Parallel (O) → ... → Fail (O)

*Where **O** is an learning object,*
→ means followed by,
***Parallel (O)** is the activation of an parallel concept link of **O**,*
***Fail (O)** is the function to determine whether **O** is failed after the evaluation*
***...** indicates other relations that is not take into account for this manifest.*

The function Fail(O) evaluates whether the student has incorrectly answered the questions in the evaluation unit that contains learning object O. If Fail(O) is true, it indicates inability to learn from analogy, and hence lower inductive reasoning ability, and vice versa if Fail(O) is false.

7.5.3 Implementation Pattern for Hypothesis Confirmation

In online learning systems, students can view an example of a concept by using link with HasExample relation. The reverse of HasExample relation is the IsExampleOf link. If any of the hypotheses is formed during the viewing of the example learning object, the best way to confirm it is to follow the IsExampleOf relation back to the original theoretical learning object. Thus, the following navigational pattern can be used to detect the existence of this MOT:

HasExample(O) → IsExampleOf (O')

*Where **O** is an learning object,*
***O'** is the example that the **HasExample(O)** links to,*
→ means followed by,
***HasExample(O)** is the activation of an HasExample relation of **O**,*
***IsExampleOf(O')** is the activation of an IsExampleOf relation of **O'**.*

7.5.4 Implementation Pattern for Previous Domain Knowledge

Domain knowledge bears influence over the inductive reason process (Hulshof, 2001; Heit, 2000). Domain knowledge, though beyond the scope of this discussion, is available in many learning systems in the form of performance-based student models (Staff, 2001; Martin, 1999). The representational value of the domain competence can be retrieved from the performance-based model of the learning environment and can be used as a factor to determine how good the learner can perform induction in this domain. It would be an interface problem instead of theoretical problem, and hence not addressed in detail in this study.

7.5.5 Implementation Pattern for Working Memory Capacity

Working memory capacity had been identified as an influential factor to the inductive reasoning process in the previous discussion. Working memory capacity is anther cognitive trait that had been modelled by the cognitive trait model (Lin, Kinshuk, Patel, 2003), and the value of the learner's working memory capacity is readily available as part of cognitive trait model. It is again only a technical problem of retrieving the value of working memory.

The five implementation patterns (IPs) translated thus far are summarised in Table 7-3.

Table 7-3 : Implementation Patterns of Inductive Reasoning Ability

	Low Inductive Reasoning Ability	High Inductive Reasoning Ability
1.	Unable to generalise from example	Able to generalise from example
2.	unable to learn from analogy	able to learn from analogy
3.	no activities for hypothesis confirmation	activities for hypothesis confirmation
4.	low domain knowledge	high domain knowledge
5.	low working memory capacity	high working memory capacity

There are, however, still more MOTs that are not suitable for translation. They are discussed in next section.

7.5.6 Other MOTs not Translated

Five manifestations of trait (MOTs) of inductive reasoning ability are not translated. They are classification ability, systematic thinking, relevance filtering, utilisation of pursuit strategy, and local hypothesis strategy.

Classification ability and systematic thinking manifest themselves more readily in experimental environments. Tests of classification ability often involve giving participants a list of items and asking them to sort the items into categories (Klauer, 1996) whereas systematic thinking tests ask participants to systematically combine the given items (Inhelder and Piaget, 1958). While there could be tasks in learning systems that involve classification ability and systematic thinking (e.g. sorting into categories), these types of tasks are not common across domains/subjects. Therefore, these two MOTs have not yet been translated.

To be able to detect relevance filtering, information, both relevant and irrelevant, has to be present. Unless the curriculum purposefully incorporates tasks to train the relevance-filtering ability, it is against logical sense for any teacher to include “irrelevant information” which could lead to confusion. Therefore, this MOT is not translated.

To be able to demonstrate local hypothesis strategy and pursuit strategy explicitly, the task/learning domain has to be procedural – i.e. needing students to complete a set of procedures as a process of learning. The scope of this study is currently set to conceptual domain. There are possibilities to extend this research work to procedural domain (Lin, et al., 2006). This possibility will be discussed in the chapter 18.

7.6 Summary

Inductive reasoning ability (IRA) is an important characteristic of human intelligence and is often included as part of aptitude tests (Pallegrino and Glaster, 1982). Induction moves from particular instances to general rules whereas deduction moves from general rules to particular instances. IRA is a significant factor in problem solving, concept learning, mathematic learning, and development of expertise (Harverty et al., 2000).

Relevant literature is reviewed in order to study the characteristics and manifestations of inductive reasoning. Ten manifestations of trait (MOTs) of inductive reasoning ability are found and they are related to:

1. Generalisation skill
2. Data relevance filtering
3. Working memory capacity
4. Activities to confirm hypothesis
5. Domain knowledge
6. Utilisation of pursuit strategy
7. Utilisation of local hypothesis strategy
8. Ability to learn from analogy
9. Systematic thinking
10. Classification ability

Among the ten MOTs, five of them are translated into implementation patterns (IPs). These five IPs are related to:

1. Generalisation skill
2. Ability to learn from analogy
3. Activities to confirm hypothesis
4. Domain knowledge
5. Working memory capacity

Inductive reasoning ability is the second cognitive trait that is investigated in this study. In the next chapter, the third cognitive trait, divergent associative learning is discussed.

CHAPTER 8

Divergent Associative Learning

8.1 Introduction

Divergent-associative learning (DAL) denotes the characteristic of learning that develops links between new and existing concepts. DAL has both similarities and differences to both *divergent thinking* and *associative learning*. DAL differs from the other two cognitive traits, working memory capacity and inductive reasoning ability, in an important aspect – the names of both working memory capacity and inductive reasoning ability explicitly point out that they are mental capabilities or abilities. On the other hand, DAL has higher resemblance to a style of cognition. In fact, one of the important psychological construct, that DAL inherits, is called divergent thinking which itself is recognised as a cognitive style (Bahar and Hansell, 2000).

The definition and name of DAL involve element of associative learning. Most of the studies about associative learning involve what is called the paired-associate learning (Bonardi, 1998; Laumann, 1999; de la Iglesia, 2004; Solso, et al., 1974; Horowitz and Gordon, 1972). Paired-associate is basically a task requiring the subjects to learn a list of associations between stimuli and responses. The focus on learning the associations between pairs of stimuli and responses has, in our opinion, limited the development of theories to understand how associations are used in a broader context about human cognition and learning. In this study about DAL, a more natural way of learning, although still associative, is explored.

While associative learning is often studied separately from divergent thinking, there are researchers, like Mednick (1962) and Baer (1993), who studied both of them together. The research contexts of Mednick (1962) and Baer (1993) were on creative production, whereas this study focuses more on learning. Their efforts on bringing together associative learning and divergent thinking provide important clues to the development and understanding of DAL in our study. Their researches are discussed in greater details later in this chapter.

Although DAL might seem like a construct proposed by this study, it however inherits characteristics from both divergent thinking and associative learning. In order to provide the contextual information of previous research works, divergent thinking and associative learning are each discussed in sections 8.2 and 8.3 respectively. Comparisons between DAL and divergent thinking and associative learning are then presented in section 8.4 . Characteristics of DAL are then studied in section 8.5 and manifestations of DAL are extracted in section 8.6 . Section 8.7 provides translations of manifestations of DAL into implementation patterns ready for implementation. Section 8.8 summarises this chapter.

8.2 Divergent Thinking

Hudson (1966) and Kolb (1984) both used the terms *divergence* and *convergence.* Although Hudson distinguished them as thinking styles and Kolb studied them as learning styles, there had been a strong relationship between their studies. In both Hudson (1966) and Kolb (1984), divergent learners are characterised as creative, whereas convergent learners are seen as doing best when there is only a single answer to a problem. Additionally, Kolb's learning style model relates the four learner types, i.e. Diverger, Converger, Assimilator, and Accommodator, to the dimensions of doing versus watching as well as to the dimensions of feeling versus thinking. Convergers are related to active experimentations (doing) and Divergers are related to reflective observations (watching).

As opposed to convergent thinking, which manifests itself by arriving at the single correct solution to the problem from many potential options, divergent thinking manifests itself by creating many responses to a single stimulus (Vartanian, Martindale & Kwiatkowski, 2003; Mouchiroud, and Lubart, 2001). An example of divergent thinking test is Wallach and Kogan's (1965) "alternate uses test" which asks subjects to write down as many uses of a common object, such as a brick, as possible in a certain time frame.

In Guilford's (1971) structure-of-intellect (SI) model, five mental operations listed are cognition, memory, divergent production, convergent production and evaluation. These five mental operations work on four different types (figural, symbolic, semantic and behavioural) of content to produce six categories of products (units, classes, relations, systems, transformations and implications). Theoretically, the SI model predicts that there exist a total of 120 unique abilities (5 x 4 x 6) among which 24 (4 x 6) are related to divergent production (thinking). In Guilford's 1974 paper, all 24 abilities related to divergent production were claimed to be demonstrated (Guilford and Pandey, 1974).

Divergent thinking is believed to be an important component of creativity (Plucker & Renzulli, 1999; Runco, 1991) and is often studied and tested as a potential of idea generation in brainstorming activities (Coskun, 2005) and creative thinking (Baer, 1993; Runco, 1991; Vartanian, Martindale & Kwiatkowski, 2003; Guilford, 1971; Eysenck, 1993; Eysenck, 1995; Mouchiroud, and Lubart, 2001). The terms divergent thinking and creative thinking are used interchangeably in this study due to:

1. the prevalence of using tests of divergent thinking as a measure of creativity (e.g. Mouchiroud, and Lubart, 2001; Runco, 1991); and
2. divergent thinking is believed to be a domain independent factor of creative thinking, among other factors which are more domain- and task-specific (Guilford, 1971; Runco, 1991; Bear, 1993).

The focus of this study is set on the domain-independent characteristic of divergent thinking and creativity.

Mednick (1962) used an associative point of view to explain creativity and proposed that serendipity, similarity and mediation are the three ways in which creative solutions might be obtained. Serendipity denotes the opportunity that the contiguity (time or location) of environmental stimuli leads to a creative solution. This is similar to Martindale's (1999) findings that creative individuals are differentiated from the non-creative ones by the distributed patterns of their cortical activations. Similarity, facilitated by analogical reasoning, can also lead to creative, novel solutions. Mediation refers to the use of a third party mechanism to bring together parted concepts to achieve creativity. Use of symbols is a typical example of mediation.

To account for individual differences in creative performance, Mednick (1962) put forwards five factors: domain-specific knowledge, quantity of solutions produced, differences in cognitive and personality style, combination of different solutions to create more creative solutions, and individual's *associative hierarchy.* Among the five factors, associative hierarchy refers to how individual's associations are formed and organised. An easier way to understand the concept of associative hierarchy is to think of a bell curve (the normal distribution curve in Statistics). The central line of the bell curve represents the most typical associative item to a stimulus item, for example, table to chair. The spread of the bell curve represents the range of ideas.

A non-creative individual's associative hierarchy is steeper – the bell curve is taller and narrower. The individual has very high possibility of producing only a few ideas in response to a stimulus. On the other hand, a creative individual has a flatter associative hierarchy. Because the bell curve of a creative individual covers a larger range of ideas, the possibility of generating less common ideas (novel ideas) is higher.

Baer (1993) argued that many divergent thinking theories, which use the number of diverse ideas that come to mind in response to some cues/stimuli as a measure of divergent thinking, are in fact associationistic in nature. Baer therefore suggested a multi-level view of creativity and suggested that the associative view of creativity (like that of Mednick, 1962) can be used as an underlying substrate of divergent thinking. Baer's view of multi-level view on creativity consisted of domain-transcending abilities (such as divergent thinking) in the higher level and some task-specific and associative abilities, such as "fluency in generating many rhyming words" and "fluency in inventing many metaphors for a given concept", in the lower levels. The abilities in the lower level tend to be associative and therefore could be learned and strengthened through repetitions and experiences. Experiences are domain specific and therefore the abilities in the lower level are domain dependent. This multi-level view on creativity can explain the common observation that experiences in a domain are required before the occurrence of creativity.

The discussion in this section covers some fundamental ideas of divergent thinking as well as some associative view of divergent thinking such as Mednick (1962) and Baer (1993). More literature about divergent thinking is examined in section 8.5 . In order to steer the discussion into divergent associative learning (DAL), literature in associative learning is looked at in next section.

8.3 Associative Learning

Many of the studies about associative learning are based on the assumption that association can be formed between simple events or stimuli (Bonardi, 1998).

Associations between the simple events, such as lights, tones and food, are the targets to be learned. One end of the association is often called the stimulus and the other the response (Laumann, 1999; de la Iglesia, 2004; Horowitz and Gordon, 1972; Feldman, Johnson, and Mast, 1972). The stimulus and the response constitute a pair to be learned and task of this type is often called paired-associate learning (Horowitz and Gordon, 1972).

This type of learning has been quite often referred to in behaviourist psychology and the subjects of study include both human (Benz, 2003; Laumann, 1999) and non-human animals (Bonardi, 1998; Giurfa, 2005).

Associative learning has been explored under several discussions about causality, which is regarded as having a central role in cognition in both human and nonhuman animals (Reboul, 2005; Castro & Wasserman, 2005; Giurfa, 2005). Reboul (2005) hypothesised that the meaning of causality is different in human and non-human animals. As a prelude, the distinction between predictive and diagnostic learning was made: predictive learning goes from cause to effect whereas diagnostic learning goes from effect to cause. Using an example consisting of two events, "Raining" and "No-Playing-Outside", Reboul (2005) then constructed the following speculation: an associative account, formed by contiguity and repetition, is sufficient for a dog but it is not enough for a child (about the age of 11) who instead needs an explanation which is based on *un-observables*. The un-observables for an 11 years old child could be the dislike of getting wet, the likelihood of getting ill, or the knowledge about the consequences (pains and discomforts) of illness.

The capacity of humans to construct and work on the un-observables is what is accountable for diagnostic learning. Diagnostic learning can be construed as a retrospective behaviour that builds explanations from the effects to the causes. An example of diagnostic learning at work is after a child gets sick (the effect), the child learns the combination of "Raining" and "Playing Outside" could cause the sickness. Diagnostic learning is reflective in nature. Reboul (2005) therefore claimed that the ability to process the un-observables is the basis that makes human and non-human animals perceive causality differently, and it is what makes human and non-human animals different.

Giurfa (2005) disagreed with Reboul's (2005) use of the ability to process the un-observables as a demarcation of human and non-human animals. Using experiments that reward honeybees with sucrose solution based on honeybees' choices of which visual pattern to land on, Giurfa (2005) showed that honeybees made their decisions not on the perceptual similarity between the learned and new stimuli, but on attributes that transcend the stimuli used to train them. For example, the experiments showed that honeybees can learn abstract rules like "larger than" and "on top of" in which stimuli may not share any common visual feature. The honeybees are able to operate on events in order to extract rules and retrospectively evaluate stimuli and their outcomes: honeybees also have complex apparatus to work on the un-observables. Giurfa (2005) therefore concluded that the diagnostic/retrospective learning, which is the related ability to work on the un-observables, is not a prerogative of human and therefore rejected Reboul's (2005) claim that human and non-human operate differently in terms of associative learning. Please note that researchers like Giurfa (2005) and Reboul (2005) had not limited their use of the term "associative learning" to the pair-associate task. Instead, the term "associative learning" denotes the learning from perceived associations.

Another line of research also involves an interesting characteristic about associative learning. An association learned between two items A and B has equal strength from either side of the association – the association is symmetrical and A elicits B as much as B elicits A. For example, if you learn a pair of arbitrary words (QYE, WPB), the chance of your correct recall of WPB from seeing QYE is the same as the chance of your correct recall of QYE when seeing WPB. This is called the principle of associative symmetry (Horowitz and Gordon, 1972). However, the symmetry only holds while the two items A and B have same availability. Availability means how easy an item can be recalled. For example, when a native English speaker is trying to learn a pair of Japanese-to-English association hashiru-run, the item run is more available to the English speaking learner than the item hashiru (the Japanese correspondence of the English term run).

When the availabilities of the two items are not the same, the association become directional – the less available tends to elicit the more available. This implies that learning hashiru-run (less available-more available) is easier than learning run-hashiru (more available-less available).

Taking this characteristic of associative symmetry as an advantage, Horowitz and Gordon (1974) suggested following order of learning to achieve optimal result:

1. learn the easier association (hashiru-run),
2. followed by increasing the availability of the less available word (hashiru),
3. then the hard association will be learned automatically (latent learning).

Horowitz and Gordon's (1974) experiment results supported their point.

Backward-blocking is also a phenomenon related to associative learning (Giurfa, 2005). Backward-blocking is a process to unlearn an element of a compound stimulus. The unlearning, in this context, is not an autonomous process like forgetting, but it is triggered by other factors. For example, using the compound stimulus *getting wet* (*W*) AND *eating ice cream* (*C*) and the response *sickness* (*S*), i.e. *WC -> S*. In other words, an individual learned that getting wet (W) AND eating ice cream (C) cause sickness (S). If later on, *S* is more frequently caused by *W*, i.e. *W -> S*, then the strength of the relationship *C->S* is decreased automatically. This effect is called backward-blocking (Giurfa, 2005).

During the backward-blocking process in the example above, C, as a stimulus, is not present during the learning. This is against the traditional view of associative learning theories that require the presence of the stimulus for learning (in this case, unlearning) to occur. The backward-blocking effect shows a weak point of the traditional (pair-associate view of) associative learning.

Another noteworthy characteristic of associative learning is called the positive transfer effect. Greeno, et al. (1978) pointed out that positive transfer of association can happen in pairs of similar stimuli and same response. For example, A-B and A'-B denote two stimulus-response pairs, and suppose A-B has already been learned. The association of A-B can be transferred to A'-B if subject notices the similarity between

A and A'. The subject's memory does not include the distinguishing feature of A, A' may be treated as a representation of A. The positive transfer effect may account for why similarity and possibly serendipity are the methods to obtain creative solutions in Mednick's (1962) associative view of creativity.

The technique to employ mental imagery to improve effectiveness of associative learning has been quite widely adopted and supported by researches (de la Iglesia, 2004). de la Iglesia (2004) pointed out that when mental imagery technique is used, greater interest and attention are given than when the material is pretended verbally alone. de la Iglesia also noted that the technique has higher effectiveness when mental images are combined rather than stored individually and therefore suggested that rather than of the two original static images, a third different object, which could be in the form of the combination of the two static images, is also stored. For combination of images to happen, higher attention needs to be given to the details to produce the combined image. Attention to details inevitably activates the super-sub (image-attributes of image) associations in both the stimulus and response image. The combined image would have more than two (the stimulus and response image) associations associated as a result. More associations imply more recall-triggers and therefore higher possibility of being recalled. Therefore, we would argue that the superiority of mental imagery technique in memory recall lies in its possibility to create greater number of associations rather than totally on the difference on types of content (i.e. pictorial vs. verbal presentation). Adler and Berkowitz's (1976) study further supports our argument.

Adler and Berkowitz's (1976) asked children to draw picture after hearing a novel story. Half of the children were shown a picture pertinent to the story content before the start of the drawing, whereas the other half went straight into drawing after the story. No difference was found in the responses (i.e. drawings) from the two groups. In this study, children in the experiment group were not asked to do anything when the picture was shown, i.e. they were not required to actively process on content of the pertinent picture. Consequently no associations about the picture were created. Therefore no difference in response between the experiment group and the controlled group was found.

Both divergent thinking and associative learning have been examined so far. The cognitive trait, divergent associative learning (DAL), inherits some characteristics from both divergent and associative learning but is not completely identical to any of them. DAL is compared with divergent thinking and associative learning in next section.

8.4 Comparisons of DAL and Divergent Thinking and Associative Learning

Most of the researches on divergent thinking focused on production – that is to create/produce some creative artefacts no matter physical or mental. Guilford (1971) even used the term *divergent production* as one of the five mental operations, and both quality and quantity of ideational generation in divergent thinking tests are often the measurement of divergent production (Vartanian et al., 2003; Nicholls, 1972).

In this study, it is more important to know how divergent thinking can help in the learning context. In the view of associative learning discussed in previous section, a new concept associated with existing concepts during the learning process gains higher potential for future recall. It is because if any of the associated existing concepts is activated, the new concept can get activated too (Anderson 1983a, 1983b). Therefore, instead of focusing on the production of new ideas, we are proposing a construct, *divergent associative learning* (DAL), that creates divergent-style associations from the new concept to existing concepts.

DAL is different from divergent thinking in two ways: firstly, the end products of divergent thinking are new concepts/ideas whereas the end products of the DAL are new associations between the new concept and existing concepts. Secondly, the focus of divergent thinking is directed forwards into an unknown space in which novel and original ideas could be (and are expected to be) discovered. On the other hand, the focus of DAL is directed backwards to what has been learned before, i.e., searching for suitable candidate concepts to associate to.

In addition of creating associations between the given stimuli and responses in traditional associative learning (e.g. Laumann, 1999; de la Iglesia, 2004; Horowitz and Gordon, 1972; Feldman, Johnson, and Mast, 1972), DAL requires also effort to search for suitable targets. Traditional associative learning, especially the pair-associate paradigm, only requires the learning of the one-to-one associations between given stimuli and responses, whereas DAL focuses on learning of one-to-many associations.

To summarise, DAL is similar to divergent thinking in its divergent-style creation of associations and is different to divergent thinking in the end products: DAL aims at producing associations between new and existing concepts whereas divergent thinking aims at producing new ideas. Both DAL and the pair-associate paradigm of associative learning produce associations, but DAL produces one-to-many associations whereas pair-associate learning produces one-to-one associations. The requirement to search for suitable targets to establish associations to in DAL is also absent in pair-associate learning.

This section clarifies the differences and similarities between DAL and its two relatives, namely divergent thinking and associative learning. Due to the scarcity of literature that could be identified to study DAL, literature about divergent thinking and associative learning are examined. Their similarities to DAL are used in next section to explore the characteristics of DAL in order to find the manifestations of DAL.

8.5 Characteristics of Divergent Associative Learning

Brief comparison of divergent associative learning (DAL) with divergent thinking and associative learning has been made. However, there are still characteristics of DAL that are inherited from divergent thinking and associative learning. This section is devoted to study the characteristics of DAL further in preparation for finding the manifestations of DAL. Associative hierarchy, which is an important theoretical basis that brings divergent thinking and associative learning together, is further discussed. Classification ability, inductive reasoning ability, relevance filtering, working memory capacity, and learning comprehension are all found to bear influence on DAL. They are also studied in details in the following sub-sections.

8.5.1 Associative Hierarchy

Associative hierarchy is the organisation of individual's associations (Mednick, 1962). As mentioned previously in the light of divergent thinking, individuals with steeper associative hierarchy have higher possibility of producing only a small number of ideas on the top of the hierarchy, whereas individuals, who have flatter associative hierarchy, have higher possibility of generating more ideas. Mednick (1962), quoting Bousfield, Sedgewick, and Cohen's study done in 1954, pointed out a highly negative correlation between rate of associative response and the total number of associations. Using Mednick's associative hierarchy to interpret, a few stereotypical associations (e.g. from table to chair) have gained such a strong associative strength which allows very quick response to the stimulus (in this case table). Manifestation of higher rate of associative response and less number of total associations for non-creative individuals fit well with the prediction of Mednick's associative hierarchy.

The number of associations is negatively proportionate to the steepness of the associative hierarchy (Mednick, 1962). It has to be admitted that higher number of associations does not guarantee creative ideas. Nevertheless, the higher number of associations indeed has higher possibility of bringing up original and creative ideas, which are likely to be located near the outskirts of the bell curve (i.e. unusually, untypical ideas). This brings up the question about how originality is defined.

In Mednick (1962, p221), "the originality of a response is simply inversely related to its possibility (of occurrence) in a given population". Eysenck (1993) and Runco (1991) followed the same definition of originality. In Runco's (1991) study, part of the index of originality was calculated as the weighted sum of statistically infrequent responses – higher score was given if a response was infrequent among responses from the whole sample. So instead of finding what are the possibilities of occurrence of each item for the population (e.g. all 16 years old in New Zealand) as suggested in Mednick (1962) , Runco's (1991) method needs only to deal with the sample (i.e. 16 years old subjects in experiment), which is assumed to be a presentation of the population after all.

Mednick also clarified the relationship between originality and creativity, by stating that "creative thinking as defined here is distinguished from original thinking by the imposition of requirements on originality" (1962, p221). Original ideas may not meet the required conditions to solve a problem – only original and useful ideas can be counted as creative ideas. "Creativity implies that original responses are relevant, ... A psychotic person's responses are original (in the sense of unusual), but they are hardly ever creative" (Eysenck, 1993, p153).

Mednick (1962) also spelled out a possible exception to normal expectation of associative hierarchy. An individual could have steep associative hierarchy but the mean of this associative hierarchies deviates greatly from the norm. In other words, the individual has strong associative strength to a few associations "unusual" to most of others. Mednick called this type of hierarchy as *deviant associative hierarchy*. In the light of divergent production, an individual with deviant associative hierarchy might be counted as very creative. However, in the light of DAL, deviant or normal associative hierarchies do not make any difference. What is important is the spread of the bell curve that is accountable for bringing up a wide range of ideas, not whether the central line of the bell curve is deviant from the norm or not.

To summarise, the associative hierarchy is analogous to the bell curve of normal distribution. The flatter the curve, the more spread the distribution is. The flatter the associative hierarchy is, the more flexible the divergent thinking can be, and therefore the higher possibility of arriving at original ideas.

8.5.2 Classification Ability

Classification ability (Sternberg, 1977, 1983; van de Vijver, 2002) is used to abstract the higher order concept-class (e.g. mammals) from stimulus concepts (e.g. dog, cow, horse). The abstraction happens prior to the existence of the concept-class (called class hereafter) itself. Once the class is established, other stimulus concepts get included into this class by means of *identification*. Despite their similarities in the steps required to analyse the characteristics of the stimuli, it is speculated in this study that the processes of abstraction and identification are cognitively different: abstraction requires an extra step of concept-class formation and is used in inductive reasoning whereas identification needs memory recall and is used in DAL. This speculation remains to be proved and is beyond the scope of current study. In relations to DAL the term classification ability is used with more emphasis on the identification of stimulus concept into concept-classes whereas in relation to inductive reasoning ability in chapter 7, classification ability is used with more emphasis on the abstraction.

If DAL is aimed at creating as many meaningful associations from a new concept to existing concepts as possible, the increased number of associations increases the likelihood to extend the associative hierarchy horizontally (i.e. increases the spread of the associative hierarchy bell curve). As a result, a flatter associative hierarchy could be formed. The flatter an associative hierarchy is the greater possibility for creative solutions to appear (Mednick, 1962).

The number of associations could in fact be greatly increased by the use of classes as mediation. This is where classification ability to identify a class for the new concept becomes useful. For example, when a student has just learned a new knowledge, such as "the feathers of ducks are waterproof", if the student can utilise the class "bird" as mediation to the concept "duck", then the student learns much more – the existing associations between the "bird" class and other associated concepts of "bird" could greatly increase the total number of associations learned.

It has to be noted that in the use of class, it is highly likely that the student needs to cater for exceptions. For example, some birds might not have waterproof feathers. The Holland, Holyoak, Nisbett, and Thagard's (1987) model of adaptive default hierarchy about inductive reasoning also has provisions for exceptions, and their model can be referred to if we wish to develop similar model for DAL or improve on Mednick's (1962) associative hierarchy. However, this task is beyond the scope of current research. Holland et al.'s (1987) adaptive default hierarchy model has been discussed in great details in chapter 7, and is not repeated here. Relationship between inductive reasoning and DAL is studied next.

8.5.3 Inductive Reasoning

Similar to the discussion of classification ability above, there exists another type of construct that could be utilised to greatly increase the number of associations other than concept-classes. The development process of this type of construct is often called inductive reasoning (Harverty, Koedinger, Klahr, & Alibali, 2000; Holland et al., 1987). The construct obtained through inductive reasoning could be a theory, a principle, a rule, a heuristic or a model that is potential to have new applications.

We will the waterproof feather as an example to demonstrate how inductive reasoning could aid DAL. In addition of creating concept-classes using classification ability, inductive reasoning allows a student to grasp the theoretical understanding (the know-why) of the observed phenomenon. The theoretical understanding should allow greater extension of learned knowledge. The know-why of waterproof feather could be extended to for example the waterproof power on the wings of butterfly, the reason why many flying animals have waterproof protection, etcetera. The extension leads to possibility of new associations and this is how inductive reasoning facilitates DAL.

In Nikolaenko's (2004) study on children with autism, it was found that associative learning and the ability to understand metaphors had positive correlation. Holland et al. (1987) and Goswami (1992) used the term metaphorical and analogical thinking interchangeably and agreed that it was the ability to utilise the similarity between two events/concepts. In the chapter 7 where inductive reasoning ability is discussed, analogical/metaphorical reasoning has already been listed as a manifestation of inductive reasoning ability. Nikolaenko's (2004) findings further strengthen the hypothesis that higher inductive reasoning ability corresponds to higher DAL.

Another line of research about inductive reasoning and DAL can be found in Mednick (1962). Mednick listed three ways in which creativity can be obtained through divergent thinking: serendipity, similarity and mediation. In the discussion about similarity, Mednick (1962, p222) explained that "the requisite associative elements may be evoked in contiguity as a result of the similarity of the associative elements or the similarity of the stimuli eliciting these associative elements". *The requisite associative elements* denoted the elements required for creative solutions. The use of the term "in contiguity" reflected Mednick's associationist view on creativity. One important factor that influences the use of similarity is what Mednick called the *primary stimulus generalisation.* The primary stimulus generalisation, is the function of extracting common patterns of the stimuli and then matches these patterns to new contexts. Generalisation, as it had been discussed in chapter 7, is primarily a function of inductive reasoning.

Furthermore, Mednick (1962, p222) described mediation by stating that "the requisite associative elements may be evoked in contiguity through the mediation of common elements." Although Mednick placed the stress on the *mediation* of common elements by means of verbal, mathematical, chemical symbols etcetera, it is apparent that commonality of elements has to be recognised in order to be used as ingredients for the mediation process. Generalisation is basically an action to produce abstract rules from common characteristics of items or cases. Therefore, generalisation is again required for the execution of mediation. Among the three ways to achieve creativity in Mednick's study, two are related to generalisation and therefore related to inductive reasoning. Mednick's (1962) study provided a rich supportive source to our claim that inductive reasoning is potentially, if not closely, related to DAL.

8.5.4 Relevance Filtering

Idiot savants are those, who in spite of a low level of general cognitive functioning, show outstanding abilities in narrowly defined areas. The idiot savant syndrome is especially prevalent in individuals with diagnosis of autism. Individuals with autism are said to have *weak central coherence* which is the inability to determine what is relevant and what is not (Eysenck, 1993). In their study, Ryder, Pring, and Hermelin (2002) found some common basis that underlay both the idiot savants phenomenon and high divergent thinking ability. Over-emphasis on the divergence can easily lose the relevance. This leads to the establishment of links between high DAL to low relevance filtering, and low DAL to high relevance filtering ability.

8.5.5 Versatile Navigation

As oppose to the *serial navigational pattern* which follows the predefined navigational path from the beginning till the end, *versatile navigation* refers to the employment of hyperlinks other than predefined links in hypermedia-based learning systems (Huai, 2000). In hypermedia-based systems, versatile navigations are facilitated by the convenience of hyperlinks; however, it cannot be denied that there are still behaviours similar to versatile navigation in the more traditional learning materials such as in printed media. It is therefore plausible to suggest that versatile navigation is a behaviour pattern manifested by a versatile learning style which is not limited to only hypermedia-based systems.

However, it is hypothesised here that the versatile learning style (or other learning style name used by other researchers) is in turn a manifestation of a cognitive style which shares an overlapped basis of divergent associative learning. The reason for such hypothesis comes from studies about divergent thinking and weak central coherence (Eysenck, 1993). Patients with diagnosis of weak central coherence lack the normal cognitive functions which "include extracting the overall gist of a story rather than the exact words, or seeing a picture in terms of an overall gestalt rather than its constituent parts" (Eysenck, 1993, p168). In other words, the habit of pursuing details instead of the overall meaning is a manifestation of weak central coherence. It is therefore highly possible that a navigational pattern similar to that of the versatile navigation could be detected in individuals with weak central coherence because of their tendency to pursuit details.

Caution has to be raised though that versatile navigation could be a result of a completely different learning style called the *global learning style* (Felder and Silverman, 1988). Individuals, who have the global learning style, deviate from the predefined navigational path not because they just want to pursue details but to understand the overall picture. If the learning system designer is not a global learner himself or herself, it is highly likely that global students have to find their own way, instead of the predefined navigational path, to learn and inevitably have to choose to navigate in a versatile manner.

8.5.6 Working Memory Capacity

Bahar and Hansell (2000) studied the relationship between divergent/convergent learning style and working memory capacity. 101 pupils between age of 16 and 17 participated in their study. Their study showed positive correlations between divergent learners and high working memory capacity, and between convergent learners and low working memory capacity. Laumannn's (1999) study also showed positive correlations between scores of high working memory and better associative learning performance, and between low working memory and poor associative learning performance. Both studies lend supports to the possibility that working memory capacity is positively related to DAL.

8.5.7 Learning Comprehension

In one of the studies about ideational originality, Runco (1991, p58) came to argue that "individual differences in divergent thinking ability are explained most accurately in terms of cognitive ability and task-perception". Runco used the term cognitive ability to mean IQ and tried to establish a link between high IQ and high divergent thinking ability. This link, however, is contrary to the original definition of divergent thinking put forward by Hudson (1966). According to Hudson's definition, convergers are those who score high in IQ tests whereas divergers are those who score high in creativity tests. This theoretical inconsistency does not hinder the progress of current discussion as we are focusing on divergers' competence in task perception instead of their scores in IQ or creativity tests.

Runco's (1991) comment about divergent thinking requiring a clear understanding and perception of the task is also supported by Nicholls (1972) and Vartanian et al. (2003). Without clear perception of the task, requirements to complete the task could also be poorly understood. The produced result, no matter divergent production of artefacts or associations, could be irrelevant or undesirable. Good comprehension of task therefore is an important basis of divergent associative learning (DAL).

Replacing task-perception by learning performance and thus claiming the link between good learning performance (and domain knowledge as a result) and good DAL could be somehow bold, but is not without evidence. Feldhusen (2002, p183) found that "the creativity process depends mightily on a knowledge base reflecting past learning". Wesiberg (1999), after reviewing many different theories about creativity, also emphasized on the important role of knowledge in the process of creativity. The line of argument in this claim is as follows: good learning comprehension leads to good learning performance which in turn leads to possession of relatively more domain knowledge. The two "leads to" in the above sentence both can be read as "is necessary and sufficient condition for". Both Feldhusen' (2002) and Wesiberg's (1999) studies focus more on the positive correlation between domain knowledge and creativity; we would argue that it is equivalent to a positive correlation between learning comprehension to creativity, given the logical relationship between learning comprehension and domain knowledge.

8.6 Manifestations of Divergent Associative Learning

Table 8-1 shows the manifestations of traits (MOTs) of divergent associative learning (DAL) as a summary of the discussion in section 8.5 .

Table 8-1: Manifestations of divergent associative learning

	High DAL	**Low DAL**
1.	flat associative hierarchy	steep associative hierarchy
2.	high classification ability	low classification ability
3.	high inductive reasoning ability	low inductive reasoning ability
4.	low relevance filter ability	high relevance filtering ability
5.	versatile navigation	linear navigation
6.	high working memory capacity	low working memory capacity
7.	high domain performance	low domain performance

The MOTs of DAL listed in Table 8-1 again show the diversity of views about what manifests DAL. Unlike working memory capacity and inductive reasoning ability which are already being studied as constructs in their own right, divergent associative learning (DAL) emerges as a result of shifting the popular emphasises of divergent thinking and associative learning. This combination, without doubt, results in the necessity to bring already separated views and ideas together. The list in Table 8-1 includes MOTs from theoretical account, such as associative hierarchy, and from behaviour account, such as versatile and linear navigation. Associative hierarchy and working memory capacity come from a more cognitive (cognitive psychology) point of view whereas inductive reasoning, classification, and relevance filtering abilities are from a more psychometric point of view. There is also inclusion of learning comprehension which breaks away from a general and domain-independent view of mental construct, and acknowledges the influence of domain- and/or task specificity on DAL. The list in Table 8-1 could not be claimed to be exhaustive; nonetheless it has quite a wide coverage of different perspectives on this cognitive trait, DAL, already.

In the next section, an attempt is made to translate the MOTs of DAL into behaviour patterns that could be observed in learning systems, in particular hypermedia-based learning systems.

8.7 Implementation Patterns of Divergent Associative Learning

From the discussion of characteristics of divergent associative learning (DAL) above, manifestation of traits (MOTs) can be extracted to indicate the level of divergent associative learning. In this section, MOTs are further translated into implementation patterns (IPs).

8.7.1 Associative Hierarchy and DAL

The steepness of associative hierarchy could determine the number of ideas generated (Mednick, 1962). Learners who tend to organise their associative hierarchy in a steep manner would therefore tend to generate less ideas that could be associated during the learning process. On the contrary, learners who tend to develop flatter associative hierarchy would have more ideas (popping up) that could be associated to the new concept encountered and hence a greater number of associations could be created. There are therefore simple predictive relationships between steeper associative hierarchy and lower DAL, and between flatter associative hierarchy and higher DAL.

One of the behaviour patterns that could be used to find out the steepness of associative hierarchy is the use of excursion links. In hypermedia-based learning systems, excursion links are hyperlinks that lead to relevant yet not curriculum-based learning materials (Kinshuk et al., 1999). It is the requirement (or likely a requirement) that all curriculum-based materials (that will appear in the final exam) should be included in the learning system, whereas excursion links likely lead to websites that are outside of the learning system itself but nonetheless relevant and value-adding to the curriculum.

Although clicking on a hyperlink does not mean learning the material that the hyperlink links to, an assumption is made that following an excursion link at least increases the exposure to the linked material and implies a higher interest in the linked material. The act of following an excursion link therefore would lend support to the indication of a flatter associative hierarchy. Those, who are not exposed to "other" ideas (available from excursion links) or are not interested in ideas other than the curriculum-based ones, are more likely to have steeper associative hierarchy.

8.7.2 Versatile Navigation and DAL

One important factor to determine versatile navigation is the linearity of navigation. Navigational linearity has already been mentioned in the discussion of working memory capacity in chapter 6. Linearity of navigation is also a manifestation of working memory capacity and is not repeated here.

8.7.3 Inductive Reasoning Ability and DAL

Inductive reasoning ability is itself one of the cognitive traits. The value of inductive reasoning ability can be retrieved from the cognitive trait model.

8.7.4 Working Memory Capacity and DAL

Working memory capacity is also one of the cognitive traits and its value can be retrieved from cognitive trait model.

8.7.5 Domain Performance and DAL

Domain performance is available from the performance-based student model if the learning system includes a performance-based student model.

MOTs translated thus far are summarised in Table 8-2.

Table 8-2 : Implementation Patterns of Inductive Reasoning Ability

	Low DAL	High DAL
1.	steep associative hierarchy	flat associative hierarchy
2.	versatile navigation	linear navigation
3.	high inductive reasoning ability	low inductive reasoning ability
4.	high working memory capacity	low working memory capacity
5.	high domain performance	low domain performance

There are, however, other MOTs that are not translated. They are discussed in next section.

8.7.6 Other Manifestations not Implemented

Table 8-1 includes two more MOTs that are deemed as not suitable to be implemented in web-based learning environment, namely classification ability and relevance filtering ability. These two MOTs are also MOTs of inductive reasoning ability discussed in chapter 7. They are also not translated. The rational has been given in chapter 7 and does not need to be repeated here.

8.8 Summary

Divergent associative learning (DAL) is the third cognitive trait investigated in this study. DAL inherits characteristics from both divergent thinking (Hudson, 1966; Kolb, 1984; Runco, 1991; Vartanian, et al., 2003; Mednick, 1962) and associative learning (Bonardi, 1998; Laumann, 1999; de la Iglesia, 2004). Both divergent thinking's and associative learning's similarity with and differences to DAL are summarised in Table 8-3.

Table 8-3: Comparison of DAL and divergent thinking and associative learning

	Similarity with DAL	Differences to DAL
Divergent thinking	Both DAL and divergent thinking aim at divergent-style creation.	DAL produces associations between new and existing concepts; Divergent thinking produce new ideas.

Associative learning	Both DAL and associative learning produce associations.	DAL produces one-to-many associations; associative learning produces one-to-one association.

Through the study of characteristics of DAL, seven manifestations are found. They are:

1. associative hierarchy
2. classification ability
3. inductive reasoning ability
4. relevance filtering ability
5. navigational linearity
6. working memory capacity
7. domain performance

Among the seven MOTs, five are translated into implementation patterns (IPs). The IPs are:

1. associative hierarchy
2. inductive reasoning ability
3. navigational linearity
4. working memory capacity
5. domain performance

The relationships between the cognitive traits are of interest to this study. Two of the MOTs of DAL, working memory and inductive reasoning, are in fact themselves cognitive traits. One of the MOTs of inductive reasoning ability is also working memory capacity. Already there are hypothesises about the relationships between cognitive traits. In order to investigate their relationships further, tests of all three cognitive traits are developed.

The tests are adoptions of popular psychometric tests. The tests serve two purposes in this study:

1. to study the relationship o f cognitive traits
2. to examine the effectiveness of the chosen methodology

Before we look the three tests in chapters 10, 11 and 12, we would like to present a theoretical validation of cognitive trait modelling because all the MOTs are already identified. The theoretical validation is discussed next.

CHAPTER 9

Theoretical Validation

9.1 Introduction

Chapter 3 introduced the *individual difference* and *perspective difference* of cognitive traits. Individual difference refers to the relativistic idea that every individual is different and the MOTs are at best statistically valid. It is possible that how a MOT influences behaviours of student A is different to that of student B. The perspective difference refers to the phenomena that different researchers might look at the same cognitive trait from different perspectives. The discussion in chapters 6, 7 and 8 has demonstrated the perspective difference by showing that each of the three cognitive traits has several associated manifestations of trait (MOTs). Each MOT of a cognitive trait represents a perspective/portrayal of the cognitive trait.

Some of the MOTs can be translated into implementation patterns (IPs). IPs are system-type dependent: they are suitable to be used only in certain types of systems. The suitable types of systems for the IPs described in chapters 6, 7 and 8 are conceptual-knowledge-oriented hypermedia learning systems – the target-systems. If the MOTs are to be used into more procedural-skill-oriented learning systems or in virtual reality based systems, the MOTs might need to be translated into different IPs.

MOTs are abstract – they are meant to be abstract so that they preserve the generality and therefore portability. IPs are system-type dependent – they have to be system-type dependent so that only a manageable set of human behaviours, which are allowed by the system-type, needs to be accounted for. For example, serial learning style (one of the MOT of working memory) manifests itself by following the predefined learning sequence (by the Next link) in target-systems. "Following the predefined learning sequence by the Next link" is a behaviour within the set of behaviours allowed in target systems. At the same time, serial learning style might have fifty other ways of manifesting itself in different learning system types or learning environment types. It is very difficult, if not impossible, to cater for those fifty other ways the serial learning style MOT manifests itself.

The MOTs exist independently of the IPs, IPs are embodiments of MOTs in a particular system-type. In terms of research contribution, MOTs and IPs should be treated differently: MOTs are part of the theoretical framework (together with the multiple portrayal network (MPN) of cognitive trait model, whereas IPs are exemplary demonstrations of the viability of the proposed theoretical framework in target-systems.

This chapter aims to validate the theoretical framework, i.e. the MOTs and the MPN. It has to be clear that we are not trying to validate every individual MOT – the MOTs are extracted from researches that are validated. Rather, we wish to validate the method of aggregating multiple MOTs to form a single representation (of a cognitive trait). This representation is likely to be unique for every individual student because of the *individual difference* of cognitive trait model. An important desired feature of this representation is that it should be more or at least equally representative to the cognitive trait than any single MOT of the cognitive trait. Only if we can prove the existence of this feature in our approach, we can confirm the contribution of our study.

The details and the aim of the validation are discussed in section 9.2 . Section 9.3 uses a computer simulation to perform the validation. Section 9.4 summarises and gives conclusion to this chapter.

9.2 Aim of Theoretical Validation

Extraction of MOTs is primarily based on existing literature – the validity of the MOTs is therefore taken as a given/premise rather than an object of current study. The aim of this study is to aggregate different MOTs, which might seem separated and unrelated, into a single entity. It is not meant to be an effort to aggregate all MOTs of the three cognitive traits into just one single entity. But each of the three groups of MOTs (for the three cognitive traits) is to be converted into a single entity. There should be in total three entities: one for working memory capacity, one for inductive reasoning ability and one for divergent associative learning. In this validation, only one entity is used as an example. Figure 9-1 is a conceptual illustration of aggregating five MOTs into a single entity.

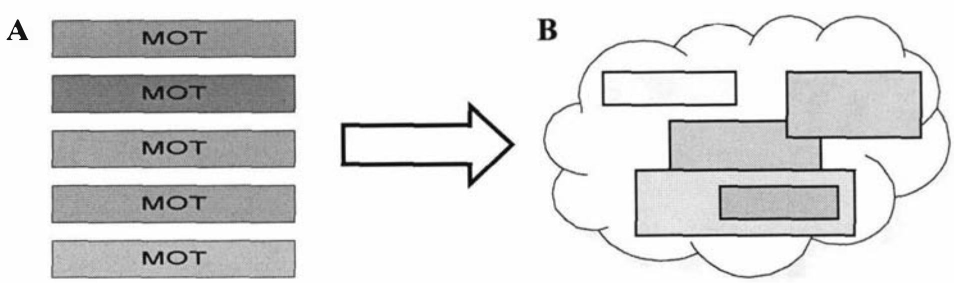

Figure 9-1: Combining different MOTs (A) into a single entity (B) – the rectangles are MOTs and the cloud is the entity

Assuming there are five MOTs of an entity. The five different MOTs, which are represented by the five rectangles, in Figure 9-1A should be combined into a single entity, which is represented by the cloud in Figure 9-1B. The reason why they should be combined is introduced shortly in Statement 9-1 and Statement 9-2.

It has to be pointed out here that "representative-ness" of a rectangle means how well/accurate the rectangle represents the entity (cloud structure in Figure 9-1B); "representative-ness" of a MOT means how well/accurate the MOT represents the corresponding cognitive trait.

The cloud in Figure 9-1B denotes the entirety of the cognitive trait – the more area a rectangle covers, the better the rectangle can represent the entity. In other words, the area covered by each rectangle in Figure 9-1B is the representative-ness of that particular rectangle. This leads to an important characteristic of the rectangles and their representative-ness, as mentioned in Statement 9-1:

Statement 9-1:

> "More rectangles can better represent the entity than a single rectangle if the total area of the former is larger than that of the latter."

Statement 9-1 is expressed in the language of the conceptual illustration in Figure 9-1B. In terms of MOTs and cognitive traits, Statement 9-1 denotes:

Statement 9-2:

> "More MOTs can better represent the cognitive trait than just a single MOT if the former account for more related phenomenon of the cognitive trait than the latter."

This characteristic of CTM, as expressed in Statement 9-2, means that it is more desirable to include multiple MOTs if a more accurate/representative CTM is sought for. It can be seen in Figure 9-1 that if the size covered by multiple rectangles is not greater than the size of any single rectangle, the two sizes are at least equal. That is, there exists a large rectangle that overlaps with all other smaller rectangles.

Aggregating multiple MOTs raises another issue: the complex relationships between different MOTs. The complexity of the relationships means that (1) there are little or none validated studies about the relationships between MOTs to our knowledge, and (2) the scale of work to study all relationships between MOTs is large.

In the discussion of multiple portrayal network (MPN), chapter 5 introduces a term called Complex-Relationship (CR-) Manageability. CR-Manageability is the ability to manage complex relationships when aggregating different portrayals of the same entity. If the CR-manageability of MPN can really be proved, it:

1. resolves the problem of complex relationship when combining MOTs; and
2. allows multiple MOTs to be used to more accurately represent cognitive traits.

In other words, the proof of CR-Manageability of MPN constitutes the validation of the theoretical framework of CTM. What this means is that if MPN can be proved to be capable of managing complex relationships then multiple MOTs can be used to represent each cognitive traits. The resulting aggregated entity should be theoretically more or at least equally representative of the corresponding cognitive trait than any single MOT.

A computer simulation has being developed to test the CR-Manageability of MPN. The simulation and the validation are presented next.

9.3 Computer Simulation of Multiple-Portrayal Network

A computer simulation tool is created using Java to:

1. simulate the execution of MPN;
2. assess the CR-Manageability of MPN; and
3. analyse the usability of MPN against different parameter values.

9.3.1 Simulating Multi-Portrayal Network

Figure 9-2A illustrates a possible entity that Multi-Portrayal Network (MPN) needs to represent. The cloud structure represents the entity and the rectangles represent the nodes. Figure 9-2B shows that an imaginary grid is imposed on the entity and the nodes. Each small squares created by the grid is called a cell.

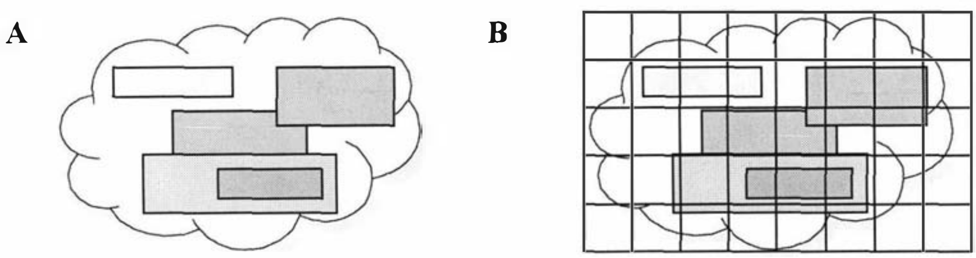

Figure 9-2: Illustration of a Possible Entity (the cloud structure) and Its Nodes (the rectangles)

Approximation of the entity can be formed by using grid cells that cover the entity. School children first learn how to find out the size of an irregular shape by drawing an imaginary grid with 1cm x 1cm cells. By counting the number of cells, the approximate size of the irregular shape can be found.

It can be seen that if sizes of the cells are quite large, such as shown in Figure 9-2B, using cells to represent nodes or the entity could bring a large bias. But if the number of cells in the grid increases, each cell gets smaller and smaller, and thereby a better approximation can be achieved. Cells will be used in the following discussion as basic units to approximate the regions of the entity and its nodes.

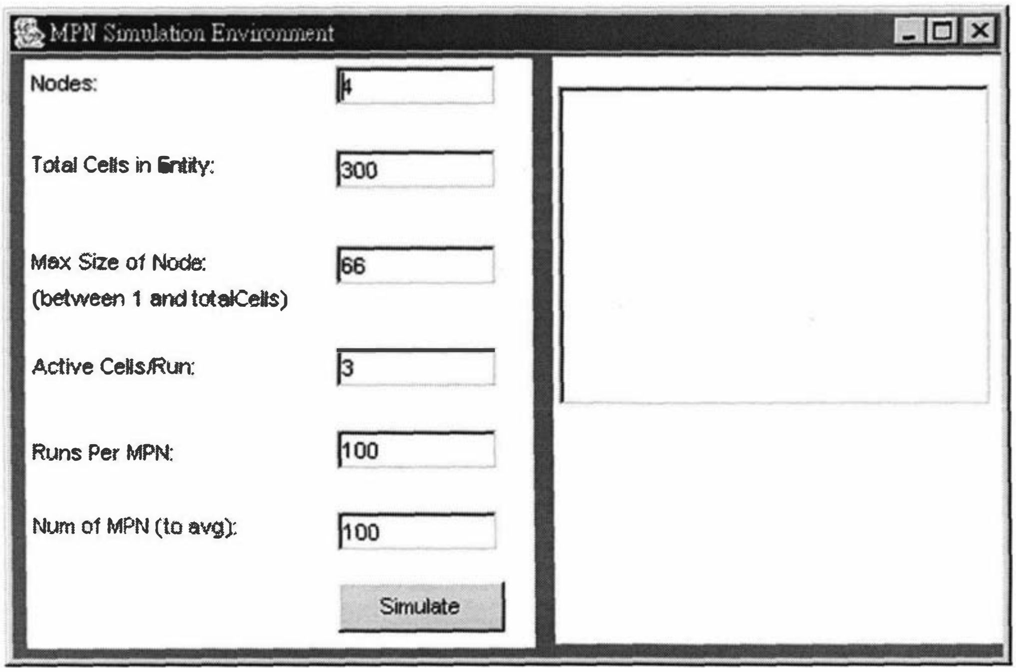

Figure 9-3: Simulation tool and its parameters

Figure 9-3 shows the graphical interface of the simulation tool. The right hand panel of the simulation tool contains messages of the simulation result, whereas the left hand panel consists of inputs for the following parameters:

P1. Nodes: The number of Nodes in the MPN.

P2. Total Cells in Entity: The total number of cells approximating the entity.

P3. Max Size of Node: The maximum possible size of each node. The lowest possible value is 1 and the highest possible value is the number of total cells in entity as specified in input P2.

P4. Active Cells/Run: The numbers of activated cells in each run of an MPN. A run represents a learning session in the context of cognitive trait model.

P5. Runs Per MPN: The number of runs for each MPN.

P6. Num of MPN (to avg): The number of MPNs. This is used to adjust the sample size of the experiment.

The simulation follows the following procedure (tasks):

T1. It first takes the parameters from the graphical interface (Figure 9-3).

T2. It randomly creates **P1** number of nodes.

T3. It calculates the condition probabilities for each pair of the nodes (i.e. P(NODE1 | NODE2), P(NODE2 | NODE1), P(NODE1 | NODE3) …), and stores it in a vector **V*org*** (stands for original vector). These conditional probabilities are called "real" as opposed to the "simulated" conditional probabilities obtained from simulation.

T4. It then runs for **P5** times, and in each run:

a. it randomly activates a number of unique cells between 1 and **P4**; and

b. a node is activated if there is more than one active cell that is contained in this node. Information of activated node is stored in a vector **V*act*** (stands for activated vector).

T5. Another vector **Vcom** (stands for vector for comparison) is created to store the conditional probability for each pair of the MOTs based on **Vact**.
T6. **Vorg** and **Vcom** are then compared to see the difference.
T7. Tasks **T1** to **T6** are repeated **P6** times in order to reach a statistically reliable sample size.

The aim of this simulation is to compare **Vorg** and **Vcom**. In other words, we want to see whether the "simulated" conditional probabilities obtained from simulation of MPN could approximate the "real" conditional probabilities obtained mathematically.

There are **P1** x (**P1** – 1) number of conditional probabilities. Both **Vorg** and **Vcom** are vectors with **P1** x (**P1** – 1) number of items. **T6** compares **Vorg** and **Vcom** and finds the averaged differences of conditional probabilities.

9.3.2 Research Setup

The main research question for the simulation was: Can Multi-Portrayal Network (MPN) achieve the desired CR-Manageability? In more specific terms, the above question was formulated as:

- $\mathbf{H_0}$ (null hypothesis): The use of MPN does not make any difference to solve the CR-Manageability issue.
- $\mathbf{H_1}$ (alternative hypothesis): The use of MPN does make a difference to solve the CR-Manageability issue.
- **Significance level** (the α value): A 97% confidence level is desired so α is set to 3%.

The result of this simulation is discussed next.

9.3.3 Result and Discussion

With the combination of P1=4, P2=300, P3=66, P4=3, P5=100, P6=1000, the difference (T6) was found to have an average of 2.06 (2dp)%, standard deviation of 2.47 (2dp), 25th percentile of 0.28 (2dp), and 75th percentile of 2.85 (2dp). The averaged difference 2.06%, which was less than 3%, gave a 97.94% (100-2.06) confidence to reject the null hypothesis and proved that MPN is capable of reaching the desired CR-Manageability. The 75th percentile, which was 2.85, showed that the dispersion of the simulation result was only little and therefore supported the reliability of the result.

Furthermore, we would like to know whether the computer-simulated data is significantly different to the real data. Performed T-test, comparing the conditional probabilities of real and simulated data (df=20), showed that the t-statistic, 0.02, was far less than the critical value (t-critical, 2 tails), 2.08. The result implied no statistically significant difference between the real and simulated data. The T-test gave a P(T<=t) equal to 98.39% which was very close to our calculated 97.94% confidence level above. The result of T-test again confirmed that MPN is capable to solve the CR-Manageability.

When P1 (number of nodes) is changed from 4 to 10, the resulting difference has an average of 2.12%, which is only a 0.06% (2.12 – 2.06) difference. It means that the variation of number of nodes does not affect in a significant way the performance of MPN.

When P2 (total cells in entity) is changed from 300 to 600, the difference is then reduced to 1.72%, and to 1.37% if P2 is further increased to 1200 (see Figure 9-4). This shows that if the size of cell in the grid (Figure 9-2B) is further reduced (by increasing the total number of cells), the better approximation of the entity (the cloud structure in Figure 9-2B) by the cells is achieved and therefore the more accurate the MPN will be. It is in accordance with what we have predicted.

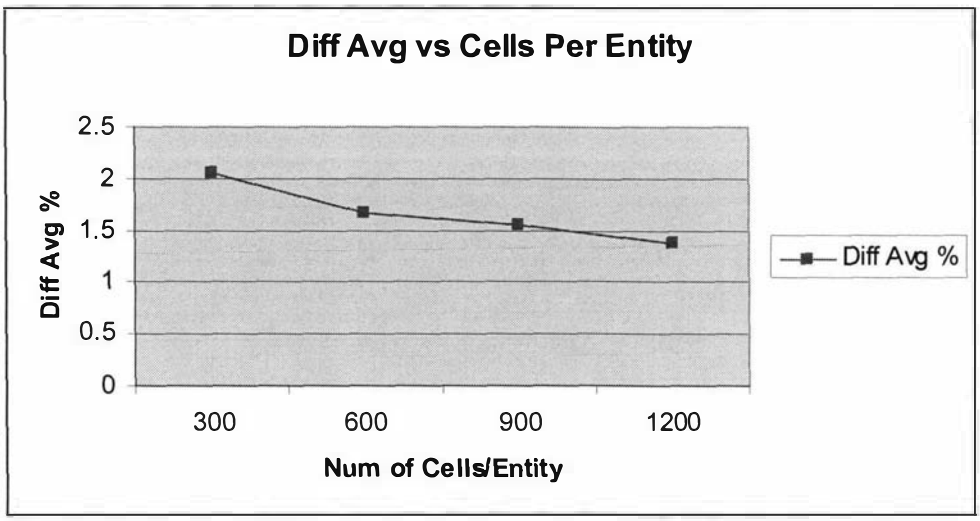

Figure 9-4: Average Difference in Conditional Probability versus Cells per Entity

When P3 (max size of Node) is changed from 33 to 132, the averaged difference rises from 1.78% to 2.74% (see Figure 9-5). The nearly 1% (2.74-1.78) difference was not significant given the four times difference of node size (132/33 = 4). Its near-linearity (see Figure 9-5) further confirms that this factor has no significant effect on the operation of CTM.

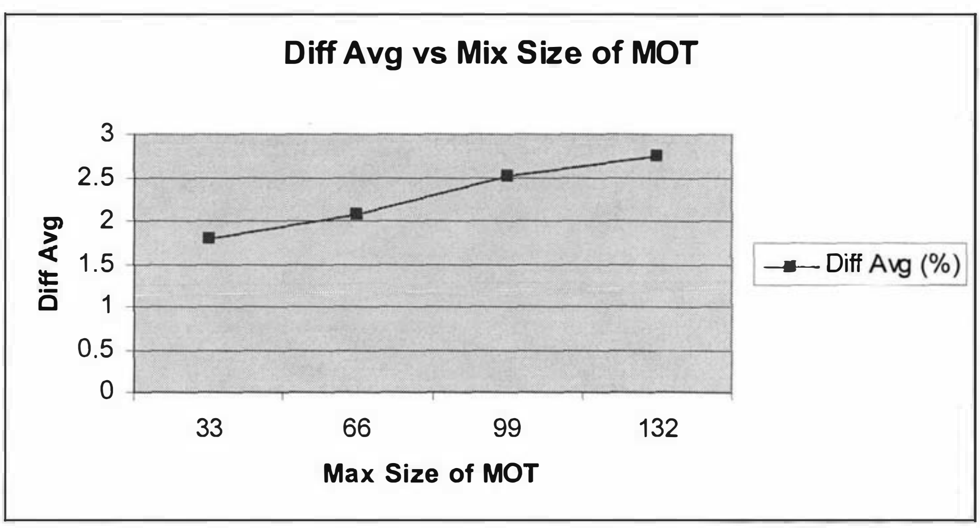

Figure 9-5: Average Difference in Conditional Probability versus Max Size of MOT

When P4 (Active Cells/Run) is changed from 3 to 10, the average difference is raised from 2.06% to 3.56%, and to 13.25% if P4 is set to the value of 40 (Figure 9-6). The greater the number of active cells in a run, the less accurate the MPN becomes. The rationale of this phenomenon is as follows: due to greater number of active cells in a single run, greater number of nodes will be activated, and therefore the conditional probability between each pair of nodes will be disrupted (misled) by the greater number of activated nodes. In the context of cognitive profiling in learning systems, the large number of active cells per run (e.g. 30) could be due to the habit of a student who never logs out the learning system. This could be easily prevented by using idle-timed-expiring technique of session control – e.g. forced logout if no action is detected in, say, 20 minutes.

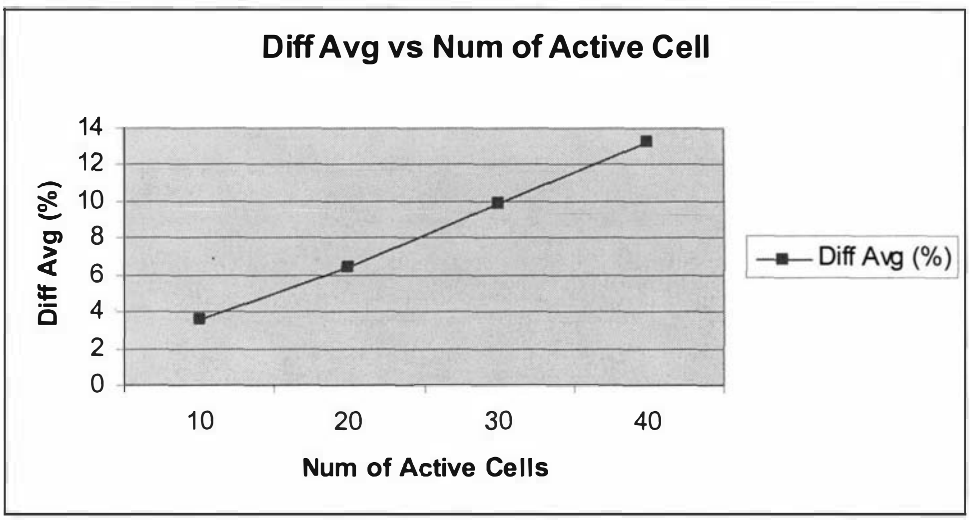

Figure 9-6: Average Difference in Conditional Probability versus Number Active Cells

When P5 (Runs per MPN) is raised to 300 from 100, the resulting difference average was reduced to 1.23%, and if raised to 500, the difference average is further reduced to 0.98%. Figure 9-7 shows the relationship. 500 runs, in terms of cognitive profiling in cognitive trait model, can be interpreted as 500 learning sessions. This interesting characteristic points out that the longer the MPN is used, the more accurate it becomes. This characteristic fits very well with the purpose of cognitive trait model which is proposed to be a life-long learning companion (Lin, Kinshuk and Patel, 2003).

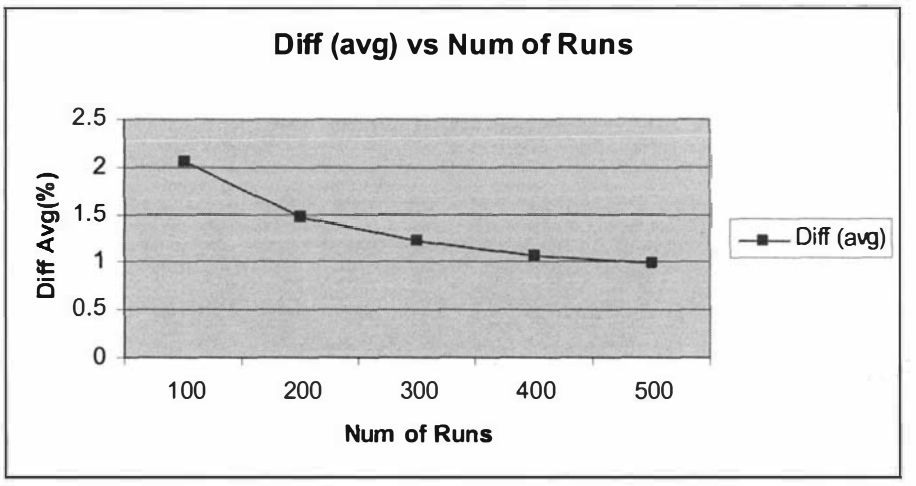

Figure 9-7: Average Difference in Conditional Probability versus Number of Runs

P6 (number of MPN) was there only for the reason to have statistically sufficient sample size for the simulation result, and therefore did not need to be altered in this study.

9.4 Summary and Conclusion

This chapter presented theoretical validation of cognitive trait model (CTM). Manifestations of traits (MOTs) are part of the theoretical framework of this study and they are system-type independent. Implementation patterns are examples of using MOTs in target systems. Validation presented in this chapter is an important task to show the theoretical soundness of CTM.

Two important characteristics mentioned in chapter 3 are individual difference and perspective difference. The task of this chapter is to validate that the proposed approach of using multiple-portrayal network (MPN) can cater for both the individual difference and the perspective difference.

With respective to individual difference, MPN allows different ways that MOTs can relate to each other. As shown in chapter 5, the types of possible relationship are inclusion, overlap, equivalent, and independent. The use of conditional probability to determine the relationships allows all four types of relationships to occur. MPN therefore has enough flexibility to develop an individually unique representation for each different student.

With respect to perspective difference, it has been argued that aggregating more perspectives (MOTs) can more or at least equally representative of the entity (a cognitive trait). The main issue is the complexity of relationships (of the perspectives) when aggregating the perspectives/MOTs. To ask whether MPN can cater for the perspective difference is to ask whether MPN can manage the complex relationships.

Computer-based simulation tool, developed as part of this study, has proven that MPN can achieve the desired CR-Manageability and is able to achieve the 97% confidence level. The simulation tool also allows close scrutiny of the characteristics of MPN to be carried out and the nature of MPN to be better understood. Two important features of MPN confirmed by the simulation tool are as follows:

1. The more the MPN is used, the more accurate it becomes; and
2. The greater the number of cells in the grid, the more accurate MPN becomes.

One important limitation of MPN learned from the simulation tool is that the accuracy of MPN will be negatively impacted by the increasing number of activated cell in a single session. This experience learned gives insight of the necessity to employ pre-emptive method, such as idle-timed-expiring technique of session control, to prevent the problem.

This chapter covers the theoretical validation of cognitive trait modelling. In addition to theoretical validation, we would also like to see if cognitive trait modelling can be empirically validated. That is, we would like to see if the values of the three cognitive traits obtained through cognitive trait modelling could be statistically match to the values of cognitive traits obtained from psychometric tests. Before we can start the empirical validation, we need psychometric tests. The next three chapters present the psychometric tests developed for the cognitive traits.

CHAPTER 10

Web-OSPAN: Web-based Computerised Measurement of Working Memory Capacity

10.1 Introduction

There are several different tests to measure working memory capacity. Earlier views of working memory capacity (then called short term memory) as a single component transient memory brought what are now called simple span tasks (Turner and Engle, 1989). In a simple span task, a subject is shown a series of stimulus items. The types of the stimulus items could be digits (the task is then called simple digit span task) or words (the task is then called simple word span task). For simple digit span task, the number of stimulus item gradually increase from 2 to 9, whereas for simple word span task, the number of items increase from 2 to 7. The maximum number of stimulus items a subject can correctly record is then attributed to the subject's short term memory measure of the simple span task (Turner and Engle, 1989). The simple span task is based on a simple unitary memory system which was then found insufficient and replaced by a multi-component memory system nowadays called working memory.

10.2 Multi-component View of Working Memory

Baddeley and Hitch (1974) found a deficiency about the concept of the simple unitary short term memory system. In the simple unitary short term memory system, the length of repetition of an item determines the strength of recall in future (i.e. how good it is memorised).

Baddeley and Hitch (1974) pointed out two problems in such simple short term memory system: 1) evidences showed simple maintenance in short term memory was a very poor way of learning, 2) neuropsychological evidence showed that patients of damaged short-term memory performed normal in tasks related to long-term memory. They therefore proposed a multi-component model of this transient memory system. The transient memory system is then called working memory. Baddeley and Hitch's (1974) model consists of an attentional controller, the central executive, and two slave systems, the phonological loop which is a system for holding auditory or speech-based information, and the visual-spatial sketchpad which is a system for holding visual information.

10.3 Complex Span Task

Baddeley and Hitch's (1974) model introduced a processing function into the working memory system for which the early measures (simple span tasks) were not designed for. During the same period, other models of working memory were also developed with one common assumption: they all assume that only a limited amount of information can be kept alive at any given time (Baddeley, 2000). This limitation affects consequent processing (Turner and Engle, 1989). Furthermore, evidence gathered began to show that the simple span tasks correlate poorly with performance on higher level tasks such as reading comprehension (Turner, & Engle, 1989). More sophisticated measurement tasks were required to reflect the advancement of knowledge about working memory.

Daneman and Carpenter (1980) developed what was called sentence-word span task (Sentence-Word) as a measurement of working memory. In Sentence-Word, subjects are required to read a series of sentences and need to recall the last word of each sentence at the end of the series. The number of sentences gradually increases. The maximum number of words a subject can recall is the sentence-word span (as a measurement of working memory) of the subject. Tests about the comprehension of sentences were carried out to ensure that subjects processed the sentence.

The Sentence-Word is a task that accounted for both the storage and the processing function of working memory. Tasks of this type are classified as complex span tasks. Turner & Engle (1989) further developed several complex span tasks including sentence-digit span task (Sentence-Digit), operation-digit span task (Operation-Digit) and operation-word span task (Operation-Word). Similar to Sentence-Word, Sentence-Digit show a digit at the end of each sentence and requires the subjects to recall the digits. In both Operation-Digit and Operation-Word, arithmetic operations, such as (2 * 3) + 4 = 10, replace the sentences in Sentence-Word. In Operation-Digit, a digit follows each operation, whereas in Operation-Word, a word follows each operation. Subjects are asked to answer true or false to a group of arithmetic operations and asked to recall the digits or words at the end of a series of operations. The number of operations in a series varies. For example, in Operation-Word, the number of operations gradually increased from 2 to 5 (Turner and Engle, 1989). For later version of Operation-Word, the number of operations in each series varied from 2 to 6 (Engle et al., 1999).

Turner and Engle's (1989) data showed that Operation-Word, among all the simple and complex span tasks, had the highest correlation with reading comprehension. De Neys et al. (2002) also stated that Operation-Word has become one of the most popular tasks to measure working memory capacity.

10.4 Computerised Version of Operation Word Span Task - GOSPAN

De Neys et al.[1] (2002) adapted the Operation-Word span task into a computerised and group administer-able task called GOSPAN. Empirical data from De Neys et al. (2002) showed that GOSPAN is highly correlated to Operation-Word task.

GOSPAN was designed for native Dutch speakers. The English words in Operation-Word are replaced by high frequency Dutch words. There are totally 60 operation strings, such as: IS (4 / 2) + 1 = 9, and 60 words, such as BALL. Each operation is followed by a word. These 60 operation-word pairs are divided into 15 series. Every 3 series are placed in a level, so there is a total of 5 levels (from level 2 to level 6). A series in level 2 has 2 operation-word pairs, in level 3 has 3 operation-word pairs and so on. The order of the series presented to subjects is random except the first and the second series which contain 3 and 2 operation-word pairs respectively.

In GOSPAN, a subject is first shown an operation on a computer screen, for example: IS (4 / 2) + 1 = 9. The subject then presses a key to chose true or false as the answer for the operation. If a subject takes more than 6 seconds gazing the operation, a warning message (in red capital letters) is display to remind the subject to give response. After selecting the answer, the operation disappears and the screen then shows a word for 800 milliseconds. Pilot studies done by De Neys et al. (2002) had proven that 800 milliseconds are sufficient to focus on and read the word and that 6 seconds are sufficient to work out and give correct answer to the operations.

A number of operation-word pairs form a series. The number of operation-word pairs varies from 2 to 6 in GOSPAN. At the end of each series, the subject is required to write down, using pen and paper, the words in this series. The order of the words is important – the answer is counted incorrect if the order is wrong. The total number of correctly answered word (in correct order) is taken as the index/measure of working memory in GOSPAN.

In GOSPAN, if a subject scored less than 85% for the operations, data from the subject is discarded because the processing requirement in the working memory task is not met. The processing, by answering the arithmetic operation, would prevent the subject to use memory strategies, such as rehearsal or grouping, to remember the words. Using of memory strategies does not reflect the actual activities when one is reading and would distort the actual working memory measure.

GOSPAN task is setup to counter the use of rehearsal strategy. Even though subjects are told to give correct response to operations as fast as they can, GOSPAN discards the subject's data if the mean response latency (averaged time taken to answer the operations) of the subject is too long. It is likely that the subject is actively rehearsing the words and spends little processing resources on solving the operations. If a subject is systematically pausing and rehearsing, the response latency would certainly increase. The threshold mean response latency allowed in GOSPAN is 6434ms which is 2.5 standard deviation of the mean of the samples (4296ms).

[1] The author would like to thank Wim De Neys for the information about GOSPAN and the advices given in personal email correspondences.

In the study of De Neys et al. (2002), subjects were administered GOSPAN in groups of 38 to 48 in large computer laboratories. Two experimenters were needed to be with the subjects in order to answer questions during the instruction phase and to supervise the experiment.

10.5 Web-based version of Operation Word Span task - Web-OSPAN

In this section, we present a web-based system for the Operation-Word task. It is called Web-OSPAN. Procedures of GOSPAN are adopted into Web-OSPAN except the experiment setting. The differences between Web-OSPAN and GOSPAN are explained in details later. The words in Web-OSPAN are the same as the words in Operation-Word[2] (Engle et al., 1999).

Web-OSPAN is accessible through Internet. Login is required to access Web-OSPAN in order to identify the subjects. **Error! Reference source not found.** shows the login page.

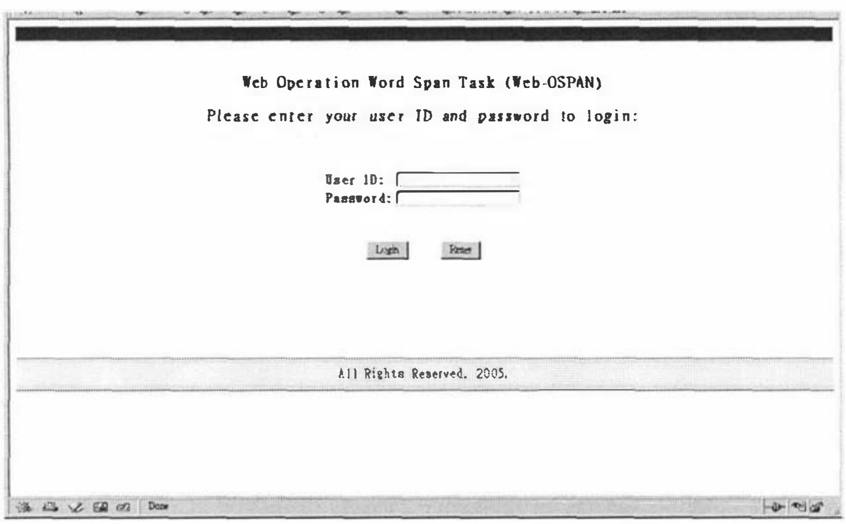

Figure 10-1: Login Screen of Web-OSPAN

[2] The author would like to thank Prof. Randall Engle and his associates for sharing the Operation-Word task.

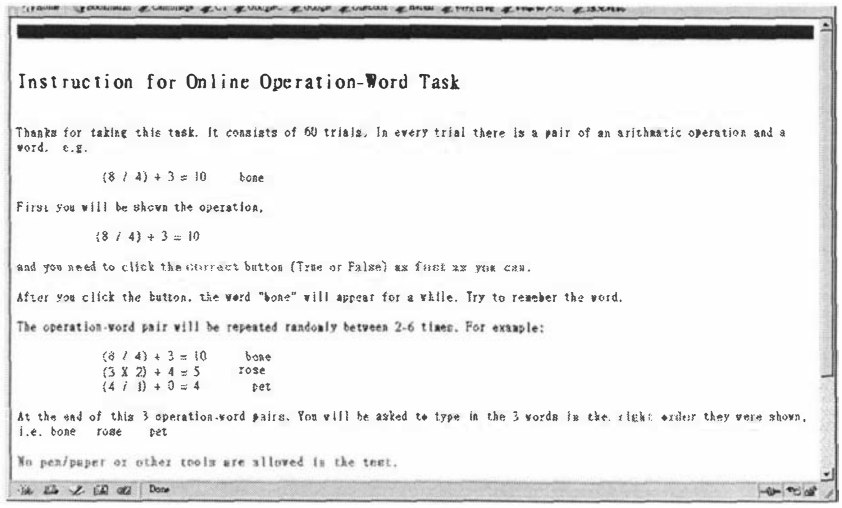

Figure 10-2: Instructions to use Web-OSPAN

After successful login, Web-OSPAN then presents the instructions (**Error! Reference source not found.**). A link, which leads to the practice session, can be clicked after the subject has read and understood the instructions. The practice session consists of 2 sets of operation-word pair. The practice session is to complement what cannot be expressed in the verbal instructions and to mentally prepare the participants for the forthcoming task. After the practice session, a message is given again to (1) stress the importance of answering the operation as quickly as possible; (2) ensure the words are entered in the sequence they are displayed; and (3) state that the main task will start after the OK button at the end of the message is clicked.

After this point, Web-OPSAN is the same as GOSPAN except that the subject needs to type the words instead of writing them down using pen and paper. Figure 10-3 and **Error! Reference source not found.** shows the display of operation and word in Web-OSPAN.

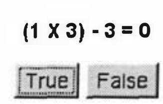

Figure 10-3: Displaying Operation

Figure 10-4: Displaying Word

After a series of operation-word, the subject is required to type in all the words in this series in the correct sequence (Figure 10-5).

Figure 10-5: Words input screen at the end of series

One more precautionary measure is taken in Web-OSPAN to counter the bias that may be caused by different network connection speeds. The response latency for the first operation is discarded. It may take a while for the Web-OSPAN applet to load and start-up. Therefore it is highly likely that a subject may not have full attention on the screen while the first operation is presented. In the extreme case, discarding 1 out of 60 may make a 1.67% (1 / 60) of difference. However, it is believed that the speed for one to solve similar arithmetic operations would be quite constant; therefore discarding the first one would, in theory, not give any significant effect while at the same time prevents the distortion of data for subjects using slow network connections. At the end of the task, the scores are displayed to the subject (Figure 10-6).

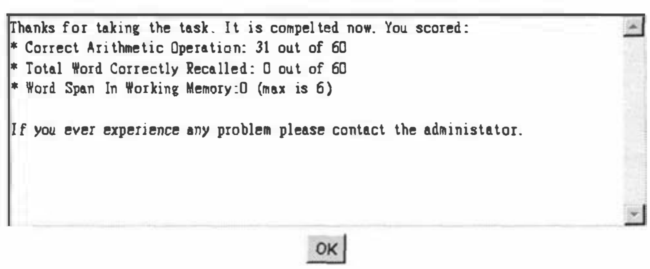

Figure 10-6: Web-OSPAN score displayed

Unlike GOSPAN where 2 experimenters are required in the computer laboratory, there is no supervisor needed when a participant is taking the Web-OSPAN task. This further increases the possibility that the task can be administered to a group of users if they have different conveniences in time and the constraints on possible group size can be removed. However, it has to be noted that a participant could be tempted to manipulate (cheat) the system in order to obtain a higher score when not supervised. Despite the fact that the motivation of doing so is discouraged by the instructions by pointing out that the score will be displayed at the end of the task and it is the real score that can give beneficial insights about oneself, mechanisms are still employed to prevent and detect dishonest manipulations (e.g. using pen to write down the words).

One such mechanism, also used by De Neys et al. (2002), is to discard participant data if the average response time is longer than 6 seconds. It is possible that other tools (e.g. pen) are used to record the words for later recall; therefore it takes longer to respond to the operations. Another possibility is that the participant is trying to use memory strategy (e.g. rehearsal) to remember word which would again bias the data gathered.

Other mechanisms are more technical. Preventing the participants to get access to the task if he/she had already done so, i.e. disable login, is an example of the technical mechanisms. Preventing the participants to use the "Refresh/Reload" button of the browser to re-do the task is another example. In latter case, refreshing the webpage is still possible by browsers' default Refresh/Reload buttons, but only the first set of data can be accepted into the database. It means that at the end of the task, a subject can "Refresh" the web-page and redo the Web-OSPAN task again, but this data will not be saved into the database. These mechanisms are built to prevent possible dishonest manipulations when subjects are taking the Web-OSPAN task.

Another difference between the Web-OSPAN and Operation-Word (Turner and Engle, 1989) is that Operation-Word instructs subjects to read the operations out aloud but Web-OSPAN does not. The author believes that the reading speed could vary among different individuals. The author also assumes that the process of reading-out-aloud is different from the process of working-out-arithmetic-operations. The individual differences in reading speed could also introduce bias – some subject might be disadvantaged in terms of memory recall because they are slower readers. The requirement of reading-out-aloud is therefore deemed as an unnecessary overhead and thus not included in the instructions of Web-OSPAN. De Neys et al. (2002) hold a similar view and removed the instructions to read-out-aloud in GOSPAN, too.

10.6 Empirical Evaluation

10.6.1 Participants

A total of 84 subjects participated in the evaluation of Web-OSPAN. Subjects were from different backgrounds and could be placed into 6 different groups as shown in Table 10-1.

Table 10-1: Participant Groups

Group	Size	Group Characteristics (Country/ University)
1	20	third year university students; studied paper offered by Department of Information System (New Zealand/Massey University)
2	9	first year university students; studied paper offered by Department of Information System. (New Zealand/Massey University)
3	13	university graduates; currently working. (USA/Berkeley University)
4	20	university students; studied Engineering paper (Austria, Vienna University of Technology)
5	4	postgraduate students; IT-related disciplines (Networking, Computer Science) (Taiwan, National Central University)
6	18	postgraduate students; enrolled in course offered by Department of Information System (New Zealand/Massey University)

Group 1, 2 and 6 were students of Massey University in New Zealand. Group 1 and 2 were undergraduate students whereas Group 6 consisted of postgraduate students (Postgraduate Diploma, Master, and Ph.D.).

Group 3 were students in Berkeley University and had participated in experimental studies before. A further study about brain activity and working memory capacity by Jesse Rissman [3] in Department of Psychology at UC Berkeley required the administration of working memory capacity task to those subjects again. Those subjects in Group 3 had finished their degree study and were working at different places. It was not easy for both the researcher and the subjects to come back to a laboratory and sit a face-to-face and individually-administered test. Web-OSPAN allowed each individual subject to take the task at a time and place suitable to the subject.

Subjects in Group 4[4] participated in studies about the relationship between learning styles and working memory capacity (Graf, Lin, Jeffrey, and Kinshuk, 2006; Graf, Lin, and Kinshuk, in press). They were the students of Vienna University of Technology in Austria. They used the German version of Web-OSPAN.

Subjects in group 5 were postgraduate students in National Central University in Taiwan studying in IT-related disciplines. They used the Chinese version of Web-OSPAN.

10.6.2 Material

In Web-OSPAN, there are 60 arithmetic operations and 60 words. The main purpose of the arithmetic operations is to activate the processing component of working memory and to prevent the employment of rehearsal strategy on the words. The purpose is not to test the mathematical ability of the subjects. Therefore, the operations are kept at quite a simple level (all numbers less than 30). The list of words is identical with the lists of words used in Engle et al. (1999).

There are, however, two other different versions of Web-OSPAN translated into two different languages. The first is German version used by Group 4, and the second is Traditional Chinese version used by Group 5. All other groups used the English version.

In the German version of Web-OSPAN, a different set of words is used. The reason for using a different set of words instead of direct English-German translation is because some translated German words exceed the 2-syllable criteria used in Engle et al. (1999) and De Neys et al. (2002). The replacement German words were carefully selected so that they fit the requirements of being 1) concrete nouns, 2) two syllable, and 3) in diverse semantic categories. These criteria are used in Operation-Word and GOSPAN too. The arithmetic operations are exactly the same as the English version of Web-OSPAN.

In the Chinese version of Web-OSPAN, the arithmetic operations are also exactly the same as the English version. The list of words is different from the one used in the English version. The words in the Chinese version are chosen with similar criteria

[3] The author would like to thank Jesse Rissman (group 3) for her permission to use the data of her subjects in this study.
[4] The author would like to thank Sabine Graf (group 4) for her permission to use the data of her subjects in this study.

used in the English version. The only difference is in the length of the words. In Chinese language, a single character can often represent a word (a noun phrase). Please see for example the Chinese-Single column in Table 10-2. The Chinese-Multiple column has semantically-equivalent nouns as the Chinese-Single column but it has nouns that comprise multiple characters. Often there is a redundant character '子' at the end of a noun phase (e.g. Table and Chair). Without this redundant character, each of the multiple-character nouns (especially everyday objects) can often be represented by just using one character. With the consideration of consistency in mind, the author decided to use just single character nouns in the Chinese version.

Table 10-2: English-Chinese Nouns

English Noun	Chinese-Single	Chinese-Multiple
Table	桌	桌子
Chair	椅	椅子
Ocean	海	海洋
Wall	墙	墙壁

10.6.3 Procedure

For the compliance to the ethical requirements of Massey University, application for research permission were made to and granted by the Massey University Human Ethics Committee (see Appendix B). Participants in all research experiments in this study were provided with an information sheet (see Appendix A) stating the nature of the research and the participants' right. After they had read and volunteered to participate in the research, they could start to login. This procedure applied to all experiments in this study.

Subjects in all the groups except Group 5 were each given a login account and a Universal Resource Locator (URL) to access Web-OSPAN. Subjects using different language versions were given different URLs. After login, subjects were shown the instructions page. The instructions page contained information about:

1) the nature of the task with examples of operations and words;
2) system requirements (especially on how to download Java Run Time Environment);
3) not undertaking any other tasks (e.g. engaging in conversation, watching TV, and so on); and
4) not using any assistant tools (e.g. pen and paper) during the task.

After understanding the instructions, subjects could then proceed to start the task. There were again two more practice exercises that the subjects could do before the real task. After the practice exercises, the importance of correct spelling and position were again emphasised. The subjects were also advised that the real task was about to start. The subjects could then click the OK button to start the Web-OSPAN task.

Subjects in Group 5 were self-registered. They chose their own usernames and passwords. They were however invited participants. 10 postgraduate students in National Central University in Taiwan were invited by the author, but finally only 4 participated.

In some groups, 4 variables were measured: *OperationScore*, *OpTotal*, *SetSize*, and *Latency*. *OperationScore* measures the number of correct arithmetic operations. It has a range from 0 to 60. A score of 55 indicates that the subject answered 55 arithmetic operations correctly, and made mistake in 5 arithmetic operations. In Turner & Engle (1989) and De Neys et al. (2002), *OperationScore* was also used.

OpTotal measures the total number of correctly recalled words and includes only those instances where all the words in a series are correctly recalled. In a series of three words, such as (tree, shoe, ball), if a subject answers all three words correctly spelling-wise and sequence-wise, then the subject gains 3 points. But if the subject answers only 2 words correctly or places the three words in wrong order, then 0 point is rewarded. *OpTotal* has a range from 0 to 60. Similar to GOSPAN (De Neys et al., 2002), the number of words in each series varies from 2 to 6 in Web-OSPAN. The same variable is used in Turner & Engle (1989) and De Neys et al. (2002).

SetSize measures maximum number of word in any word set that was ever correctly recalled. For example, if a subject had ever answered a set of 5 words correctly, then the *SetSize* of the subject is set to 5. If later, the subject answered a set of 6 words correctly, then the *SetSize* is updated to 6. Incorrect answers do not discredit any previous achievement. *SetSize* has a range from 0 to 6 (technically, the range should be 0, 2, 3, 4, 5, and 6 because the smallest word set is 2). Turner & Engle (1989) found that the *SetSize* had high correlation with the *OpTotal*, and therefore only *OpTotal* was used as the index of working memory capacity. The same variable is used in Turner & Engle (1989) and De Neys et al. (2002).

Latency measures the averaged response time for the subject to answer arithmetic operations. This variable is used to guard against cheating. For example, if a subject uses pen and paper to assist the arithmetic operation, then the *Latency* will be very large. The same variable is used in De Neys et al. (2002).

PartialCorrectWordSpan is the fifth variable. Similar to *OpTotal*, *PartialCorrectWordSpan* also measures the total number of correctly recalled words but it does not require entire set of words to be correct. For example, if a subject is expected to recall the three words say (tree, shoe, ball), but only tree and ball are recalled, the subject still gains 2 points. For *PartialCorrectWordSpan*, the order does not matter too. For example, if the subject typed in (ball, tree, shoe), 3 points are awarded despite of the incorrect order. *PartialCorrectWordSpan* was recorded for all subjects in Group 3, and some subjects in Group 4.

10.6.4 Result and Discussion

Data of 12 subjects from the English version were deleted because those subjects were not native English speakers. Data of 2 subjects were deleted because the subject made more than 15% error in arithmetic operations. The same criterion is also used in Turner & Engle (1989) and De Neys et al. (2002). De Neys et al. (2002) had also removed some subject data because the subjects were not native Dutch speakers.

The overall data are first analysed using descriptive statistics and summarised in Table 10-3.

Table 10-3: Descriptive Statistics of Result from Web-OSPAN

	Operation Score	*TotalMemory Span*	*SetSizeMemory Span*	*Latency (ms)*	*PartialCorrect WordSpan*
Mean	56.43	28.80	4.97	3282.51	46.04
Standard Deviation	2.41	11.36	0.92	556.28	8.68
Range	9	42	3	2425	29
Minimum	51	7	3	2217	28
Maximum	60	49	6	4642	57
Count	70	70	70	70	26

It can be seen from the number of correct operations (mean=56.43) that subjects were taking the Web-OSPAN task seriously. They were not just selecting answers randomly. Furthermore, the mean response latency (time taken to solve each operation) is 3.28 second and its standard deviation is 0.56 second. This shows that subjects indeed had followed the instructions quite well and had devoted their time to complete the task, i.e. they were not doing other tasks (e.g. talking on phone).

De Neys et al. (2002) used *OpTotal* as the score for working memory capacity because of high correlation between *OpTotal* and *SetSize*. In our study, there is also a very high correlation between *OpTotal* and *SetSize* (see Table 10-4). There is also a very high correlation between *OpTotal* and *PartialCorrectWordSpan*. Therefore, *OpTotal* alone could be used as score of working memory capacity.

Table 10-4: Pearson Correlations of Variables

		Operation Score	*OpTotal*	*SetSize*	*Latency (ms)*	*PartialCorrectWordSpan*
OperationScore	Pearson Correlation	1				
	Sig. (2-tailed)					
	N	70				
OpTotal	Pearson Correlation	.251(*)	1			
	Sig. (2-tailed)	.036				
	N	70	70			
SetSize	Pearson Correlation	.131	.811(**)	1		
	Sig. (2-tailed)	.281	.000			
	N	70	70	70		

Latency	Pearson Correlation	-.160	-.306(*)	-.084	1	
	Sig. (2-tailed)	.186	.010	.491		
	N	70	70	70	70	
PartialCorrectWordSpan	Pearson Correlation	.319	.958(**)	.793(**)	.012	1
	Sig. (2-tailed)	.112	.000	.000	.954	
	N	26	26	26	26	26

Note: * Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

A significant negative correlation exists between the *OpTotal* and *Latency* (see Table 10-4). This negative correlation entails that the design of Web-OSPAN task has successfully blocked the employment of rehearsal strategy that the subjects should not be using. If subjects are actively rehearing the words, their response latencies for the arithmetic operations should be larger. But the data shows that those who answered the arithmetic operations faster (i.e. those who are not using rehearsal strategy) also have higher score of working memory capacity.

De Neys et al. (2002) and Engle et al. (1999) both separated their data into 3 subsets to test the reliability of GOSPAN and Operation-Word respectively. Each subset consist of operation-word pair from different set size (from 2-6). The 3 subsets gave 3 scores which were then used to calculate internal reliability. We would argue that the correlation between *OpTotal* and *SetSize* could also serve to prove the internal reliability of Web-OSPAN. The reason is explained as follows. A subject, who can remember larger set of words (as measured by *SetSize*) in a time, could theoretically have more correctly recalled words (as measured by *OpTotal*). Also, in order for a subject to have high score in *OpTotal*, the subject should have *consistently* correctly answered more large sets (sets of 4, 5, or 6) of words. Consistency in answering is what the reliability tests are for in De Neys et al. (2002) and Engle et al. (1999). There is a very high correlation between *OpTotal* and *SetSize* in Table 10-4 at 0.811 (2 tailed, significant at 0.01 level) in this study. This high correlation could be used to prove the consistency of subjects' performances in Web-OSPAN and therefore confirms the internal reliability of Web-OSPAN.

There is a notable increase in *OpTotal* score in Group 5, in which subjects used the Chinese version of Web-OSPAN (see Table 10-5). The mean score of *OpTotal* is the highest among all groups and is 10 points higher than the mean of all subjects. The small size in Group 5 is not enough to draw any substantial conclusion, but some possible reason(s) for the marked increase could be:

1. individual differences in working memory capacity; or
2. shorter length of words in the Chinese version which perhaps are easier to remember; or
3. different sets of words are used and the words in the Chinese version perhaps are easier for subject to recall.

Table 10-5: Comparison of Scores among Groups

Groups	N	Language	OpTotal Mean	OpTotal SD
Group1	16	English	23.06	11.81
Group2	8	English	31.63	6.3
Group3	13	English	25.46	3.37

Group4	16	German	34.19	10.36
Group5	4	Chinese	38	5.31
Group6	13	English	27.23	10.56
All	70		28.8	11.36

If the observed increase in score is not due to the first reason, then there is a need to further analyse the following:

1. the effect of language on working memory score – bilingual subjects might need to take Web-OSPAN task in 2 different language versions; and
2. the impact of different sets of words on working memory score.

10.7 Conclusion

This chapter introduces a web-based computerised tool, called Web-OSPAN, to measure working memory capacity. Web-OSPAN follows the concepts and criteria from both the pen-and-paper Operation-Word (Turner and Engle, 1989; Engle et al., 1999), and the computerised GOSPAN used in supervised computer laboratories (De Neys et al., 2002). The words used in the English version of Web-OSPAN are identical to the ones in Operation-Word (Engle et al., 1999).

GOSPAN (De Neys et al., 2002) is itself an effort to computerise Operation-Word (Turner and Engle, 1989; Engle et al. 1999) and it makes it easier to administer the Operation-Word task in a group. Web-OSPAN takes a step further and makes the Operation-Word task accessible through Internet.

Comparing with Operation-Word and GOSPAN, Web-OSPAN is available with a wider range of language options. Furthermore, Web-OSPAN could also be administered in supervised computer laboratories. It has both the conveniences offered by the Internet and the flexibility to select the most suitable venue for the experiment. The author believed that Web-OSPAN could benefit both the researchers and the subjects. The benefits are listed in Table 10-6.

Table 10-6: Benefits offered by Web-OSPAN

For Researchers:
1. **Larger samples**: The researcher can reach wider potential sample through Internet. There are situations where it is hard to bring all subject to an experiment venue. For example, follow-up studies on subjects who had previously participated in another study and had moved to other states or countries.
2. **Resource (financial and time) economy**: less financial and time commitments are required for researchers to setup and carry out experiment using Web-OSAPN.
3. **Data ready for analysis**: The data collected in Web-OSPAN do not need to be manually entered into computer again for processing, and can be easily exported to formats (text or spreadsheet) that are ready for data analysis software (e.g. SPSS, Excel).
For Subjects:

1.	**Conveniences**: Subjects can choose a time and place of convenience to work on the Web-OSPAN task.
2.	**Mental readiness**: Subjects can choose to work on Web-OSPAN task in an environment that they are familiar with so that there are no anxieties incurred by any new surrounding.
3.	**Instant feedback**: Subjects do not need to wait to get the feedback of their performance on Web-OSPAN. The performance result is displayed at the end of the task.

With respect to distractions, one important point has to be made. When a subject is taking Web-OSPAN, there are other possible types of distractions, for example, the subject might need to answer a telephone call, or family members might interrupt. However, the subject does have certain control over those distractions, for example, by choosing a different venue (closed room) or a different time when there is minimal possible distractions.

There are also potential distractions from the experiment setting in GOSPAN such as noises made by other participants or anxiety caused by unfamiliar environment. For those distractions, subjects would have very little control over them. All types of distraction are unwanted no matter in which task (Operation-Word, GOSPAN or Web-OSPAN). However, subjects do have more control over potential distractions in Web-OSPAN than the other two tasks by having the freedom to choose suitable time and venue to take the task. In Table 10-3, the mean response time (Latency) of 3.3 seconds to solve each arithmetic operation and the mean correct number of operations (OperationScore) of 56.43 out of 60 shows little, if not none, sign of distractions for the subjects in this study. Compared with the mean response time of 4.3 seconds in De Neys et al. (2002), subjects in this study even have quicker response time. The standard deviation in this study is also smaller than that of De Neys et al.'s study. The acceptable threshold of response latency in De Neys et al. (2002) is 6.43 second; none of the subjects in this study exceeds this threshold.

In addition to the convenience and flexibility, we have also proved the internal reliability of Web-OSPAN. The reliability is found by showing the consistency of subjects' performances.

Due to the small sample size in the group using the Chinese version, more research effort is required in order to study subjects' performance in difference language versions of We-OSPAN. Such research should ideally involve bilingual subjects. But, because this study is not capable of and is not aimed to standardised working memory performance (e.g. to find out the statistically average performance of 20 years old adults in New Zealand), the difference in different language versions would not be an problematic issue if all subjects in an experiment are using the same language version.

This chapter discusses a web-based psychometric tool to measure working memory capacity. In a similar format, the next two chapters will discuss tools to measure inductive reasoning ability and divergent associative learning.

CHAPTER 11

Web-based Tools to Measure Inductive Reasoning Ability

11.1 Introduction

Inductive reasoning ability (IRA) is the general ability to see patterns among examples (Rescher, 1980; Harvery et al., 2000). Literature on different theories about inductive reasoning ability has been reviewed in chapter 7 and is not repeated here. However, it has not been an easy task to find an inductive reasoning test that meets:

1. financial constraint: most of the test batteries have prices above what we can afford;
2. task specificity: inductive reasoning test is usually just a subset of a larger test about intelligence (e.g. Hall, 1985; van de Vijver, 2002); and
3. deployment capability: existing inductive reasoning tests usually are not capable of being deployed through the Internet (e.g. Brown, Glass, and Park, 2002; Laumann, 1999).

Therefore, a web-based test (task) of inductive reasoning ability is developed as part of this research. It is called Web-IRA. Web-IRA is developed with references to available information, mostly through literature, about other inductive reasoning tests (e.g. van de Vijver, 2002; Bailenson et al., 2002; Ekstrom et al., 1976; Laumann, 1999). The nature of the different tests is discussed in more detail in Section 11.2 to provide a reference framework on what the existing inductive reasoning tests are like. The tool we developed in this study is then discussed in Section 11.4 .

When examining a representative inductive reasoning task called Wason's 2-4-6 task (Wason, 1960) and subsequent and relevant discussions about it (i.e. Whetheric, 1962; Gorman and Gorman, 1984; Gorman et al., 1984; Tukey, 1986), a theme, although implicit, consistently surfaced to our attention. We have noticed that these discussions about Wason's 2-4-6 task are primary focused on external behaviours. In these discussions, although there are inferences about cognitive activities, such as eliminative strategy, the cognitive activities are mainly used to explain observed behaviours. This causes insufficient understanding of the cognitive activities underlying the 2-4-6 rule finding task. We believe that the observed behaviours should be used to understand the cognitive activities which can then be used as models/lens to interpret behaviours. We therefore propose a hypothesised construct called *systematic thinking ability* that could potentially account for the cognitive activities in Wason's 2-4-6 task.

Our aim in this study is not to obtain a comprehensive and extensive knowledge on Wason's 2-4-6 task in the cognitive level. We believe that the systematic thinking ability is also highly relevant to inductive reasoning ability. Besides, we have already listed systematic thinking ability as one of the manifestations of trait of inductive reasoning ability in chapter 7. It is worth exploring this relationship further empirically. Section 11.3 presents more discussion on systematic thinking ability. A tool to measure systematic thinking ability is also developed. This tool is called Web-Sys and is discussed in Section 11.4.2 .

Another tool, called Web-RF (short for Rule Finding), is also developed. Web-RF follows Wason's 2-4-6 task but sets it up in a computerised environment. The reason to develop this tool is to further our understanding in the rule finding task, and to test our hypotheses on the relationships between inductive reasoning ability and rule finding ability and between systematic thinking ability and rule finding ability. Details of Web-RF are discussed in Section 11.4.3 .

Empirical evaluations were carried out to study Web-IRA, Web-Sys and Web-RF. For the purpose of discussion, the evaluation is presented in three experiments. Experiment 1 is an evaluation of Web-IRA and is discussed in Section 11.5 . Experiment 2 is an evaluation of Web-Sys and the relationship of inductive reasoning ability and systematic thinking ability. Experiment 2 is presented in more details in Section 11.6 . Experiment 3 examines the relationships between the rule finding ability to inductive reasoning ability and systematic thinking ability. Experiment 3 is discussed in Section 11.7 . Section 11.8 summarises our findings and gives conclusion of this chapter.

11.2 Tasks in Inductive Reasoning Test

Tasks involved in measuring IRA can often be categorised into groups depending on what characteristics of IRA that particular task is trying to explore. Among the categories, *series extrapolation*, *analogical reasoning*, and *exclusion tasks* are the ones that are quite often used by researchers (van de Vijver, 2002).

In the series extrapolation task, the subject is shown a series of stimulus items which were placed in an order governed by a rule. The rule is unknown to the subject and is hereafter called the Target-Rule (T-Rule) of the task. The subject is asked to find out what is the next item that will be generated by the T-Rule. The stimuli can be numbers, string of characters or symbols. An example of a series extrapolation task is "What should come after 2-4-6-8-10?", and the correct answer is 12.

The series extrapolation task involves the ability to generate hypothesis which in term requires subjects to find out what are the relevant attributes that are common in the stimuli by using comparison (e.g. odd or even number, ascending or descending). The result of the comparison can then be used to classify those common attributes into a group that belong to a hypothesis or group of hypotheses that the T-Rule is consisted of. The "sorting task" (Bailenson et al., 2002) that requires subjects to sort pictures of birds that go together by nature is a more specific example of testing the classification ability.

In the analogical reasoning task, the subject is often given a relationship and is asked to use this as an analogy to find the next relationship. An example would be "Road to

Car as Rail to?", and the answer should be "Train". The analogical reasoning task requires one to be able to see what the relevant attributes of the given relationship are, and map those relevant attribute from one context to the other.

In the exclusion task, the subjects are give a set of stimuli and are asked to detect irregularity among the stimuli. An example would be "In 2, 3, 4, 6, 8, which is the least similar with others?", and 3 is the answer because it is the only odd number. The exclusion task again requires the subjects to be able to classify attributes into groups and form hypothesis. The "Letter set task" (Ekstrom et al., 1976; Laumann, 1999) that requires subjects to mark the odd one out from five sets of four letters is a type of exclusion task.

11.3 Systematic Thinking Ability

Rule finding is one of the early definitions of inductive reasoning by Thurston in 1938, whereas later researchers saw inductive reasoning more as generalisation (Shye, 1988). Wason's 2-4-6 task is a typical rule finding task.

By using the 2-4-6 task, Wason (1960) found that the utilisation of eliminative strategy had higher correlation to the success rate. Eliminative strategy refers to one's purposeful employment of negative instance to falsify hypothesis. Wason (1960) found that those, who performed better in the 2-4-6 task, tended to both eliminate more possibilities and to generate more negative instances. In other words, they gave more tries to falsify potential but incorrect rules. In Wason's study, these subjects was said to employ *eliminative strategy*. As oppose to the eliminative strategy, some subjects employed the enumerative strategy with the common mistaken assumption that confirming evidences alone could justify their conclusions. Wason's (1960) results showed that the eliminative strategy yielded better performance than the enumerative strategy. Falsification (eliminative strategy) can lead to a smaller search space in which candidate hypothesis in principle has higher potential to be correct. Falsification therefore is a more efficient strategy than mere verification (enumerative strategy) from both theoretical and empirical point of view.

In Wason's (1960) version of the 2-4-6 task, the subjects were instructed to discover the rule that governs a triplet or "triad" of numbers. The triad, 2-4-6, was offered as an exemplary triad that followed the rule. The target rule (T-Rule) to be found is "*three numbers in increasing number of magnitude*". The subjects started by writing down a triad (e.g. 1-2-3) and a hypothesis (e.g. three number less than 10). The experimenter then told the subject whether the triad conform to the target rule or not.

Whetheric (1962) criticised Wason's (1960) work by stating that (1) the example of 2-4-6, a conforming triad, given to the subjects as part of the instructions was misleading the subjects to use enumerative strategy, (2) the methodology Wason used did not provide any evidence of subjects actively using eliminative strategy.

Whetheric proposed another scheme to classify subjects' behaviour. The classification scheme included four cases: confirming-positive, confirming-negative, disconfirming-positive, and disconfirming-negative. In Whetheric's scheme, if a subject's hypothesis is "*three number less than 10*", and then the subject proposes the triad 1-2-3, this is classified as confirming-positive – the triad is confirming to the subject's current hypothesis (confirming), and the experimenter also gives a positive answer (positive). If the subject, holding the same hypothesis, but writes down the triad 3-2-1, then this is classified as confirming-negative – the triad confirms to the subject's current hypothesis, but the experimenter gives a negative answer. The similar principle is applied for disconfirming-positive and disconfirming-negative. Under his classification scheme, Whetheric pointed out that only conforming-negative and disconfirming-positive can be use to eliminate hypothesis and only they can be said to be eliminative strategy.

The number of confirming or disconfirming hypothesis can in fact depend on the nature of the task. In the experiment 1 of Gorman and Gorman (1984), the T-Rule was "*at least one even number*", and in experiment 2, the T-Rule was "*no two numbers the same*". The number of disconfirming-negative hypothesis in the group instructed to follow the eliminative strategy was higher in experiment 2 than that of in experiment 1. In general, disconfirming-negatives are not useful to determine whether the hypothesis should be given up or not. As a direct consequence, the group performed worse in experiment 2 than in experiment 1. Gorman and Gorman (1984) speculated that this phenomenon was caused by the fact that it was more difficult to create confirming hypothesis to the "*no two numbers the same*" rule in experiment 2, i.e. the subjects could not obtain enough number of falsifying triads in order to successfully complete the task.

Also, falsifying triads or verifying triads alone could not yield optimal performance. In other study by Gorman et al. (1984), it was demonstrated that the proportion of falsifying triads to verifying triads was a key predictor of success. It is interesting to note that the choice of different T-Rule has such great impact on subject's behaviour. The fact that only a minority of subjects employed the eliminative strategy may lead to the possibility to think that the eliminative strategy is not easy to be employed in the 2-4-6 task. This speculation is further supported by Mahoney and DeMonbreun's (cited in Gorman and Gorman, 1984) experiment which showed that neither university students nor working scientists tend to disconfirm hypothesis on the 2-4-6 task unless instructed or hinted to do so.

These aforementioned researchers (i.e. Wason, 1960; Whetheric, 1962; Gorman and Gorman 1984; and Gorman et al., 1984) limited their research to behaviour output only. What are the cognitive processes involved in the eliminative strategy? What happens mentally when someone is said to use eliminative or enumerative strategy? In Whetheric's scheme, disconfirming-positive can in fact be used to indicate subject's intention to employ the eliminative strategy, and therefore be a starting point to answer the above questions. However, Whetheric did not orient his article to answer our question.

In order to obtain further insights about cognitive processes involved in eliminative strategy, an example is used. What is required to find out the target rule (the T-Rule) "*three numbers in increasing order of magnitude*"? In terms of magnitude of the triad, the T-Rule can be represented as "S-M-B" (short for Small-Medium-Big). "S-M-B" represents a class of triads that confirm to the T-Rule. "1-3-5", "1-5-7", "100-1000-10000", and "2-7-15" are all members of the "S-M-B" class.

In this task, the key action to success is to falsify "*three numbers not in increasing order of magnitude*" (hereafter called the falsifying rule, the F-Rule). Unlike T-Rule, which has only one class of triads, F-Rule has five classes of triads – "B-M-S", "M-B-S", "M-S-B", "S-B-M", and "B-S-M". Logically speaking, one needs to falsify all these five classes in order to falsify the F-Rule and hence work out the T-Rule otherwise, it can only be called guess. Although one can argue that sometime humans make decisions based on probabilities instead of complete knowledge, but pursuit of this argument is beyond the scope of this study. What we wish to stress is that when it is difficult to find the F-Rule, such as the experiment 2 of Gorman and Gorman (1984), it becomes difficult to find the final answer using eliminative strategy (falsification).

The inference about the need to falsify the F-Rule "*three numbers not in increasing order of magnitude*", and the enumeration of the five classes of triads in the F-Rule, are in fact deductive reasoning. This deductive reasoning is what we called the deduction-in-induction – the deduction needed for the completion of an inductive reasoning task (Wason's 2-4-6 task). The ability to systematically enumerate and examine all possibilities (in this example, the five classes of triads in the F-Rule) is what we called the *systematic thinking* in this study. "Induction may lead to incorrect conclusions if antecedent information is not accurate or representative, and systematic validity checks should be conducted to maintain confidence" (Marchionini, 1997).

Systematic thinking is not only important to the hypothesis testing stage, but equally or more important in the hypothesis generation stage of inductive reasoning. What are the possible categories that the triads could be classified in, their magnitude, their order of sequence, are they odd or even number, or multiple of a constant? If the subjects could have those categories in mind, they could then systematically test whether the T-Rule belongs to any one of the categories, instead of trial-and-error or wasting time on repeated tests of same category.

The questions now are about systematic thinking. What is systematic thinking and how is it related to inductive reasoning ability. Let's try to use an example to elucidate those questions. For example, when a subject is required to find the T-Rule "*3 numbers in ascending order*" (i.e. the T-Rule in Wason, 1960), the key is to falsify "*3 numbers not in ascending order*" (falsifying rule, F-Rule). The focus here is the "*sequence of the order of magnitude*" (target focus, T-Focus) of the 3 numbers. For another example, when the T-Rule is "*no two numbers the same*" (T-Rule used in Gorman and Gorman, 1984), the F-Rules become "*a=b or a=c or b=c*", where a, b, c represents the first, second, and third number in the triads. In the second example, one needs to focus on the "*equality of 2 of the numbers*" (T-Focus).

Harverty et al. (2000) distinguished "experiment space", which is a mental mode that one is gathering data in order to form hypothesis, from "hypothesis space", which is a mental mode where one has acquired a hypothesis to be tested. For example, in the 2-4-6 task, when one is first trying some triads with any expectation, then one is working in the experiment space; and when one sees the 3 pairs of triads (2-4-6), (4-6-8), (10-20-30) with positive confirmations, one may form the hypothesis "*3 even numbers*" in the hypothesis space. One needs to come back to the experiment space to try out some more triads to test whether the hypothesis is correct or not.

Harverty et al. (2000) further distinguished "local hypothesis" from "global hypothesis". A local hypothesis is formed from some observed pattern of the data in the experiment space. When a local hypothesis gathers its creditability, it can be promoted to a global hypothesis. It is only when one has found the T-Focus, it is possible to develop a local hypothesis into a global hypothesis. Figure 11-1 illustrates different stages of inductive reasoning.

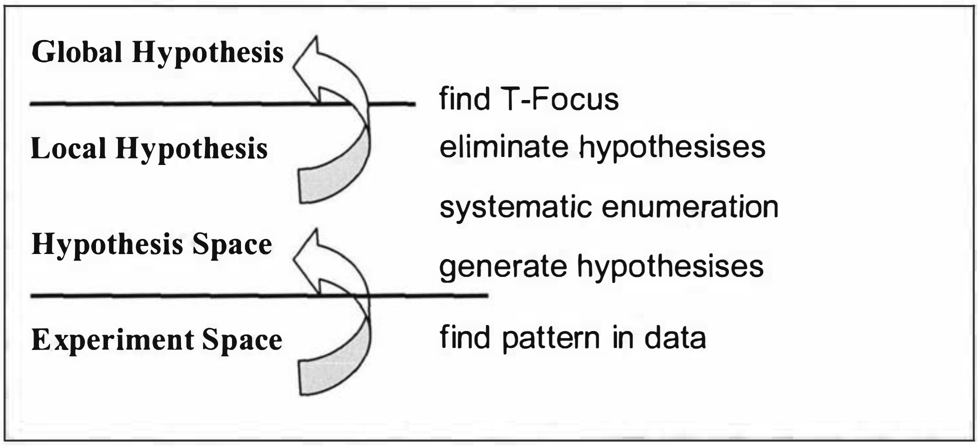

Figure 11-1: Transition of different stages in inductive reasoning

In order to find the T-Focus among all the candidates, researchers have found the employment of eliminative strategy to be an efficient one (Wason, 1960; Whetheric, 1962).

What is the individual difference that determines whether eliminative strategy is used or not? An important ability called systematic thinking can help to investigate this question in more detail.

In their study of children's growth of logical thinking from a developmental perspective, Inhelder and Piaget (1958) hypothesized the existence of the mental construct called *combinatorial schema* which is the ability to make systematic combinations of given factors in order to obtain a desired effect. Inhelder and Piaget used chemical problem solving as the experiment and therefore stressed on the ability to systematically process given factors. In our study however, focus is placed on systematic thinking itself, which is the ability to systematically list and test factors, because of the assumption that the knowledge required to solve the problem has already been acquired.

Two stages precede the elimination of a candidate solution, namely the formation stage of the candidate solution and the test stage of candidate solution. In the formation stage, the systematic thinking is important if not essential. Using Wason's (1960) 2-4-6 task as an example, a subject may start by considering the following aspects:

- whether there is a threshold (e.g. all 3 numbers less than 20),
- whether the order of magnitude of numbers matters in the sequential order,

- whether there is a common difference between adjacent numbers (e.g. a, a+2, a+2+2),
- odd or even numbers, for all or for at least a certain amount or for at a certain order/position, and
- more others.

Even though systematically listing all possibilities is impossible, the identification of those broad categories allows the starting point of elimination. That is, without taking any of these broad aspects into consideration, no elimination strategy is possible in a logical sense because of not knowing what to eliminate.

In the test stage, systematic thinking has even a more critical role. Using an example of testing the candidate hypothesis "no 2 numbers are the same", one needs to negate the following three rules (F-Rule).

1. a=b
2. a=c
3. b=c

when the triad is represented by (a-b-c).

The act of negating the three rules is actually what was called the eliminative strategy by Wason (1960), Whetheric (1962) and Gorman and Gorman (1984). This leads to our hypothesis that there exists a close relationship between systematic thinking and eliminative strategy – maybe eliminative strategy is in fact of a function of systematic thinking. This is also one of the questions we would like to find out. Answering this question would aid our overall understanding of the nature of inductive reasoning ability.

The hypothesis is tested in the later sections of this chapter. Before we do that, the three tools used to measure inductive reasoning ability, systematic thinking ability and rule finding ability are presented in detail.

11.4 Description of Tools

Three tools are used in this chapter. They are Web-IRA for testing inductive reasoning ability, Web-Sys for testing systematic thinking ability and Web-RF to test rule finding ability. These three tools are described in details in this section.

11.4.1 Web-IRA for Inductive Reasoning

Web-IRA is a task consisting of thirty questions. The questions in Web-IRA include all three types of task in inductive reasoning tests (series extrapolation, analogical reasoning and exclusion) described above. Web-IRA has a web interface as shown in Figure 11-2. What a subject needs is a standard web browser to access Web-IRA. The materials are text and images only. No additional software packages or plug-ins are required by the web browser.

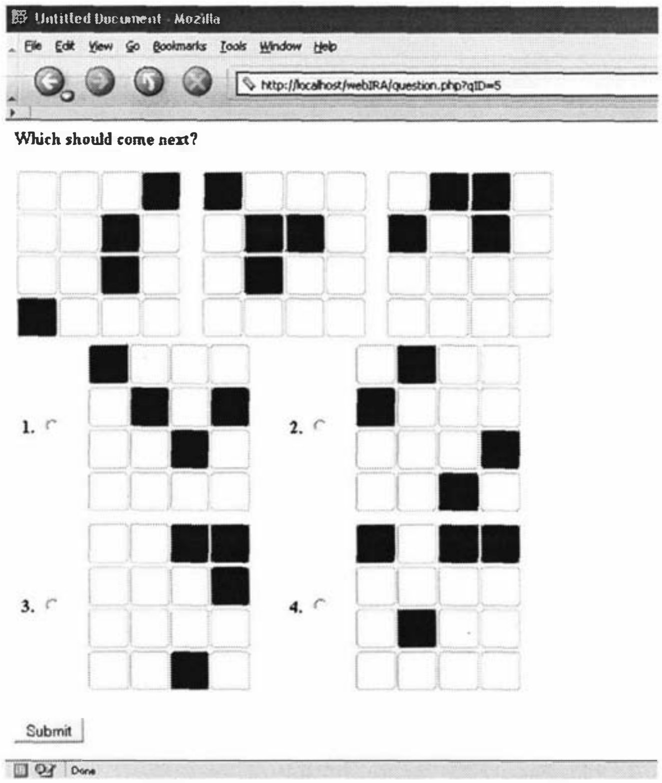

Figure 11-2: Web-IRA Interface

The questions are presented to subjects in a sequential order. A question must be solved before a subject can move to the next one. And once solved, the subject cannot return to it anymore. This is to ensure that the subject cannot go back to the same question to cheat.

The Web-IRA system can be either deployed onto a local computer network or the World-Wide-Web (WWW), and the working conditions of both deployments are basically identical – Web-IRA is taken individually by using web browsers. While deployed in a local computer network, experiments can be conducted in a supervised group in computer laboratories.

The ability to deploy Web-IRA on WWW increases its availability especially for those experiments where supervision is too costly or impossible. Web-IRA is also ideal when the experiment needs to bring back participants who are no longer accessible (e.g. graduated) for follow-up study. But due to the higher possibility of interference while subject is taking the Web-IRA in an unsupervised environment, timing mechanism is built into Web-IRA so that detection of abnormality can be possible. Also the timing mechanism is designed in a way that it starts after the web page is loaded, so that subjects with slow computers or connection speed are not disadvantaged.

In addition, Web-IRA can also be used in the traditional one-supervisor-to-one-subject experiment design. In this case, userIDs and passwords are only given to the supervisor who can then login on behalf of the subject at the beginning of the experiment.

The advantages of Web-IRA provided by the ability to be deployed on the WWW also apply to Web-Sys and Web-RF and are not repeated in the subsequent sections.

11.4.2 Web-Sys for Systematic Thinking

Web-Sys is a task consisting of 3 questions. Web-Sys starts with a standard login process. After success login, subjects are shown the instructions. In the instructions, the subjects are advised to avoid any interruption. The subjects are allowed to use pens, papers or other text-editor tools to help solving the questions.

Similar to Web-IRA, Web-Sys has a web interface. A subject needs only a standard web browser to access it. In all three questions, the questions are shown at the top of a page, and a large text field is available for subject to answer (see Figure 11-3). In all three questions, subjects are asked to use comma (,) to separate their answers. The natures of the 3 questions are described next.

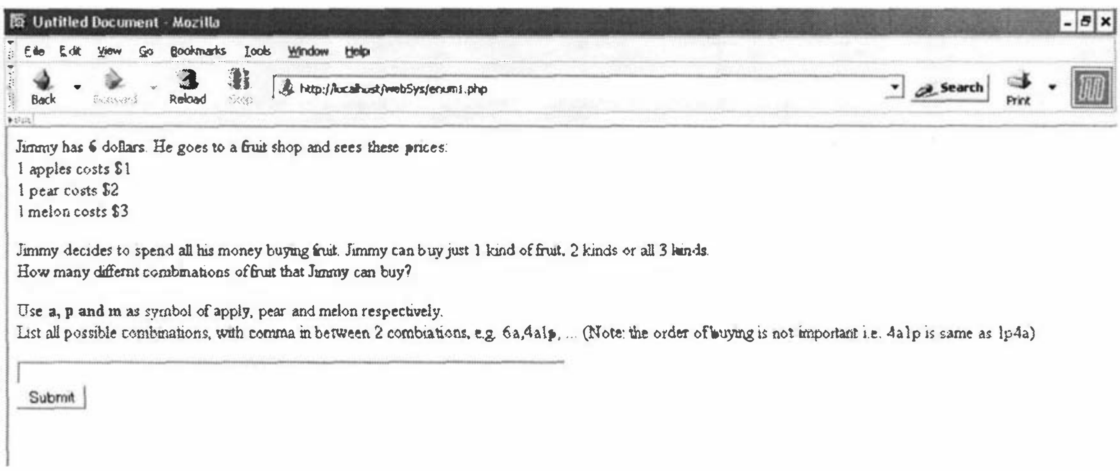

Figure 11-3: Web-Sys Interface

The first question in Web-Sys is to examine subject's ability to use different combinations of elements to achieve a target. Semantically, the question is about a boy going to a fruit shop with a fixed amount of money. There are 3 fruits available in the fruit shop and each of them has a fixed price. The subjects are asked to input as many different combinations of fruit that the boy can buy. The order of the elements (fruits) does not matter in this question. Not all elements need to be included in each answer too, i.e. the boy can spend all his money buying just one kind of fruit.

The second question in Web-Sys is about bridge-crossing. A farmer travelling with his four animals has to line the animals up to cross a narrow bridge. There are rules that dictate the possible orders of combination. For example, one of the rules is "the dog cannot directly follow the cat". The subjects are asked to input as many different sequences of lining up the animals as possible. In this question, the order of the animals does matter and all animals have to be included in each answer.

The third question is purely designed for enumeration. The subjects are asked to input all the prime numbers between 1 and 50 inclusively. The order of the prime numbers does not matter in this question.

The three questions have different rules. Following the rules requires various cognitive efforts. All three questions are designed to test whether subjects can systematically enumerate all possible answer items.

11.4.3 Web-RF for Rule Finding

Web-RF is a computerised version of Wason's 2-4-6 task (Wason, 1960). The target rule (T-Rule) is the same as Wason's and the exemplary triad, which is 2-4-6, is also the same as Wason's. Similar to Web-IRA and Web-Sys, Web-RF also has a web interface (see Figure 11-4).

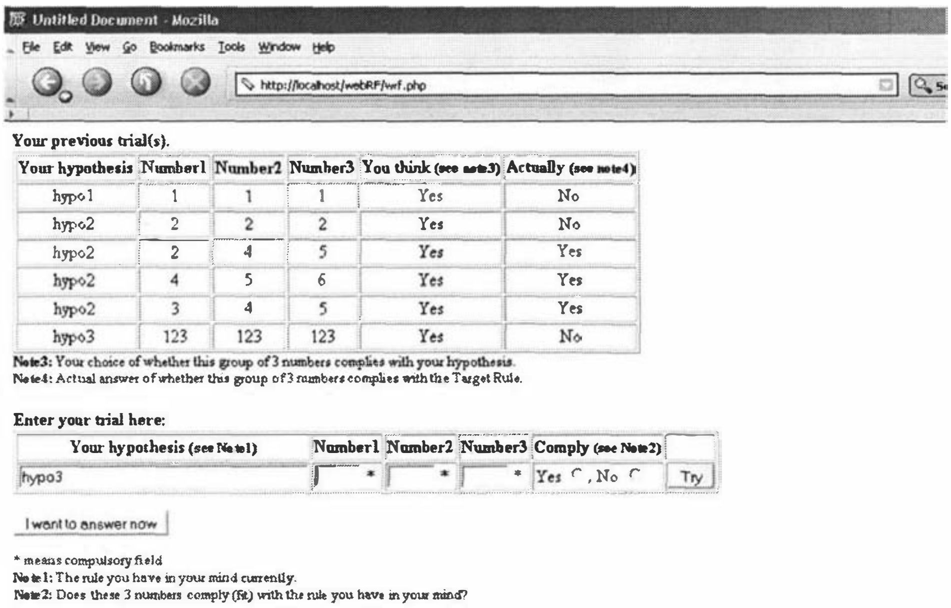

Figure 11-4: Web Interface of Web-RF in the Trial-Stage

The first stage in the Web-RF task is the trial-stage. In the trial stage, a subject is allowed to try as many 3-number triads as desired. For each triad, the Web-RF system responds with either a positive or a negative answer. All of the subject's triads and system's responses are displayed on the top of the web page to serve as the subject's reference of further trials (see Figure 11-4).

For each triad tried, the subject has the option to write down a hypothesis and indicate whether the triad complies with the hypothesis. The triad, subject's hypothesis and subject's indication are all recorded in the database automatically.

When the subject thinks that he/she is ready and decides to give the final answer, the Web-RF task moves into the answering-stage. A warning message, which explicitly points out that it is not allowed to come back to the trial-stage after entering the answering-stage, is shown before the start of answer-stage. Upon seeing the warning message, the subject can choose to have more trials or confirm the decision to enter the answering-stage.

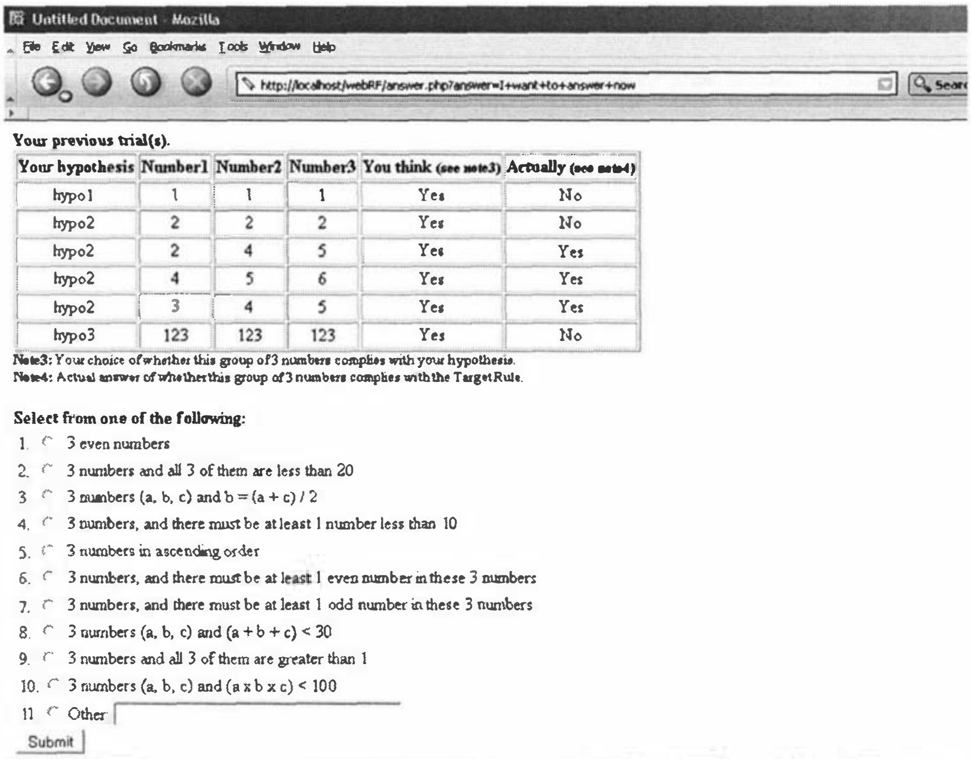

Figure 11-5: Web Interface of Web-RF in the Answering-Stage

In the answering-stage, all of the subject's previous trials and system's responses are also displayed (see Figure 11-5). In addition, a list of rules is displayed for the subject to choose what he/she think is the target rule. There is also provision for the subject to type in the subject's answer manually. If the subject chooses to type in the answer manually, then the experimenter has to check this answer manually as well during data analysis because it is possible that the subject uses a different format to express the same T-Rule.

The above are the descriptions of the three tools used in this chapter. Empirical evaluations were carried out using these tools. Evaluations can be divided into three experiments. There is no distinctive boundary in terms of time for these experiments because most of the subjects in these experiments were given access to all three tools at the same time. But for the aim of our study, the evaluations can be divided into three practical units (experiments). Each of the experiment is described in detail next.

11.5 Experiment 1

Experiment 1 is primarily aimed at evaluating the Web-IRA task. Its participants, material, procedure, and result are discussed below. Furthermore, the validity and reliability of Web-IRA are also examined.

11.5.1 Participants

There were total 93 subjects in Experiment 1. The subjects could be split into 5 different groups (see Table 11-1).

Table 11-1: Participants in Empirical Evaluation

Group	Size	Group Characteristics (Country/ University)
1	20	third year university students; studied course offered by Department of Information System (New Zealand/Massey University)
2	31	first year university students; studied course offered by Department of Information System. (New Zealand/Massey University)
3	9	postgraduate students; studied course offered by Department of Information System (New Zealand/Massey University)
4	41	Undergraduate students; studied course offered by Department of Computer Science (Finland/University of Joensuu)
5	5	postgraduate students; IT-related disciplines (Networking, Computer Science) (Taiwan, National Central University)

Groups 1, 2 and 3 were students of Massey University in New Zealand. Group 1 and 2 were undergraduate students whereas Group 3 consisted of postgraduate students (Postgraduate Diploma, Masters, and PhD).

Subjects in Group 4 participated in a study about inductive reasoning and programming (Lin et al., 2006). They used the Finnish version of Web-IRA[1]. Subjects in Group 5 were postgraduate students in National Central University in Taiwan studying in IT-related disciplines. They used the Chinese version of Web-IRA.

11.5.2 Material

Groups 1, 2 and 3 used the English version of Web-IRA. Group 4 used the Finnish version and Group 5 used the Chinese version of Web-IRA. Most of the questions in both the Finnish version and the Chinese version were direct translations from the English version. Some modifications were made to cater for different cultural and educational background. For example, in the English and Chinese version, a rainbow has 7 colours: red, orange, yellow, green, blue, indigo and purple (violet), but in the Finnish version, it has 6 colours (without the indigo). Different versions just had to be tailored to the common understanding of the target population.

11.5.3 Procedure

Two subjects in Group 2 and one subject in Group 5 did not complete all 30 questions. Their data were excluded from the following analyses. Remaining 89 subjects completed all 30 questions. Total number of correct answers was recorded and it was counted as the main index of inductive reasoning ability in this experiment.

[1] The author would like to thank Andres Moreno, and Niko Myller for their permissions to use the data in this thesis and their helps in translating Web-IRA into Finnish language.

In addition, answers to each question and the time to answer each question were also recorded. Due to some technical glitch in the initial setup of the system, the answers of 6 subjects to individual questions were not recorded; however the total numbers of correct answers (i.e. the final scores) of these 6 subjects were successfully recorded.

11.5.4 Result and Discussion

Statistics of experiment 1 is presented in Table 11-2. For the group of 89 subjects, the mean of correct answers (represented by *iraCorrect*) is 17.65 with a standard deviation of 4.14. Because of the 6 subjects for whom the individual answers were not collected, answers for all questions and the time taken to answer each question are only available for 83 subjects. For these 83 subjects, the averaged time spent on each question (represented by *AvgTime*) is 41.06 seconds with standard deviation of 27.62 seconds.

Table 11-2: Descriptive Statistics of Experiment 1

	N	Minimum	Maximum	Mean	Std. Deviation
iraCorrect	89	4	25	17.65	4.14
AvgTime	83	3.67	139.20	41.06	27.62
Valid N (listwise)	83				

It can be seen from Table 11-3 that performances are quite consistent among groups except for Group 3. Performed t-Test (2 samples assuming unequal variance) between Group 3 and the entire sample confirmed that the difference between them is statistically significant with confidence level reaching 99% for non-directional (2 tail) and 98% for directional (1 tail) test.

Table 11-3: Group Means and Standard Deviation

	Group 1	Group 2	Group 3	Group 4	Group 5
Mean	17.2	17.72	20.11	17.07	17.75
Standard Deviation	4.26	3.92	2.37	4.79	2.99

The higher performance in Group 3 could be due to the reason that participants in Group 3 were postgraduate students. Mwamwenda (1999) had also reported the positive relation between high reasoning ability and high educational attainment. However,:

1. participants in Group 5 were also postgraduate students;
2. performance in Group 5 was not significantly higher than Group 1, 2, and 4; and
3. group size in Group 5 was small,

further research effort is needed to see the relationship of educational attainment and performance in Web-IRA.

Because there is no set time limit on Web-IRA except the default session expiry time from the web server (Apache 2), we are also interested to know whether there is a relationship between performance and time spent on the Web-IRA task.

Table 11-4: Correlation between Performance and Time Spent

		iraCorrect	AvgTime
iraCorrect	Pearson Correlation	1	.513(**)
	Sig. (2-tailed)		.000
	N	89	83
AvgTime	Pearson Correlation	.513(**)	1
	Sig. (2-tailed)	.000	
	N	83	83

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

Table 11-4 shows the correlation between performance (*iraCorrect*) and averaged time spent on each question (*AvgTime*). The correlation coefficient of 0.513 indicates that the relationship between performance and time spent on Web-IRA is strongly significant. On average, each subject spent 41.06 seconds on each of the 30 questions. This indicates that 1) subjects were taking the Web-IRA task seriously, 2) the difficulty level of Web-IRA for university student is suitable.

Reliability

In order to examine the internal reliability of Web-IRA, three analysis tasks were performed. The first was Cronbach's alpha, the second was t-Test on split scores, and the third was Pearson's correlation on split scores.

The Cronbach's alpha is calculated as 0.696. Although 0.696 is not over 0.8, given the number of items (30 questions), it is nevertheless quite a good score in terms of reliability (Bryman and Cramer, 2005).

For the second and third analysis tasks, the 30 questions were divided into 2 sets of 15 questions. The 2 sets had equal number of different types of questions (Exclusion, Extrapolation, and Analogy) but the selection of questions into sets was done randomly. In doing so, 1 score became 2 scores. Paired-sample t-Test was then performed on the 2 scores to find out whether there was difference between the 2 scores.

Table 11-5: t-Test results of the 2 scores

	Score1	Score2
Mean	8.903614	8.650602
Variance	6.088158	5.376433
Observations	83	83
Pearson Correlation	0.507746	
df	82	
t Stat	0.969337	
P(T<=t) one-tail	0.167614	
t Critical one-tail	1.663648	
P(T<=t) two-tail	0.335228	
t Critical two-tail	1.98932	

The result of the t-Test is shown in Table 11-5. The data in Table 11-5 indicates no significant difference between the 2 scores. The calculated Pearson correlation of 0.51 is also statistically significant to 0.01 level. Although the Cronbach's alpha is slightly less than ideal, both the results of the t-Test and Pearson correlation give credence to the reliability of Web-IRA.

Validity

In order to examine the validity of Web-IRA, two analysis tasks were carried out. The first analysis task involved factor analysis. Principle component analysis was the technique used in factor analysis. Principle component analysis is one of the most popular technique to find out the common variance among scores (Bryman and Cramer, 2005). In this study, principle component analysis is used to find the common variance between the 30 questions. The result of the principle component analysis is shown in Table 11-6.

Table 11-6: Factor Analysis (Principal Component Analysis) on 30 Questions

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	4.122	13.741	13.741
2	2.343	7.811	21.551
3	1.979	6.595	28.147
4	1.801	6.004	34.151
5	1.704	5.681	39.832
6	1.549	5.162	44.993
7	1.491	4.971	49.965
8	1.364	4.547	54.512
9	1.270	4.233	58.745
10	1.175	3.915	62.660
11	1.096	3.654	66.314
12	1.020	3.399	69.714
13	.932	3.107	72.821
14	.879	2.930	75.751
15	.807	2.691	78.442
16	.752	2.507	80.949
17	.718	2.394	83.342
18	.674	2.248	85.591
19	.623	2.078	87.668
20	.570	1.901	89.569
21	.509	1.696	91.266
22	.450	1.499	92.765
23	.397	1.325	94.090
24	.337	1.125	95.215
25	.332	1.107	96.321
26	.305	1.017	97.338
27	.243	.811	98.149
28	.204	.678	98.828
29	.191	.638	99.466
30	.160	.534	100.000

Although we are not aiming at reducing the 30 questions into groups, Table 11-6 shows 12 possible groups (the components with Eigenvalues > 1). Instead, we are interested to know whether these 30 questions are measuring the same construct or not. It can be seen in Table 11-6 that the largest component, which is represented by the Component 1, singularly accounts for 13.7% of total variance and is almost double of the second largest component and more than twice the size of all other components. Although Component 1 accounts for only 13.7% of total variance, it has already shown a promising signal given the facts that there are:

1. three different questions types;
2. textual or visual representation of question; and
3. requirements to draw on knowledge from different domains.

The 13.7% could possibility approximate what we called inductive reasoning ability. However, it is still only a possibility. We need further proof to show that the 30 questions were measuring the same construct, therefore the second analysis tasks was carried out.

The second analysis task was to find the correlation of subjects' performance on each type of questions (Exclusion, Extrapolation, and Analogy). First of all, the percentages of correct answers in each type of questions were calculated. The Pearson correlations between the percentages (represented by *Exclusion*, *Extrapolation*, and *Analogy* in Table 11-7) and the total number of correct answers (represented by *iraCorrect*) were then calculated. The correlations are displayed in Table 11-7.

Table 11-7: Correlations of Subjects' Performance on Each Question Types

		Exclusion	Extrapolation	Analogy	iraCorrect
Exclusion	Pearson Corr.	1	.465(**)	.365(**)	.799(**)
	Sig. (2-tailed)		.000	.001	.000
	N	83	83	83	83
Extrapolation	Pearson Corr.	.465(**)	1	.263(*)	.806(**)
	Sig. (2-tailed)	.000		.016	.000
	N	83	83	83	83
Analogy	Pearson Corr.	.365(**)	.263(*)	1	.634(**)
	Sig. (2-tailed)	.001	.016		.000
	N	83	83	83	83
iraCorrect	Pearson Corr.	.799(**)	.806(**)	.634(**)	1
	Sig. (2-tailed)	.000	.000	.000	
	N	83	83	83	83

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

In Table 11-7, there are significant correlations between each of all the pairs without any exception. Five out of the six correlations are significant at the 0.01 level. Each type of questions is related to the other two types and the total number of correct answers. It is likely that the Component 1 in Table 11-6 has consistent effect on all 3 types of questions. On the other hand, Component 2 to Component 12 in Table 11-6 could also possibility reflect certain facets of inductive reasoning ability or they could accounts for other factors, but this is an issue that lies beyond the scope of current study. Our data has proven that the 30 questions are in fact measuring the same construct and therefore gives support to the validity of the web-based tool – Web-IRA.

11.6 Experiment 2

Experiment 2 is an extension of Experiment 1. Subjects who did both the Web-IRA and Web-Sys tasks were studied and their performances on the two tasks were examined. Our previous discussion in chapter 7 and in section 11.3 of this chapter leads us to hypothesise the existence of a relationship between inductive reasoning ability and systematic thinking ability. That is, a relationship should exist between performances on Web-IRA and Web-Sys. We are interested to know whether the data gathered in Experiment 2 supports our hypothesis.

11.6.1 Participants

There were a total of 35 subjects in the Experiment 2. The subjects could be split into 4 different groups (see Table 11-8).

Table 11-8: Participants in Experiment 2

Group	Size	Group Characteristics (Country/ University)
1	12	third year university students; studied course offered by Department of Information System (New Zealand/Massey University)
2	16	first year university students; studied course offered by Department of Information System. (New Zealand/Massey University)
3	4	postgraduate students; enrolled in course offered by Department of Information System (New Zealand/Massey University)
4	3	postgraduate students; IT-related disciplines (Networking, Computer Science) (Taiwan, National Central University)

Groups 1, 2 and 3 were students of Massey University in New Zealand. Group 1 and 2 were undergraduate students whereas Group 3 consisted of postgraduate students (Postgraduate Diploma, Master, and Ph.D.). Subjects in Group 4 were postgraduate students at National Central University in Taiwan studying in IT-related disciplines.

11.6.2 Material

Groups 1, 2 and 3 used the English version of Web-Sys as described in Section 11.4.2 . Group 4 used the Chinese version of Web-Sys. The Chinese version was direct translated from the English version.

11.6.3 Procedure

Four subjects in Group 1 and one subject in Group 2 did not take the Web-IRA task. Therefore, data of these 5 subjects were discarded.

Subjects in Experiment 2 were each given an account to login to Web-Sys. After login, instructions were displayed. A link was available to start the Web-Sys task once the subjects had read and understood the instructions. Contact email address was available if the subjects had any queries. The subjects were allowed to login multiple times whereas answers were only recorded at the first submission.

11.6.4 Result and Discussion

There are three questions in Web-Sys: enum1 (the fruit shop question), enum2 (the bridge-crossing question), and prime1 (the prime number question). The descriptive statistics for these questions are shown in Table 11-9.

Table 11-9: Descriptive Statistics for Web-Sys

	Mean	Std. Deviation	Possible Maximum
enum1	6.43	1.399	7
enum2	7.22	3.577	11
prime1	14.23	3.655	17

In each question, there is a maximum score. For example, prime1 is about listing all the prime numbers between 1 and 50 (inclusive). There are 17 prime numbers within the range and therefore maximum score a subject can get is 17. It is possible that a subject may have answered only 8 out of the 17 correct prime numbers and therefore only scored 8 points. Enuml has a maximum score of 7, enum2 has a maximum of 11 and prime1 has a maximum of 17. The total points (called *Sum* in Table 11-10) a subject can get is therefore 35. In addition, the scores were also converted into percentage. Using the above example, the subject would get 47% (8 divide by 17) for prime1. The percentage from the three questions were also summed (called *SumPer* in Table 11-10). The two summed values are analysed using Pearson correlation together with the score from Web-IRA, called *iraCorrect* in Table 11-10, and the result is shown in Table 11-10.

Table 11-10: Correlations between Web-IRA and Web-Sys scores

		iraCorrect	Sum	SumPer
iraCorrect	Pearson Correlation	1	.471(**)	.468(**)
	Sig. (2-tailed)		.009	.009
	N	30	30	30
Sum	Pearson Correlation	.471(**)	1	.981(**)
	Sig. (2-tailed)	.009		.000
	N	30	30	30
SumPer	Pearson Correlation	.468(**)	.981(**)	1
	Sig. (2-tailed)	.009	.000	
	N	30	30	30

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

It can be seen in Table 11-10 that all of the three variables are correlated to the other two. The very high correlation between *Sum* and *SumPer* allows us to use *SumPer* as the index of performance in Web-Sys. The strong correlation between *iraCorrect* and *SumPer* (and also *Sum*) confirmed our hypothesis that systematic thinking ability is indeed related to inductive reasoning ability.

11.7 Experiment 3

Experiment 3 is an extension of Experiments 1 and 2. Subjects who did all three of the Web-IRA, Web-Sys and Web-RF tasks were studied. We have hypothesised that:

1. there should be a relationship between subjects' performances on Web-IRA and Web-RF; and
2. there should be a relationship between subjects' performances on Web-Sys and Web-RF.

In Experiment 3, we are interested to find out whether these hypothesises could be validated empirically.

11.7.1 Participants

There were total 35 subjects participated in Experiment 3. But among these 35 subjects, only 28 also used either Web-IRA or Web-Sys or both. Because we were interested to see the relationship between the performance of Web-RF to Web-IRA and Web-Sys, data of the other 7 subjects were discarded. The 28 subjects could be divided into 4 different groups and described in Table 11-11.

Table 11-11: Participants in Experiment 3

Group	Size	Group Characteristics (Country/ University)
1	13	third year university students; studied course offered by Department of Information System (New Zealand/Massey University)
2	14	first year university students; studied course offered by Department of Information System. (New Zealand/Massey University)
3	5	postgraduate students; enrolled in course offered by Department of Information System (New Zealand/Massey University)
4	1	postgraduate students; IT-related disciplines (Networking, Computer Science) (Taiwan, National Central University)

Groups 1, 2 and 3 were students of Massey University in New Zealand. Groups 1 and 2 were undergraduate students whereas Group 3 consisted of postgraduate students (Postgraduate Diploma, Master, and Ph.D.). Subjects in Group 4 were postgraduate students in National Central University in Taiwan studying in IT-related disciplines.

11.7.2 Material

Groups 1, 2 and 3 used the English version of Web-RF as described in Section 11.4.3 . Group 4 used the Chinese version of Web-RF. The Chinese version was direct translation of the English version.

11.7.3 Procedure

The procedure in Experiment 3 is similar to Experiment 2 except that a different URL was given to access Web-RF instead of Web-Sys.

11.7.4 Results and Discussion

In the Web-RF task, five scores were recorded for each subject: subject's performance (*RF*), number of confirming-positive (*CP*) trials, number of confirming-negative (*CN*) trials, number of disconfirming-positive (*DP*) trials, and number of disconfirming-negative (*DN*) trials. The four scores (*CP*, *CN*, *DP*, and *DN*) follow Whetheric's (1962) definition, for example, a trial is counted as *CP* when a subject thinks that the trial triad (3 integers) confirms to the subject's current hypothesis (confirming), and it indeed confirms to the T-Rule (positive).

From the experience of Wason (1960), we are expecting to see that the subjects' performance in Web-RF should have a positive correlation to the use of eliminative strategy i.e. the score of *DP*. But the correlation between *RF* and *DP* shown in Table 11-12 is only mild (significant to 0.108 and directional).

Table 11-12: Spearman Correlation between RF and DP

		RF	DP
RF	Correlation Coefficient	1.000	.242
	Sig. (1-tailed)	.	.108
	N	33	28
DP	Correlation Coefficient	.242	1.000
	Sig. (1-tailed)	.108	.
	N	28	28

In other words, our findings could not re-produce that of Wason's (1960). However, when we computed the proportion of falsifying triads (called *Ratio* in Table 11-13) by using (*DP* + *DN*) / (*CP* + *CN*), we found what Gorman et al. (1984) had found, namely the proportion of falsifying triads indeed has a correlation to the performance of Web-RF. This relation is shown in Table 11-13.

Table 11-13: Spearman Correlation between WebRF and Ratio

		RF	Ratio
RF	Correlation Coefficient	1.000	.362(*)
	Sig. (1-tailed)	.	.029
	N	33	28
Ratio	Correlation Coefficient	.362(*)	1.000
	Sig. (1-tailed)	.029	.
	N	28	28

* Correlation is significant at the 0.05 level (1-tailed).

The correlation between *Ratio* and *RF* confirms that using verifying or falsifying triads alone is not a good strategy to solve the Web-RF task. It is the combination of them that optimises performance. This echoes our discussion in chapter 7 about the need of deductive reasoning (falsifying) in inductive reasoning.

While checking the correlations between the performance of Web-RF, Web-IRA and Web-Sys, the result is not strong enough to show clear relationships. With respect to the performance between Web-RF and Web-IRA, there is no obvious correlation between subjects' performances on the Web-IRA task and on the Web-RF task. There is also no correlation between the use of eliminative strategy and inductive reasoning ability. However, a correlation does exist between enumerative strategy (*CP*) and performances on the Web-IRA (*iraCorrect*). This correlation is shown in Table 11-14.

Table 11-14: Spearman Correlation between CP and iraCorrect

		CP	iraCorrect
CP	Correlation Coefficient	1.000	.341(*)
	Sig. (1-tailed)	.	.041
	N	28	27
iraCorrect	Correlation Coefficient	.341(*)	1.000
	Sig. (1-tailed)	.041	.
	N	27	37

* Correlation is significant at the 0.05 level (1-tailed).

This correlation leads us to rethink about the types of questions in Web-IRA. The analogy questions (e.g. 45311 to deck is 371918 to?), the extrapolation questions (e.g. which should come next: 13 37 159 183 241?), and the exclusion questions (e.g. which one is least like the others: 21, 14, 28, 63, 32?) are all tapping into similar mental resources (faculties) which are also used by enumerative (verifying, confirming) strategy. On the other hand, tasks such as Wason's 2-4-6 task, represented by the Web-RF task in this study, need both enumerative strategy and eliminative strategy. The rule finding tasks are obviously using a set of mental resources different to those used in the three inductive reasoning tasks in Web-IRA. The lack of correlation could therefore be expected. However, the rule-finding task is typically considered as an inductive reasoning task (e.g. Wason, 1960; Tukey, 1986; Vartanian, 2003). Our findings suggest a serious reconsideration about the nature of tasks when choosing tests for inductive reasoning ability. Caution has to be exercised even when choosing among popular existing tests. That is, distinction has be made whether the intended "inductive reasoning ability" to be about rule-finding (Wason, 1960) or about generalisation (Rescher, 1980; Harvery et al., 2000).

With respect to subjects' performance on Web-RF and Web-Sys, there is no correlation between *CP*, *CN* (both for enumerative strategy) and performance on Web-Sys. But we found that *DP*, which represents the use of eliminative strategy, does have a correlation to the second question in Web-Sys (called *WebSys2* in Table 11-15). The proportion of falsifying triads, which is discussed above and is represented by (*DP* + *DN*) / (*CP* + *CN*), also has a correlation to *WebSys2* (see Table 11-15).

Table 11-15: Spearman Correlation between DP and Performance of Web-Sys

		DP	Ratio	WebSys2
DP	Correlation Coefficient	1.000	.904(**)	-.347(*)
	Sig. (1-tailed)	.	.000	.049
	N	28	28	24
Ratio	Correlation Coefficient	.904(**)	1.000	-.366(*)
	Sig. (1-tailed)	.000	.	.039
	N	28	28	24

WebSys2	Correlation Coefficient	-.347(*)	-.366(*)	1.000
	Sig. (1-tailed)	.049	.039	.
	N	24	24	32

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (1-tailed).

Why *DP* and *Ratio* are not correlated to the first or the third question in Web-Sys? When the three questions are examined in detail, it is not hard to see the reason. The first (enum1, about fruit shop) and the third (prime1, about prime number) questions involve the requirement to enumerate all the answers as the second question (enum2, about bridge-crossing). But the second question differs from the other two in an important way – it requires constant checking of the rule when forming an answer item. It means that when a subject is working on question 2, the subjects needs to check the rules (about whether one animal can follow another animal) multiple times in order to formulate each answer item. Whereas, in questions 1 and 3, the subject only needs to check the rule(s) once for every answer item.

The difference predominately lies in the cognitive resources required. For solving question 2, it needs both memory to hold on to a partially formulated answer and cognitive processing to check the rules. The need to also check the rule in questions 1 and 3 implies that the cognitive processing demand stays the same as in question 2. But for questions 1 and 3, there is a relatively smaller demand on the memory, i.e. a subject only needs to hold on to one memory item (current potential answer item) at a time. In comparison, because there are 4 animals in question 2, there are times when the subject needs to hold up to 3 items in memory and simultaneously process the forth item.

It seems that the employment of eliminative strategy also requires a similar pattern of cognitive activities as required by question 2 in Web-Sys. Using the example given above about finding the T-Rule "*three numbers not in increasing order of magnitude*", we can point out the similarity as follows. In order to employ eliminative strategy to solve the T-Rule (which can be represented by "Small-Medium-Big" or "S-M-B"), a subject needs to falsify five F-Rules ("B-M-S", "M-B-S", "M-S-B", "S-B-M", and "B-S-M"). During the falsifying process, the subject needs to remember which one of the F-Rules has being falsified so that the triad does not belong to it – this requires holding multiple items in memory. At the same time, the subject needs to form the triad in a way that it can be used to falsify the next F-Rule – this needs cognitive processing. It is a similar pattern of cognitive activity, like that of the eliminative strategy, in action again. The correlation found in Table 11-15 is therefore likely to be a reflection of the said similarity.

11.8 Summary and Conclusion

In this chapter, three tools were introduced. They are: Web-IRA for inductive reasoning ability, Web-Sys for systematic thinking ability and Web-RF for rule finding. All of these tools have web interfaces and can be accessed through the Internet. This allows both experimenters and subjects to harness the advantages provided by the Internet in carrying out or participating in experimental studies.

Three experiments were carried out. In Experiment 1, Web-IRA was evaluated. The evaluation validated the internal validity and reliability of Web-IRA.

Experiment 2 was conducted to study inductive reasoning ability and systematic thinking ability. Web-IRA and Web-Sys were the tools used in Experiment 2. The strong correlation found between scores in Web-IRA and scores in Web-Sys confirmed our hypothesis that systematic thinking is closely related to inductive reasoning ability. However it has to be noted that our finding cannot be used to infer the causality of the relationship between Web-IRA and Web-Sys scores, i.e. we cannot say that one ability subsumes or causes anther. Nonetheless, this correlation is enough to support our claim that systematic thinking can be a manifestation of inductive reasoning ability in chapter 7.

Experiment 3 was aimed at studying the relationships between Web-IRA and Web-RF, and between Web-Sys and Web-RF. We hypothesised that performance in Web-RF should be related to performances in both Web-IRA and Web-Sys. Although, the result is not sufficient to confirm our hypothesis for both relations, there are several important findings from Experiment 3. First of all, our experiment cannot replicate what Wason (1960) had found, i.e. performance of the 2-4-6 task depends on the use of eliminative strategy. The reasons could be that:

1. the exemplary triad, i.e. 2-4-6, was misleading the subjects to use enumerative strategy as Whetheric (1962) suggested;
2. it is not natural for subjects to employ eliminative strategy unless they are instructed to do so as Gorman and Gorman (1984) suggested; and
3. there were differences in research setup between Web-RF and Wason's (1960) experiment.

Secondly, Experiment 3 did replicate the findings of Gorman et al. (1984) which pointed out that the proportion of falsifying triads is the key to success in the rule finding task. This supported our view in chapter 7 that there is element of deductive reasoning in apparently inductive reasoning task. The lack of correlation between performance in Web-IRA and Web-RF also gives a warning to researchers when choosing inductive reasoning tests – the commonly called inductive reasoning ability might cover different components which are accountable for different behaviours. Shye (1988) had also pointed out the ambiguity when researchers use the term inductive reasoning – whether they mean rule finding or generalisation. Understanding the natures of the tests is therefore an essential step before choosing an appropriate test for experiment.

Finally, Experiment 3 shed light on an important relationship between systematic thinking ability and rule-finding ability, more specifically the use of eliminative strategy during rule-finding activity. There is a similar pattern of cognitive activity during the solution of systematic thinking question and the employment of eliminative strategy. But the similarity only exists when subjects are solving particular type of systematic thinking question which has high demand on memory and processing simultaneously. When solving systematic thinking questions that do not have high requirement on memory, the relationship becomes less salient.

The existence of the demand for both memory and processing also possibly reflects the cognitive difference between the use of enumerative strategy and eliminative strategy, i.e. the use of enumerative strategy require less memory whereas the use of eliminative strategy requires more memory. However, this is beyond the scope of current study and further research is required to study this possibility.

This is the second of the three chapters devoted for the discussion of web-based psychometric tools. The last tool, called Web-DAL, will be discussed in the next chapter.

CHAPTER 12

Web-DAL: Web-based Computerised Tool to Measure Divergent Associative Learning

12.1 Introduction

Divergent Associative Learning (DAL) is a construct of this study and it denotes the characteristics of learning that develop links between new concepts and existing concepts. This chapter introduces a web-based test, called Web-DAL for divergent associative learning.

The chapter starts with introduction of divergent thinking tests in section 12.2 and associative learning tests in section 12.3 . Because of the differences between DAL and divergent thinking and associative learning, Web-DAL was developed to meet our need to test DAL. Web-DAL is presented in section 12.4 . An empirical evaluation was carried out using Web-DAL and it is discussed in section 12.5 . Finally, section 12.6 summarises this chapter.

12.2 Divergent Thinking Tests

A range of tests exist for divergent thinking. One of the earlier tests is Wallach and Wallach and Kogan's (1965) Alternate Uses Test (AUT). In AUT, participants are asked to write down as many uses of a common object as possible. Vartanian, Martindale and Kwiatkowski (2003) used brick, shoe and newspaper as the common objects of AUT and set the time frame to be 3 minutes for their subjects. Divergent thinking (ideational) fluency was calculated by adding up the total number of the alternative uses a subject could come up with in the set time frame. Fluency alone was used as an index of divergent thinking in Vartanian, et al.'s (2003) study.

Also in the 60s, Hudson also used tests for divergent thinking (Bahar and Hansell, 2000). Hudson used two types of tests, one of them was a typical Alternate Uses Test, and the other involved the semantic of words, e.g. "How many meaning can you think of for the following words?". The test of semantic of words requires divergent thinking about the contexts of the concepts represented by the words whereas the AUT requires divergent thinking on the applications of the concepts. Both of them use the same divergent thinking process but in the test of semantic of words, the different mastery level of language could introduce bias into subjects' performances.

Torrance Test of Creative Thinking (TTCT) is also another commonly used test for divergent thinking (Mouchiroud, and Lubart, 2001). In TTCT (the version discussed in Mouchiroud, and Lubart, 2001), there are both verbal and figural tasks. The verbal task is similar to that of the AUT. The figural task requires the manipulation of figures. For example, a figure task could be asking subjects to create as many drawing as possible from an empty circle. In addition to the fluency score measured in AUT, TTCT also measured originality (the unusualness of the responses), flexibility (the range of categories in the responses) and elaboration (amount of details in the responses). The elaboration score was only available from the figural task. Among the four scores, fluency and originality were found to be highly correlated (Mouchiroud, and Lubart, 2001) suggesting redundancy among the two. This could be an important reason that other researchers, such as Vartanian et al. (2003), used only fluency as the main score for divergent thinking.

12.3 Associative Learning Tests

Word Association Test (WAT) is a common test used to examine the memory structure of learned material (Bahar and Hansell, 2000). In WAT, participants are asked to give a sequence of responses to a stimulus word in a fixed length of time. The underlying assumption is that the order of responses reflects how those responses were organised in memory (long-term memory). The distance between two responses in the answer can be interpreted as the semantic distance of the two concepts that the responses represent. The semantic distance in turn determines the time required to retrieve the other related concept from one concept. This temporal measurement is very similar to the rate of associative response, as discussed in Mednick (1962), which is also a measurement of how quick an associated response is generated given a stimulus word.

Another test for associative learning is the paired-associate task (Laumann, 1999; de la Iglesia, 2004; Horowitz and Gordon, 1972; Feldman, Johnson, and Mast, 1972). Paired-associate task had obtained such popularity that Feldman et al. (1972, p423) had called it “a standard paradigm in psychology for decades”. There are two stages of learning in a paired-associate task, the associative learning and the response learning (Horowitz and Gordon, 1972). Associative learning denotes the learning of the association between the stimulus and the response. Response learning is required if the response item is something new, for example a word in new foreign language. There is no particular order about which stage (associative or response relearning) should happen first (Horowitz and Gordon, 1972). Performance in the paired-associate task is the number of corrected remembered associations.

12.4 Web-DAL: A Divergent Associative Learning Test

The focus of divergent thinking test is the divergent production (of ideas) whereas the focus of associative learning test, in particular the paired-associate task, is on learning of the associations between given stimuli and responses. However, none of the tests mentioned were intended to measure divergent associative learning (DAL), which is divergently developing associations between a newly learned concept and existing concepts. A test is devised in this study to meet the particular characteristics of DAL and it is called Web-DAL. Web-DAL is a computerised test, and the prefix “Web” indicates its ability to be deployed on the Internet.

A subject taking the Web-DAL is first presented with a new concept. After learning the new concept, the subject is asked to write down as many related concepts as possible in one minute. The selection of new concept is from a domain that the target subjects are familiar with. Selection of such a domain removed the possible bias that some domains could be remote for some subjects.

Vartanian et al.'s (2003) study allowed the subjects for three minutes to write down as many uses of three objects as possible. In the Web-DAL task, however, there is only one new concept. After preliminary evaluation by us, one minute time frame was deemed enough to differentiate subjects with high or low DAL.

The difference of Web-DAL and other divergent thinking tests, such as Kogan's (1965) Alternate Uses Test (AUT), is that there is learning involved in Web-DAL but not in AUT. In AUT, subjects simply were told to create as many keywords that they can think of relevant to a daily object. On the other hand, in Web-DAL, subjects are required to learn the new concept and then create divergent associations to existing knowledge that are pertinent to the new concept.

The difference of Web-DAL to other associative learning tests, such as paired-associate task (Laumann, 1999; de la Iglesia, 2004), is the duration of time between learning and testing. In paired-associate task, subjects are tested shortly (minutes or hours) after they learn the associations. However, the duration between learning and testing is much longer (weeks or months) in Web-DAL. Except for students cramming for exams, we believe that the application of the long term learning is more common than that of the short term learning. Tasks, such as Web-DAL, that test the long term associative learning can better reflect a subject's usual performance than tasks, such as paired-associate, that test on short term associative learning.

12.5 Empirical Evaluation

12.5.1 Participants

There were total 19 subjects participated in the evaluation of Web-DAL. The 19 subjects could be placed into 2 different groups as shown in Table 12-1.

Table 12-1: Participant groups

Group	Size	Group Characteristics (Country/ University)
1	8	third year university students; studied course offered by Department of Information System (New Zealand/Massey University)
2	11	first year university students; studied course offered by Department of Information System. (New Zealand/Massey University)

All participants in this evaluation were undergraduate students of Massey University in New Zealand. All students in each group were from the same course. Subjects in group 1 were each given a set of login username and password whereas subjects in group 2 did self-registration.

12.5.2 Material

The Web-DAL task described in Section 12.4 is used in this evaluation. The question in Web-DAL was material relevant to the subjects' courses and was related to very basic concepts in the courses. By doing this, subjects could draw on knowledge learned from the course instead of arbitrary sources of which the possession might vary among subjects and therefore create bias in the evaluation.

12.5.3 Procedure

After subjects logged in successfully, they were shown a message that outlined the basic prerequisite knowledge of the Web-DAL task. Subjects were told that if they do not know the prerequisite knowledge, they were not advised to proceed.

Subjects who chose to continue were then presented a description of a new concept related to what they had learned during the course. After reading the concepts, subjects followed a hyperlink to the answer-instructions page where subjects were instructed what and how to write in the next step. Subjects were also explicitly told in the answer-instructions page that they had only 1 minute to write their answer. After understanding the answer-instructions, subjects then proceeded to the answering page where they typed in as many keywords, which they thought were relevant to the new concept introduced, as possible in 1 minute.

At the end of the 1 minute period, a message window popped up and the system automatically loaded another page indicating the completion of the task.

12.5.4 Result and Discussion

The number of keywords is used as the index of performance in Web-DAL. The descriptive statistics of this evaluation is presented in Table 12-2.

Table 12-2: Descriptive Statistics for Web-DAL Evaluation

	N	Minimum	Maximum	Mean	Std. Deviation
webDAL	19	2	17	8.95	4.490
Valid N (listwise)	19				

Although there are subjects who answered very few keywords, such as 2 or 3 (only 1 case for each), the averaged number of keywords around 9 indicates that most of the subjects did understand the new concept and spent the 1 minute duration trying to associate what they had learned previously that was relevant to the new concept. The said pattern of activity, i.e. learning and then associating, is indeed what is called divergent associative learning in this study. Bryman and Cramer (2005) discussed about face validity, which is about whether the measure could reflect the content of the concept in question. While the said pattern of activity truly reflects what we want to measure, we can see that the face validity of the Web-DAL task is well demonstrated.

The total number of keywords is the same as what is called the fluency score in Vartanian et al. (2003). The fluency score is also used in this study and is represented by *Fluency* in Table 12-3. In addition to the fluency score, the Torrance Test of Creative Thinking (TTCT) also calculates the originality score (Mouchiroud, and Lubart, 2001). The originality of each answer item is calculated from the inverse of its frequency of occurrence in the sample. For example, if many subjects have "Internet" as one of their answer item, then the keyword "Internet" is not very original.

In this study, same approach for originality score is taken. All distinctive keywords from subjects' answers were listed, and their frequencies summed. An originality weight, which is 1 divided by its frequency, is then assigned to each keyword. The variable called *SumOrig* in Table 12-3 is the sum of all originality weights of a subject's answer. But because there are different number of keywords in different subject's answers, subjects who answered more keywords are likely to have a higher *SumOrig* score. We decided to compute another variable called *NormOrig* (short for normalised originality) by dividing *SumOrig* by *Fluency*. What *NormOrig* stands for is how original each of the subject's keywords is on average. Some subjects might answer only a few keywords, but if these keywords are very original then the subject's *NormOrig* score could still be higher then someone who answered a lots of un-original keywords.

Table 12-3: Correlation of Originality and Fluency

		SumOrig	Fluency	NormOrig
SumOrig	Pearson Correlation	1	.895(**)	.760(**)
	Sig. (2-tailed)		.000	.000
	N	20	20	20
Fluency	Pearson Correlation	.895(**)	1	.453(*)
	Sig. (2-tailed)	.000		.045
	N	20	20	20
NormOrig	Pearson Correlation	.760(**)	.453(*)	1
	Sig. (2-tailed)	.000	.045	
	N	20	20	20

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 12-3 shows the correlations between *SumOrig*, *Fluency* and *NormOrig*. Each of the variables is correlated to the other two. The correlation between *SumOrig* and *Fluency* is very high as expected. The correlation between *Fluency* and *NormOrig* indicates that the keywords from those subjects, who answered more keywords, are also more original than the keywords from those who answered less keywords. In other words, quantity and quality of keywords are highly correlated. This means that Web-DAL is capable of measuring a distinctive construct common to the generation of both high quality and high quantity keywords. The nature of this distinctive construct is very similar to what we called DAL.

When a subject generates a keyword in response to thinking of the new concept, the association between the keyword and the new concept has already been established/ learned. The ability to generate both high quality and high quantity keywords means the ability to have both high quality and high quantity associative learning. This validates our hypothesis that a construct exists that accounts for both high quality (i.e.

original, divergent) and high quantity associative learning. This proves the construct validity of divergent associative learning.

However, it has to be noted that if we remove the experimental context, it is difficult to judge the quality of associative learning (i.e. how original and novel the association is). In some contexts, certain association is more original than in other contexts. In order to preserve the exact definition of DAL, the quantity is the only criterion to determine DAL. By doing this, we were originally afraid that DAL would lose its relationship (as discussed in chapter 8) to divergent thinking and creativity which place more emphasis on the quality than the quantity. But the correlation between *Fluency* (quantity) and *NormOrig* (quality) in Table 12-3 assures us that what we have measured and defined about DAL preserves DAL's relationship to divergent thinking and creativity.

12.6 Summary

In this chapter, tasks of divergent thinking and associative learning are briefly reviewed to provide a background for the task that we have developed in this study, namely Web-DAL. Web-DAL is a web-based task that requires subjects to learn a new concept and then input keywords about other concepts that the subjects can associate to the new concept.

In the data analysis, the fluency and originality scores are calculated. They are significantly correlated to each other. Although the Web-DAL task is not purely a divergent thinking test, the correlation between fluency and originality replicates the findings of the divergent thinking test by Mouchiroud and Lubart (2001). Finally, data in this evaluation also supports the face validity of the Web-DAL task and the construct validity of the construct we proposed in this study, namely divergent associative learning.

This is the last of the three chapters about psychometric tools. In the discussions of the cognitive traits and their MOTs in chapters 7 and 8, we have hypothesised the existences of relationships between cognitive traits. The data we gathered from the psychometric tools allow us to test the said hypothesises. We will use the psychometric data to examine relationships between cognitive traits in the next chapter.

CHAPTER 13

Relations of Cognitive Traits from Psychometric Tests

13.1 Introduction

In chapters 10, 11 and 12, tools, which are used to measure working memory capacity, inductive reasoning ability and divergent associative learning, are introduced. They measure the three cognitive traits psychometrically.

In chapter 11, we have analysed and found relationships between inductive reasoning ability, systematic thinking ability and rule-finding ability. But systematic thinking and rule finding abilities are treated as manifestations of inductive reasoning ability. We have not explored the inter-trait relationships so far.

From theoretical inferences in chapters 7 and 8, we have hypothesised the existences of the following relationships:

1. working memory and inductive reasoning ability;
2. working memory and divergent associative learning; and
3. inductive reasoning ability and divergent associative learning.

Given that there are overlaps in subjects in the empirical evaluations described in chapters 10, 11 and 12, current chapter is an attempt to examine if the three relationships can also be seen empirically as well. We divided this empirical study into three experiments for the purpose of discussion. Experiment 1 is presented in Section 13.2 and examines the relationship between working memory capacity and inductive reasoning ability. Experiment 2 is discussed in Section 13.3 and it examines the relationship between working memory and divergent associative learning. Experiment 3 is presented in Section 13.4 and it examines the relationship between inductive reasoning ability and divergent associative learning. Section 13.5 summarises the findings of this chapter.

It has to be noted that all of the three experiments in this chapter have small number of participants (from 15-21). It is more difficult to assume normal distribution on the variables when sample size is small. Furthermore, because we are comparing variables gathered from different tools, the scales used for different variables are also quite different. Therefore, we have to use non-parametric tests, such as Kendall's tau test or Spearman's rho test, when analysing correlations in this chapter (Bryman and Cramer, 2005).

13.2 Experiment 1: Working Memory and Inductive Reasoning

In Experiment 1, we examine whether there is a relationship between working memory and inductive reasoning ability as hypothesised in chapter 7.

13.2.1 Participants

There were total 21 participants who did both the Web-OSPAN and Web-IRA. These participants were the subjects of experiment 1.

13.2.2 Material and Procedure

Subjects in experiment 1 used Web-OSPAN and Web-IRA. Web-OSPAN and Web-IRA are each described in chapters 10 and 11 respectively and are not repeated here.

The variable *opTotal* is used as the main index of performance in Web-OSPAN. It represents the total number of correctly recalled words and it is the main index of working memory capacity. In Web-IRA, we called the variable that represents total number of correct answer *iraCorrect*, and it is the main index of performance in Web-IRA. Furthermore, three sub-scores are also calculated for each of the three types of questions in Web-IRA, namely *exc* for exclusion, *ext* for extrapolation, and *ana* for analogy.

13.2.3 Results and Discussion

We found that the correlation between *opTotal* and *iraCorrect* is not significant at all (correlation coefficient is 0.23, significance at 0.46, 1 tailed). This is different from what we have hypothesised in chapter 7. But the rationale of our hypothesis in chapter 7 is that working memory serves as a cognitive resource required to perform inductive reasoning. High working memory capacity therefore could facilitate solving complex inductive reasoning tasks.

The 30 questions in Web-IRA are divided into 3 types that have different requirements in terms of cognitive resources. Analogy tasks (e.g. X to Y is Z to?) require subjects to develop one pattern from the first pair (X and Y) and then switch the context (from X to Z) and then apply the pattern to find the second pair (Z and ?). Exclusion tasks (e.g. what is least like others?) require subjects to find a suitable pattern among the majority of the test items and then find one test item that fits the found pattern least and therefore should be excluded. Extrapolation tasks (e.g. A, B, C, D, what should come next?) require subjects to find the pattern among the items and then extend the pattern to find the next item. Extrapolation task is the one that requires least cognitive processes among the three types of tasks and therefore we would expect that individual differences in working memory would have the least effect in extrapolation tasks.

Data from the experiment supports what we have expected. While the *ext* score is controlled, the partial correlation between *opTotal* and *iraCorrect* increases the most than when *exc* or *ana* is controlled. The partial correlation after *ext* is controlled has a coefficient 0.32 and the significance level of 0.097. Although the significance level is not yet below the 0.05, it is not too far away. After controlling the *ext* score, the significance level has reduced nearly 5 times. This indicates that individual differences of working memory have greater impact on inductive reasoning performance when the inductive reasoning task demands more cognitive resources (e.g. in exclusion tasks and analogy tasks).

13.3 Experiment 2: Working Memory and Divergent Associative Learning

In experiment 2, we examine the relationship between working memory capacity (WMC) and divergent associative learning (DAL) empirically.

13.3.1 Participants

Participants of experiment 2 had to complete both Web-OSPAN and Web-DAL. Given that there were only 19 subjects who completed Web-DAL (see chapter 12), and among the 19 subjects, only 15 also completed Web-OSPAN, we could only study the data gathered from these 15 subjects.

13.3.2 Material and Procedure

Subjects in experiment 2 completed both Web-OSPAN and Web-DAL. Details about the materials and procedures of these two tasks are described in chapters 10 and 12 respectively and are not repeated here.

It has being mentioned in experiment 1 that *opTotal* is the main index of performance in Web-OSPAN. For Web-DAL, we used the variable called *Fluency* to denote the total number of keywords and the main index of divergent associative learning. We also used the variables *SumOrig* and *NormOrig* to denote the sum of originality weight and normalised originality score respectively. These two variables, although not used as index of DAL, represent the level of originality (novelty) in subjects' answers.

13.3.3 Results and Discussion

Data analysis shows that *Fluency* and *opTotal* are indeed correlated to each other (see Table 13-1). This correlation confirms our hypothesis that working memory capacity is related to divergent associative learning.

Table 13-1: Correlation between Fluency and opTotal

			Fluency	opTotal	SumOrig	NormOrig
Kendall'	Fluency	Correlation Coefficient	1.000	.406(*)	.776(**)	.324

s tau_b						
		Sig. (2-tailed)	.	.040	.000	.050
		N	20	15	20	20
	opTotal	Correlation Coefficient	.406(*)	1.000	.379	.087
		Sig. (2-tailed)	.040	.	.052	.654
		N	15	15	15	15
	SumOrig	Correlation Coefficient	.776(**)	.379	1.000	.556(**)
		Sig. (2-tailed)	.000	.052	.	.001
		N	20	15	20	20
	NormOrig	Correlation Coefficient	.324	.087	.556(**)	1.000
		Sig. (2-tailed)	.050	.654	.001	.
		N	20	15	20	20

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

We can also see in Table 13-1 that although *NormOrig* is not flagged (with the star signs) as significantly correlated to *opTotal*, it is just right on the edge of significance level (on the 0.05 level). The variable *SumOrig* has a quite high correlation coefficient to *opTotal*. Although we have not studied the relationship between working memory and originality/creativity in chapter 8, the correlations between *opTotal* and the two scores related to originality indicate that it is quite possible that working memory is positively related to originality and creativity, too.

In sum, Experiment 2 confirms our hypothesis that working memory is related to divergent associative learning. Working memory could also possibly relate to originality and creativity. Further research effort is required to examine this possibility. Please note that although the sample size in Experiment 2 is quite small, which makes it difficult to obtain enough power to achieve significant correlations, the fact that data in our study could still display correlations lends strong support to our hypothesised relationship between working memory and divergent associative learning.

13.4 Experiment 3: Inductive Reasoning and Divergent Associative Learning

In Experiment 3, we are examining the relationship between inductive reasoning ability and divergent associative learning.

13.4.1 Participants

There were total 18 participants who did both Web-IRA and Web-DAL. These participants were the subjects in Experiment 3.

13.4.2 Material and Procedure

Web-IRA and Web-DAL were the tools subjects used in experiment 3. These two tools are presented in more details in chapters 11 and 12 respectively. The same procedures were followed as discussed in chapters 11 and 12.

In Web-IRA, the variable *iraCorrect* denotes the number of correct answers and is the main index of performance in Web-IRA. Because there are three types for the 30 questions in Web-IRA, questions from each type can also be summed to form a score. The *exc* score is for exclusion questions; the *ext* score is for the extrapolation questions; and the *ana* score is for the analogy questions.

In Web-DAL, the variable *Fluency* represents the number of keywords generated and is the main index of Web-DAL performance. We also have variables for originality, namely *SumOrg* and *NormOrig*.

13.4.3 Results and Discussion

In chapter 8, we have hypothesised that inductive reasoning ability (IRA) is a manifestation of divergent associative learning (DAL) because both the generalisation and the rule-finding aspects of IRA facilitate DAL. It is therefore expected that those who perform well in Web-IRA would also perform well in Web-DAL. But our data did not support our expectation; direct correlation between performances in Web-IRA and Web-DAL cannot be seen.

Using correlation analysis, we found that the correlation coefficient between *Fluency* and *iraCorrect* is 0.22 and the significance level is 0.187 (1 tailed, Spearman's rho). This is not a significant correlation. Hence, our hypothesis cannot be validated.

One thing to note is that we found that the partial correlation between *Fluency* and *iraCorrect* is increased if the variable *ext* is controlled. The purpose of partial correlation is to exclude the influence of the third variable (i.e. *ext*) on the two variables of interest (i.e. *Fluency* and *iraCorrect*) (Kerr, Hall, and Kozub, 2003). The significance level of the partial correlation drops to 0.10 (see Table 13-2).

Table 13-2: Correlation between Fluency and IRA when ext is controlled

Control Variables			Fluency	iraCorrect
ext	Fluency	Correlation	1.000	.326
		Significance (1-tailed)	.	.100
		df	0	15
	iraCorrect	Correlation	.326	1.000
		Significance (1-tailed)	.100	.
		df	15	0

In Experiment 1, the correlation between performances in Web-OSPAN and Web-IRA also increased when the variable *ext* is controlled. As we have mentioned, one possible reason for that is because the need for more working memory capacity becomes obvious when subjects encounter highly demanding tasks. In this experiment, the correlation between *Fluency* and *iraCorrect* increases too when *ext* is controlled. This is a phenomenon worth studying and it is referred as phenomenon A in the following discussion.

It is not sensible to interpret phenomenon A as "*Fluency* in Web-DAL is accountable for high-demanding tasks in Web-IRA" because our hypothesised relationship between IRA and DAL is directional, i.e. IRA facilitates DAL. The causal direction goes from IRA to DAL.

One sensible interpretation of phenomenon A is that "the construct responsible for the performance in Web-DAL is related to the construct responsible for solving high-demanding tasks in Web-IRA". This interpretation makes further sense when we bring in the correlation between *Fluency* and *opTotal* (index of working memory) as we found in Experiment 2. There are two points worth noting:

1. The construct responsible for performance in Web-DAL correlates to working memory capacity.
2. Working memory capacity correlates to the construct responsible for solving high-demanding tasks in Web-IRA,

Because of the two points above, we could therefore say that there is an overlap between working memory capacity, inductive reasoning ability, and divergent associative learning when *ext* is controlled, i.e. when we partial out, i.e. remove the effect of, the influence from less-cognitively-demanding tasks. The directionality of the relationship is still preserved, that is:

1. working memory facilitates divergent associative learning (Experiment 2: WMC -> DAL);
2. working memory facilitates inductive reasoning (Experiment 1: WMC -> IRA); and
3. working memory facilitates the overlap between inductive reasoning ability and divergent associative learning (Experiments 1, 2, and 3: WMC -> the union of IRA and DAL).

For points 2 and 3, inductive reasoning only includes inductive reasoning to solve high-demanding tasks. It is likely that there is a common construct accountable for performances in Web-OSPAN, Web-IRA (only for demanding tasks), and Web-DAL. Our data show a promising sign for the existence of this common construct, but the search on this common construct is beyond the scope of current study.

Another point to note is that if we further control *NormOrig*, in addition to controlling *ext*, the correlation between *Fluency* and *iraCorrect* further increases to 0.399, and its significance level drops to 0.063 which is very close to being significant (see Table 13-3).

Table 13-3: Correlation between *Fluency* and iraCorrect when *NormOrig* and *ext* are controlled

Control Variables			Fluency	iraCorrect
NormOrig & ext	Fluency	Correlation	1.000	.399
		Significance (1-tailed)	.	.063
		df	0	14

	iraCorrect	Correlation	.399	1.000
		Significance (1-tailed)	.063	.
		df	14	0

Data from Table 13-3 points out that originality, which is represented by the *NormOrig* variable, does not correlate to high-demanding inductive reasoning task (*iraCorrect* with *ext* controlled). Furthermore, because the ability to solve high-demanding inductive reasoning tasks correlate to working memory capacity (see Experiment 1), it is plausible for us to say that the acts of producing original artefacts perhaps do not need high working memory capacity. But because we have learned that a correlation exists between working memory (*opTotal*) and originality (*NormOrig*) in Experiment 2, the possibility we just mentioned should be interpreted as follows: the acts to produce original artefacts require working memory but do not need very high working memory. In other words, beyond a certain threshold, the effect of working memory on originality starts to fade. This coincides with our theoretical understanding about DAL especially from the perspective of associative hierarchy (Mednick, 1962).

Associative hierarchy has been discussed in a great deal in chapter 8 and we wish to point out here that every individual has different associative hierarchy. In other words, those individuals who possess associative hierarchies that are easier to produce original/creative ideas do not need extra mental effort to produce original ideas. Those individuals are said to have deviant associative hierarchy (Mednick, 1962). They, even though without very high working memory capacity, could still produce original ideas because of the way they structure their associative hierarchies.

But working memory certainly has an effect on originality as shown by the correlation in Experiment 2. This effect could account for individuals who do not have deviant associative hierarchies, i.e. those who think typically. For them, higher working memory capacity means the ability to extend their associations into the areas which are recognised as original. Therefore, for those individuals, the possession of high working memory capacity does give them a better chance to produce original and creative ideas.

13.5 Summary

This chapter is aimed at studying the inter-cognitive-trait relationships. Using the data gathered in chapters 10, 11 and 12, this chapter is organised into three experiments for the sake of discussion. Please note that the small numbers of participants in all three experiments make it difficult to find significant correlations, and could bias what we have found. The findings in this chapter therefore could not be posed as strongly valid, but nonetheless they bring our attention to several noteworthy points which could be very useful as directions for further study.

Experiment 1 examines the relationship between working memory capacity (WMC) and inductive reasoning ability (IRA). We found that WMC has higher correlation to IRA when the IRA tasks are cognitively-demanding. In other words, individual differences in WMC do not have an apparent effect on IRA when the IRA task is simple.

Experiment 2 examines the relationship between WMC and divergent associative learning (DAL). Data analysis shows a correlation between the performance of WMC and DAL. Moreover, our analysis also shows a possible positive correlation between WMC and originality which could lead to further research exploration between WMC and creativity.

Experiment 3 examines the relationship between IRA and DAL. Data analysis shows no direct relationship between IRA and DAL. But we found that DAL has higher correlation to IRA when tasks of IRA are more cognitively-demanding and need WMC. We therefore see a possibility that WMC, IRA and DAL share a common underlying construct. However, further research efforts are required to explore this possibility.

In Experiment 3, we also found that although WMC is needed for production of original ideas, this is not essential for everyone. From the perspective of associative hierarchy (Mednick, 1962), individuals, who have deviant associative hierarchies, could still produce original ideas even without high WMC. We can see the trace of difference in associative hierarchies affecting subject's score of originality in the data, but we do not have direct proof of that yet. A method to differentiate deviant associative hierarchy from typical associative hierarchies is needed. We see this as a possible future research direction.

Next, we are going to describe the learning system that was implemented to gather student behaviour data. The behaviour data will be used to compare with the psychometric data in the forthcoming empirical evaluations of this dissertation.

CHAPTER 14

Implementation Details of Learning System

14.1 Introduction

In our discussions, we have covered the overall structure of cognitive trait model (CTM) in chapter 3 and discussed about learning object relations and semantic relation analysis in chapter 4. This chapter aims to describe the learning system in which the content is organised by linked sets of learning objects. The learning objects are linked by the list of learning object relations presented in chapter 4 so that semantic relation analysis can be performed on the navigational records of students in terms of learning object relations. The learning system also serves as a tool to collect data for the analysis in subsequent three chapters.

The overall structure and the technical details of the learning system are first presented in section 14.2 . There are two learning modules implemented for this study using the same system architecture but different content. The two learning modules are the PHP Learning Module and IT Infrastructure Learning Module. They are discussed in sections 14.2.1 and 14.2.2 . Section 14.3 discusses the types of learning supported in the learning modules in terms of the revised Bloom's taxonomy.

It has to be noted that the learning modules discussed in sections 14.2.1 and 14.2.2 do not provide adaptivity. The purpose of these two learning modules is to collect data in this study to evaluate the proposed cognitive trait modelling approach. In a previous study done by the author and colleagues, the author had created an adaptive learning module that teaches Marginal Costing in Accounting. Section 14.4 briefly discusses the Marginal Costing adaptive learning module so that readers can understand the usefulness of cognitive trait model. Finally, section 14.5 provides summary to our discussions in this chapter.

14.2 Structure of Learning System

The learning system has a 3-tiered structure that includes a presentation tier, a logic tier and a data tier. The 3-tier structure increases the flexibility, extendibility and ease of maintenance of the system (Haag, Cummings, and McCubbrey, 2004). Figure 14-1 shows the main components in the learning system. Please note that the technical structure discussed in this section is exactly the same for the two learning modules that are discussed in subsequent sections.

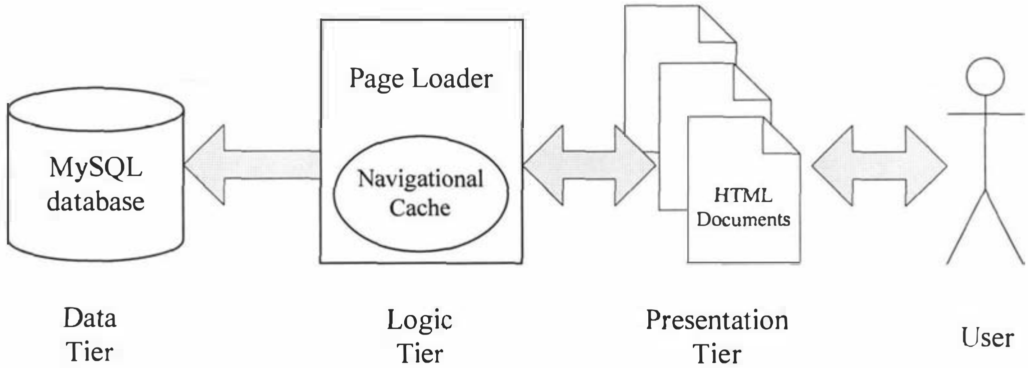

Figure 14-1: 3-tiered structure of learning system

The presentation tier consists of 2 sets of web pages, one for each learning module. The web pages are simple static Hyper Text Markup Language (HTML) documents. Figure 14-2 shows an example of a web page in the learning system. Each HTML document is structured to represent a learning object. In the learning system, each learning object has its own unique identification called LOID (short for learning object identification). The hyperlinks between two HTML documents can be translated into a learning object relation by looking-up the table (in the data tier) that has all the learning object relations using the LOIDs of the two documents.

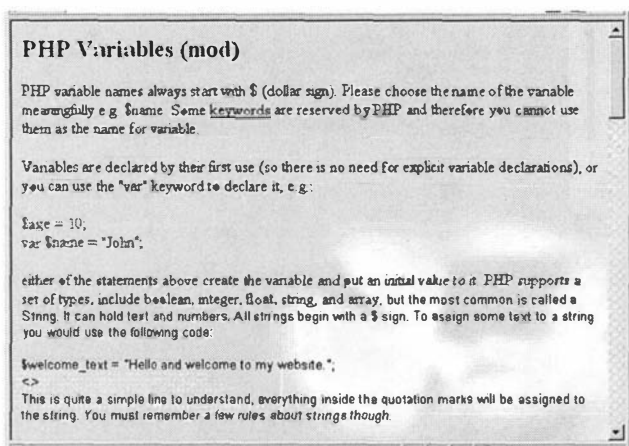

Figure 14-2: A web page in the learning system

The logic tier is implemented by PHP (http://www.php.net/), an open source scripting language for web systems. It contains two components, the Page Loader and the Navigational Cache. Functionally speaking, the Navigational Cache is a part of the Page Loader. All the requests of web pages are sent to the Page Loader, which then uses a function to include the required HTML document. The LOID for the HTML document is then stored in the Navigational Cache. When the Page Loader receives another request of web page, it then stores the LOID of the currently requested web page and the LOID in the Navigational Cache as a pair of navigation into the data tier. Each navigation, therefore, has two LOIDs which can then be translated into a learning object relation. A series of navigations can therefore be translated into a series of learning object relations which can be analysed using semantic relation analysis.

When the Navigational Cache is empty, that is when the student has just logged in, the Page Loader uses a special marker to replace the LOID from the Navigational Cache. The special marker can then be used to locate the beginning and the end of learning sessions.

There are also evaluation units inside the learning system. The learning objects are placed into conceptual groups, such as Conditions and Loops. There are multiple learning objects in each group. At the end of a group, there is an evaluation unit for the group. The evaluations are in the form of multiple choice quizzes. The score for the evaluation units are also saved in the data tier.

The data tier was implemented by MySQL database (http://www.mysql.com/) which is an open source database system. Two databases are created with exactly the same schema/structure for the two learning modules – each module uses its own database so that the data of different student groups can be easily separated. All students' navigational data and their scores in the evaluation units are stored in the data tier. Navigational data and evaluation scores are the main sources of data for the analysis in next three chapters.

The same structure of learning system, as described above, is used to create two learning modules which have different target audiences and contents. The two learning modules are the PHP learning module and the IT Infrastructure learning module. They are described next.

14.2.1 PHP Learning Module

The PHP learning module is created for students enrolled in a course to learn PHP and multimedia in web-based systems. The learning module contains the fundamental concepts about PHP scripting. The learning objects and their relations are shown in Figure 14-3.

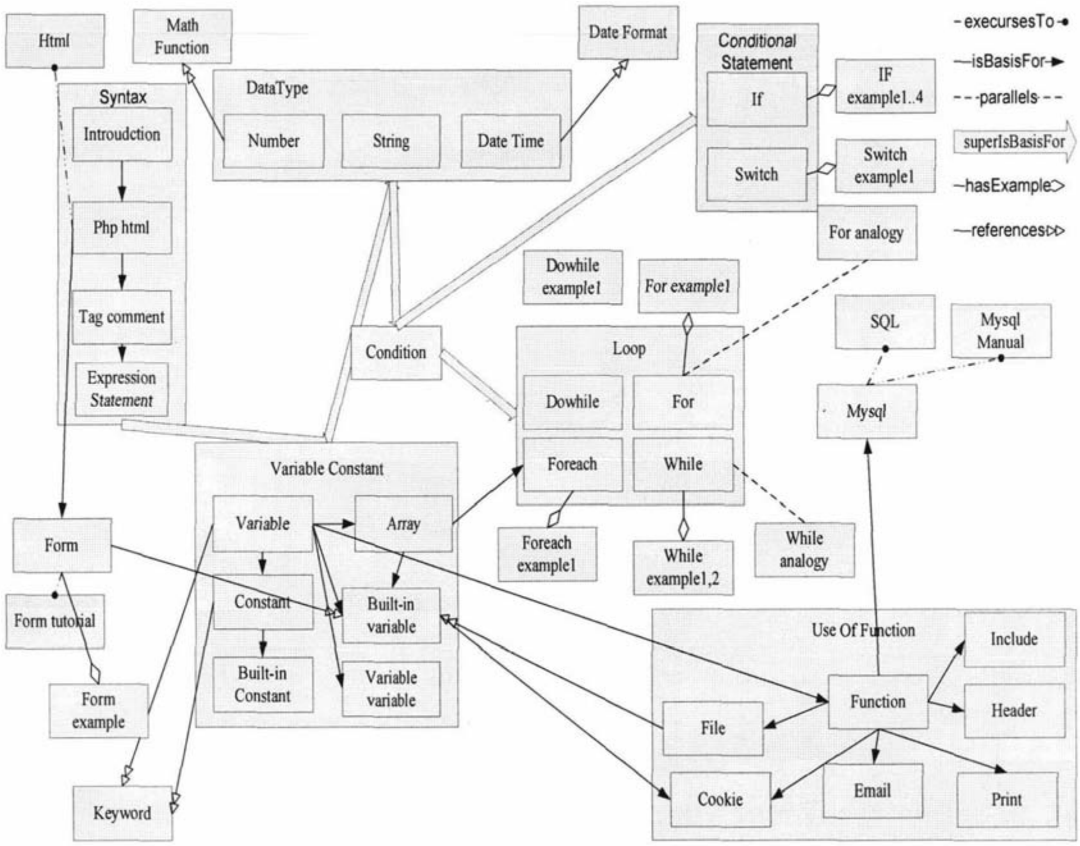

Figure 14-3: Learning objects and relations in the PHP learning module

The lines in Figure 14-3 represent relations between learning objects. There are different types of relations used in the PHP learning module represented by different types of lines. The meanings of different type of lines are shown in the legend in Figure 14-3. The larger boxes represent the learning object groups. The small boxes represent the learning objects in the PHP learning module. The names of the learning objects are inside the boxes and they are the titles for the HTML documents that the learning objects correspond to.

14.2.2 IT Infrastructure Learning Module

The Information Technology (IT) Infrastructure learning module is designed for students studying in a course about fundamentals Information Systems. IT Infrastructure is an essential part of the course. The learning objects and their relationships are shown in Figure 14-4.

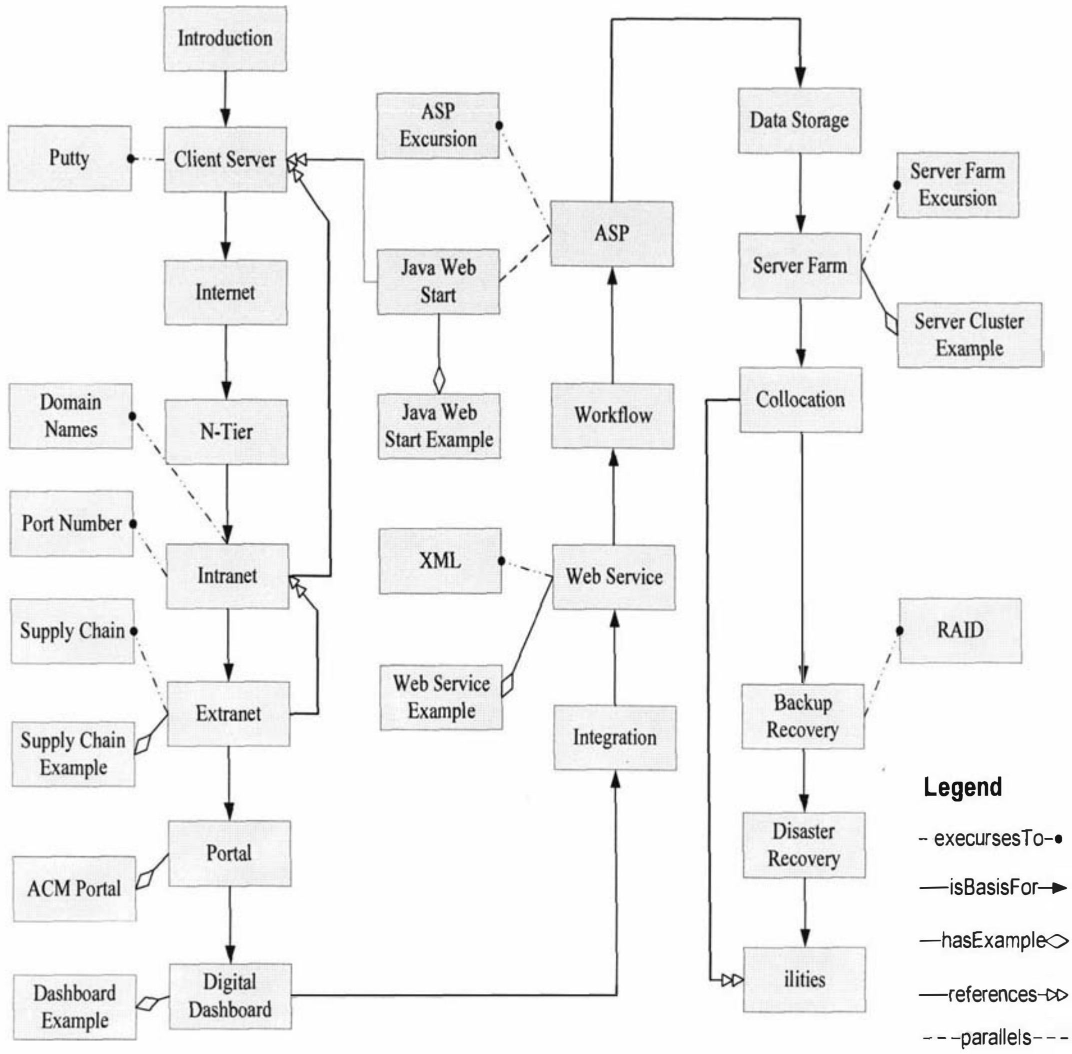

Figure 14-4: Learning objects and relations in the IT Infrastructure learning module

The lines in Figure 14-4 are the learning object relations and the boxes are the learning objects in the IT Infrastructure learning module.

14.3 Types of Learning

The learning modules are designed to support different types/aspects of learning. The types of learning are analysed in this section using the revised version of Bloom's taxonomy (Krathwohl, 2002).

In the revised taxonomy, two categories are included: the knowledge category and the cognitive process category. The knowledge category consists of:

1. Factual knowledge,
2. Conceptual knowledge,
3. Procedural knowledge and

4. Meta-cognitive knowledge.

The cognitive process category consists of:

1. Remember
2. Understand
3. Apply
4. Analyse
5. Evaluate
6. Create

The type of knowledge supported in the learning system is more domain-dependent. For example, in the IT Infrastructure domain, there is more emphasis on the factual knowledge – students need to remember meanings and definitions of terminologies. On the other hand, the PHP learning module has more focus on the procedural knowledge based on the fact that PHP is a procedural language. Conceptual knowledge is supported in both modules.

It has to be pointed out that the support for the learning of meta-cognitive knowledge is minimal and implicit in both modules. The only supports are the evaluation quizzes at the end of each learning units. After doing the quizzes, some students might be able to reflect on how to improve their learning approach for the coming learning units.

In terms of the cognitive processes, the learning modules have better support for remembering, understanding, and evaluating. The support for analysing is weak. One of the reasons is because the quizzes were not developed to be essays which usually better promote analysing. Another reason is that the learning system developed in this study is not learning activity based (e.g. Hagen et al., 2006). The support for applying and creating are not designed into the learning system and the two learning modules.

14.4 Marginal Costing Adaptive Learning Module

In a previous study (Kinshuk, Lin and Patel, 2003) done by the author and colleagues, an adaptive learning module is created to teach the topic of Marginal Costing in Accounting. This adaptive learning module used a hypothetical student model that contains student attributes such as working memory capacity, inductive reasoning ability, associative learning and domain knowledge, etcetera. The aim of this dissertation is to create the real (as opposed to the hypothetical) student model to serve the same purpose – that is providing student information to the learning system. The Marginal Costing adaptive learning module, hereafter called MCALM, is therefore briefly discussed here to show how to use CTM in adaptive learning systems.

Six exploration space elements are identified in Table 2-1 in Chapter 2 for the cognitive adaptive framework. They are 1) the number and 2) the relevant of navigational links, 3) the amount, 4) the concreteness, 5) the structureness of the content and 6) the number of different information resources. Table 2-6 in Chapter 2 has also provides recommended changed to these six exploration space elements for each particular student. In this context, the student is represented by the values of their cognitive traits in the student model.

In the MCALM, the domain content is constructed using eXtendible Markup Language (XML) documents. A Data Type Definition (DTD) provides the validation of the correctness and completeness of the corresponding XML documents. The MCALM uses an eXtensible Style Language (XSL) style sheet to render the display elements. XSL can transform XML pages into several different views that can have different information, media types, or even different order of display, for different students. Figures Figure 14-5 and Figure 14-6 show examples of different views on chapter overview.

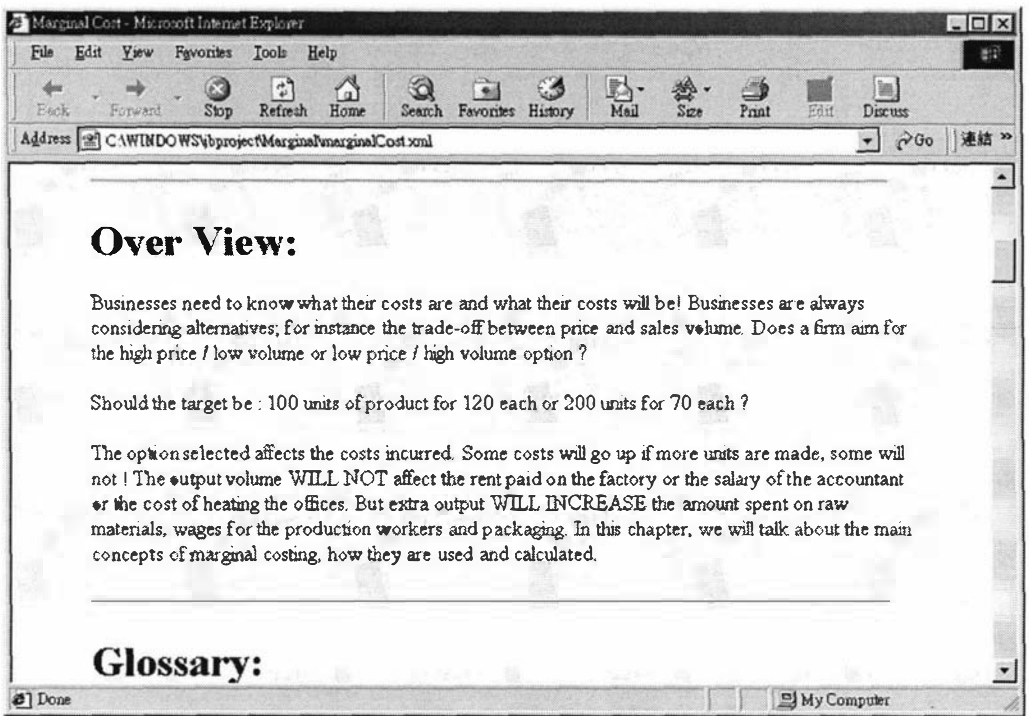

Figure 14-5: Detailed chapter overview

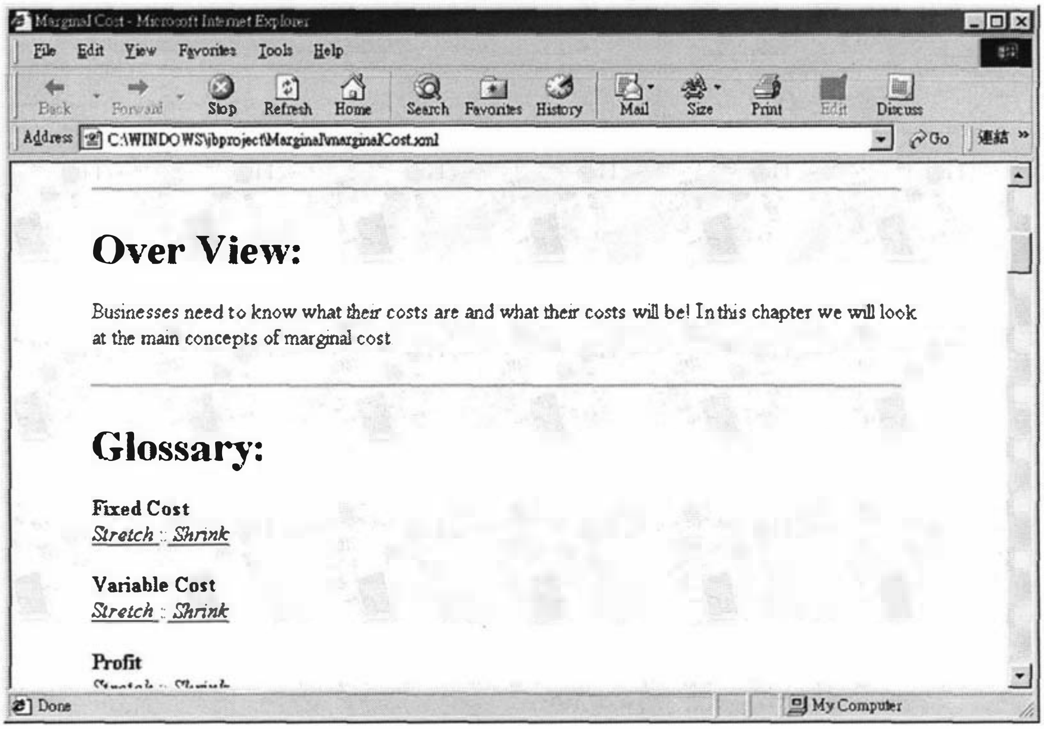

Figure 14-6: Simplified chapter overview

The changes about the chapter overview are made according to the adaptive framework documented in Kinshuk, Lin and Patel (2003). The MCALM shows an example of how an adaptive system could use information in the cognitive trait model to customise the learning content to meet the needs of students with different cognitive capacities.

14.5 Summary

This chapter presented the description of the learning system and the two learning modules. The learning system has a 3-tier structure that separates data, program logic and presentation. The separation of the three tiers enhances the flexibility, extendibility and ease of maintenance of the learning system. MySQL, PHP, and HTML are the technologies used in the learning system.

The structure of the learning system is used to create two learning modules: the PHP learning module and the IT Infrastructure learning module. The PHP learning module has the materials for the students to learn about fundamentals of PHP scripting language whereas the IT Infrastructure learning module has the materials for students to learn about Information Technology infrastructure.

Data gathered in the two learning modules constitute the behaviour data of the students. On the behaviour data, cognitive trait modelling can be applied to infer student cognitive traits in the form of numerical values. These cognitive trait values can then be statistically compared to the data obtained from the psychometric tools in order to evaluate cognitive trait modelling. The following three chapters are each about the evaluation of one of the cognitive traits. The sequence starts with working memory capacity in chapter 15, then inductive reasoning ability in chapter 16 and finally divergent associative learning in chapter 17.

CHAPTER 15

Empirical Evaluation of Working Memory Capacity

15.1 Introduction

In chapter 6, different theories about working memory capacity (WMC) were introduced and a list of 11 manifestations of WMC was enumerated. The manifestations were called manifestations of trait (MOTs). Among the 11 MOTs of WMC, 5 MOTs are able to be translated into implementation patterns (IPs). The 5 IPs were coded in implemented CTM to analyse student behaviours.

In the current chapter, we aim to evaluate the proposed approach of cognitive trait modelling. The evaluation takes the form of comparing the results of the proposed approach and results from psychometric means. We use the performance in Web-OSPAN, as discussed in chapter 10, as psychometric measure of WMC.

Because there are 5 IPs of WMC, this chapter starts by evaluating each of the IPs individually. These evaluations are presented in section 15.2 . According to the evaluation in section 15.2 , one IP is abandoned because of the discrepancy between hypothesised and actual results. In section 15.3 , the remaining four IPs are included into the Multiple Portrayal Network (discussed in chapter 5) in order to test the practical validity of cognitive trait modelling. Section 15.4 then summarises this chapter.

15.2 Implementation Patterns of Working Memory Capacity

In this section, each of the five IPs is evaluated individually against the performance of Web-OSPAN. The main index of performance in Web-OSPAN is the variable called *opTotal*. It represents the total number of correctly recalled words in the Web-OSPAN task. Another variable from Web-OSPAN, called *setSize*, is also included in current discussion. It represents the maximum number of words (from 2 to 6) that a student had correctly recalled.

15.2.1 Navigational Linearity

Linear navigation refers to the navigational pattern where a student is following the pre-defined sequence of viewing the learning material. In terms of learning object relations discussed in chapter 4, linear navigation means the invocation of IsBasisFor relations. In the implemented system discussed in chapter 14, linear navigation is achieved by using the Next Unit link provided at the bottom of web pages.

Huai's (2000) empirical study indicated the relationship between serial learning style and larger short term memory. Although we use the term linear rather than serial, they are semantically equivalent to each other.

Data in our study echo Huai's result. By computing the percentage of linear navigation (the IsBasisFor relation), we found near-significant correlation between the averaged percentage of linear navigation (called *average*) and *opTotal*. Table 15-1 shows the correlation.

Table 15-1: Correlation between average and opTotal

			average	opTotal
Spearman's rho	average	Correlation Coefficient	1.000	.409
		Sig. (1-tailed)	.	.073
		N	67	14
	opTotal	Correlation Coefficient	.409	1.000
		Sig. (1-tailed)	.073	.
		N	14	14

Furthermore, by splitting students into low working memory capacity (LWMC) group and high working memory capacity group (HWMC) using the mean score of Web-OSPAN (28.8), we found that the average percentage of linear navigation (the IsBasisFor relation) for the HWMC group is 53%, whereas the average for the LWMC group is only 24%. A marked difference exists between the behaviours of HWMC and LWMC groups in terms of navigational linearity. Therefore, we are able to assert the effectiveness of the proposed implementation pattern as one of the MOTs of WMC.

15.2.2 Reverse Navigation

Reverse navigation refers to the action of going back to a previous page. In the systems discussed in chapter 14, the action of reverse navigation is performed by clicking the Previous Unit link. Students can also use the Back buttons in their web browsers to navigate reversely. More precisely, we have to define reverse navigation as the invocation of the IsBasedOn relation.

The IsBasedOn relation is the opposite of the IsBasisFor relation we used to define linear navigation. The need to review the content in the previous page is the main argument we use to qualify reverse navigation as a manifestation of low WMC. Although not all visit to the previous pages could be counted as a sign of low WMC, but both systems (see chapter 14) that students used in this study, there is only one relation that is not IsBasedOn when the student used the Previous Unit link. The only other relation is a References relation from Extranet to Intranet in the IT-Infrastructure system. Given that only one such relation exists, the chances that the student's intention is not to review the pervious page is slight and can be ignored. We can therefore still treat the invocation of the IsBasedOn relation as a need to review previously viewed content.

Similar to the study on linear navigation, we compute the average number of reverse navigation (the IsBasedOn relation) among all the navigation and this value is represented by the variable *average* in Table 15-2. The correlations between *average*, *opTotal* and *setSize* are shown in Table 15-2.

Although the correlations between *average* and *opTotal* and between *average* and *setSize* are not significant in Table 15-2, but both correlations are negative. This is what we expected: the student who has higher WMC should, in theory, have less reverse navigations. Moreover, the correlation between *average* and *setSize* is -0.424. The significance of this correlation is 0.65 which is quite close to being statistically significant.

Table 15-2: Correlations of Reverse Navigation to Results from Web-OSPAN

			average	opTotal	setSize
Spearman's rho	Average	Correlation Coefficient	1.000	-.285	-.424
		Sig. (1-tailed)	.	.162	.065
		N	61	14	14
	opTotal	Correlation Coefficient	-.285	1.000	.885(**)
		Sig. (1-tailed)	.162	.	.000
		N	14	14	14
	setSize	Correlation Coefficient	-.424	.885(**)	1.000
		Sig. (1-tailed)	.065	.000	.
		N	14	14	14

** Correlation is significant at the 0.01 level (1-tailed).

Furthermore, if we split the students into the LWMC and HWMC groups as we did in section 15.2.1 , the LWMC group has an average reverse navigation of 3.83%, whereas the HWMC group has an average reverse navigation of 0.67%. The students who are in the LWMC group are nearly 6 times more likely to perform reverse navigation than students in the HWMC group. The data supports the effectiveness of proposed implementation pattern.

15.2.3 Distraction from Excursion

The ability of interference resistance is deemed as a function of WMC (Bunting, Conway and Heitz, 2004) and it is included as a manifestation of WMC in chapter 6. In terms of implementation patterns, the ability of interference resistance is translated as whether a student can still maintain the learning performance level when taking excursions from the main curriculum. Excursions lead students to information situated in other websites. Excursions could provide information supplementary to the curriculum but could also potentially distract the students and interfere with what they are learning in the curriculum.

We hypothesised that those students who have high WMC will maintain the performance level whereas those who have low WMC will be negatively impacted by excursions because of the interferences caused by excursions.

First of all, it has to be pointed out that for the purpose for our study, students have to fulfil the following four requirements: 1) using the learning systems; 2) taking any excursions (by the activation of excursesTo relation), 3) completion of the quiz about the unit that the excursion was taken from, and 4) completion of the Web-OSPAN task.

Only two students met all four requirements. The number is too little to give any substantial account. However, it is found that taking excursions does not negatively impact on learning performance. In fact, the average score for the units that students had had excursions from is 87.1%, which is still higher than the overall average score of 54.7%. It could mean that taking excursions has helped students' understanding and improved their performance.

However, it is also possible that those students who were willing to follow the links to the excursions are diligent students whereas those who did not bother to take the excursions might be rushing through the web-pages and therefore did not learn well.

Both possibilities could not hinder the rejection of using excursion as implementation pattern for interference resistant ability. The reason could be that taking excursions do not interfere immediately the processing of content in working memory. Excursions could be treated as a unit of study on its own. Therefore, an excursion is processed in its entirety with clear boundaries of its start and end. The unit that the student took excursion from is either restarted or continued from the last point of study when the student returns from the excursion. Excursions, although they interfere, do not create the impact of interference in working memory capacity due to different time span: taking excursion interferes in hours or days, but interferences in working memory needs to happen in seconds or minutes.

Furthermore, we have also examined the possibility that excursions distract the LWMC students away from the curriculum. The reason comes from Logie et al.'s (2004) findings that perspective memory is highly correlated to working memory. Perspective memory refers to goal maintenance. It is therefore possible that students with LWMC are more likely to be dragged away by the excursions whereas students with HWMC visit excursions and come back to the curriculum straight after.

However, our data shows no sign of such possibility too. The correlation is insignificant as well. We can only say that there could be other factors involved in students' decisions on when to return to the curriculum after excursions or we might need a larger sample to study this further.

We therefore have to conclude that excursion is not a good candidate for implementation of the MOT of interference resistant ability. Shorter types of interference, in terms of time span, need to be sought for in future studies if we are expecting to see its relationship with working memory capacity. The possibility of using the fact whether students are dragged away by excursions as the implementation pattern is also inconclusive.

15.2.4 Simultaneous Tasks

The limited resource view on WMC, which was discussed in chapter 6, leads us to hypothesise that those with LWMC are more likely to be negatively affected by simultaneous tasks and those with HWMC are less likely to be negatively affected. Our data supports this hypothesis.

All simultaneous tasks of each student are first extracted using the *Overlaps* function defined in chapter 6. For each pair of learning objects (called *V*, and *U*) involved in a simultaneous task, a function is called to check the performance on *U*. If the student passed the quiz that evaluates *U*, a *simu* score is incremented. If the student failed the quiz, the *simu* score is decremented. Finally, correlation of the *simu* score and *opTotal* is calculated as shown in Table 15-3.

Table 15-3: Correlation between simu and opTotal

			opTotal	PredictSum
Spearman's rho	opTotal	Correlation Coefficient	1.000	.845(*)
		Sig. (1-tailed)	.	.017
		N	6	6
	PredictSum	Correlation Coefficient	.845(*)	1.000
		Sig. (1-tailed)	.017	.
		N	6	6

* Correlation is significant at the 0.05 level (1-tailed).

The correlation coefficient 0.845 between the two variables is quite high. It confirms that performing task simultaneously has more (negative) impact on learning performance of the LWMC students. The impact on HWMC student is less obvious. To sum, the data proves the effectiveness of using the current IP to infer students' WMC.

15.2.5 Retrieval from Long Term Memory

Retrieval of learned content from long term memory is listed as one of the MOTs in chapter 6. This MOT is translated into an IP that checks whether a student re-visits learned concepts. The term "learned" in this case means that the student had passed the evaluation of the said concept and is different from merely browsing the webpage that contains the concept. The reason is that we have to make sure that the concept had entered into long term memory before we can test whether the retrieval of the concept from long term memory is successful or not.

A variable, called *lwmc*, is used record the frequency that the current IP occurs. For example, if student *Stu-A* has visited learning object *LO-1* at two different points in time, *timeBefEval* and *timeAftEval* (*timeBefEval* is before *timeAftEval*). We have to find whether the *Stu-A* had done and passed the evaluation of *LO-1*. The time when *Stu-A* had done the evaluation is recorded as *timeEval*. If *Stu-A* had passed the evaluation of *LO-1*, and *timeEval* is in between *timeBefEval* and *timeAftEval*, then *lwmc* gets incremented. The correlations between *lwmc* and *opTotal* and *setSize* are shown in Table 15-4.

Table 15-4: Correlations between lwmc and opTotal

			lwmc	opTotal	setSize
Spearman's rho	lwmc	Correlation Coefficient	1.000	-.612	-.642
		Sig. (1-tailed)	.	.072	.060
		N	7	7	7
	opTotal	Correlation Coefficient	-.612	1.000	.861(**)
		Sig. (1-tailed)	.072	.	.006

	N	7	7	7
setSize	Correlation Coefficient	-.642	.861(**)	1.000
	Sig. (1-tailed)	.060	.006	.
	N	7	7	7

** Correlation is significant at the 0.01 level (1-tailed).

In Table 15-4, the correlation between *lwmc* and *opTotal* is -0.612. The significance level of this correlation is 0.072, which is very close to being statistically significant. The minus sigh before 0.612 indicates a negative correlation which is what we expected – those who show more signs of *lwmc* should have lower score in Web-OSPAN. A similar correlation exists between *lwmc* and *setSize*. It can therefore be maintained that the IP of effective retrieval from long term memory could be used to infer the WMC of students.

15.3 Combination of Selected Implementation Patterns

In previous section, we have examined each of the implementation patterns (IPs) and found that four out of five IPs are good candidates to infer WMC in the target system. These four IPs are navigational linearity, reverse navigation, ability to perform simultaneous task, and effective retrieval from long term memory. These four are selected for the combined study in this section.

So far, the selected IPs have only been examined individually. Among the selected IPs, ability to perform simultaneous task has significant correlation to performance in the Web-OSPAN task. Navigational linearity, reverse navigation and effective retrieval from long term memory, on the other hand, have close-to-significant correlations to performance in the Web-OSPAN task. We have presented the theoretical validation of the proposed approach of cognitive trait modelling in chapter 9. In this section, we shall examine whether cognitive trait modelling works in practical situation.

First of all, for each student, the navigations are segmented into sessions. Each navigation has a FromObjectID (the learning object ID where a navigation session starts), and a ToObjectID (the learning object ID where a navigation session ends) and a timestamp when the navigation took place. After student logs in, the first FromObjectID is set to value "Begin" which is specially designed to demarcate the boundaries of sessions. All navigations in a session are then fed to the MOT Detection Component which has the four selected IPs discussed earlier in this chapter. The detection result from the MOT Detection Component is then fed to the Multiple Portrayal Network which determines the result of current session. For every session, there are two possible results: LWMC group wins or HWMC group wins. For the former result the value of *wmc* in the database gets decremented and vice versa for the latter result.

Correlations between *wmc* and *opTotal* and *setSize* are then calculated. The result of the correlations is displayed in Table 15-5.

Table 15-5: Correlations between CTM's Calculation and Performance in Web-OSPAN

			wmc	opTotal	setSize
Spearman's rho	wmc	Correlation Coefficient	1.000	.730(*)	.490
		Sig. (1-tailed)	.	.031	.132
		N	7	7	7
	opTotal	Correlation Coefficient	.730(*)	1.000	.861(**)
		Sig. (1-tailed)	.031	.	.006
		N	7	7	7
	setSize	Correlation Coefficient	.490	.861(**)	1.000
		Sig. (1-tailed)	.132	.006	.
		N	7	7	7

* Correlation is significant at the 0.05 level (1-tailed).
** Correlation is significant at the 0.01 level (1-tailed).

In Table 15-5, the variable *wmc* represents the score of working memory capacity approximated by the CTM. The variables *opTotal* and *setSize* represent the performance in Web-OSPAN. We can see that the correlation between *wmc* and *opTotal* is quite high and is statistically significant. The data shows that we are able to combine different MOTs/perspectives to form a single representation of working memory capacity (represented by the variable *wmc* in Table 15-5). In other words, the data demonstrates:

1. practical validation of cognitive trait modelling; and
2. proof of the effectiveness of the selected IPs.

15.4 Summary

There are five implementation patterns (IPs) for working memory capacity. Each of the five IPs is evaluated empirically. Among all the IPs, one is found to be inappropriate to be used. The other four IPs, namely navigational linearity, reverse navigation, ability to perform simultaneous task, effective retrieval from long term memory are then included in a combined evaluation of cognitive trait modelling.

The results in the combined evaluation show a significant correlation between the approximations of WMC obtained from cognitive trait modelling and the scores obtained from the psychometric tool Web-OSPAN. The correlation provides a practical validation to cognitive trait modelling as well as proves the effectiveness of the selected four IPs.

Following a similar format and purpose, next chapter presents the evaluation of inductive reasoning ability and its IPs.

CHAPTER 16

Empirical Evaluation of Inductive Reasoning Ability

16.1 Introduction

In chapter 7, five implementation patterns (IPs) of inductive reasoning ability (IRA) where enumerated. The IPs are translated from the manifestations of trait (MOT) of IRA based on the context of the target-systems in this study. In this chapter, each of the IPs are individually evaluated. The evlauation takes the form of comparison: comparing whether the detection of the IPs matches the performance in the Web-IRA task. Web-IRA is an inductive reasoning test introduced in chapter 11.

The main performance index in Web-IRA is the total number of correct answers in the Web-IRA task. This performance index has a range from 0 to 30, and is represented by the variable *iraCorrect* in the discussions of this chapter.

In this chapter, section 16.2 presents evaluations of each of the 5 IPs of IRA. Among the 5 IPs, 3 are selected according to the evaluation results. Section 16.3 then discusses the evaluation of cognitive trait modelling using the selected 3 IPs. Section 16.4 finally summarises this chapter.

16.2 Implementation Patterns of Inductive Reasoning Ability

16.2.1 Generalisation from Example

This implementation pattern (IP) mainly checks whether a student is able to generalise from examples. Generalisation from example involves inductive reasoning. The argument is that if the student can generalise from examples, the student would have a better conceptual understanding of the learning materials and therefore would perform better in the evaluation. If, on the other hand, the student fails to generalise from examples, it leads to poor or incorrect conceptual understanding and therefore poor performance in the evaluation.

In terms of learning object relations discussed in chapter 4, the HasExample relation is used in this IP. The detection of this IP consists of the following procedures. For every student, all the navigations that involve the HasExample relation are extracted. The Pass function discussed in chapter 7 is used to find out the evaluation score of the learning objects that the extracted navigations originate. If the score is a pass, a variable *hira* is incremented. If the score is a fail, another variable *lira* is incremented.

At the end, the variable *sum* is computed by *hira – lira*. The variable *sum* represents the predicted IRA by the current IP. The correlation between *sum* and *iraCorrect* is shown in Table 16-1.

Table 16-1: Correlation between sum and iraCorrect

			sum	iraCorrect
Spearman's rho	sum	Correlation Coefficient	1.000	.304
		Sig. (1-tailed)	.	.079
		N	23	23
	iraCorrect	Correlation Coefficient	.304	1.000
		Sig. (1-tailed)	.079	.
		N	23	23

The correlation of 0.304 has a significance level of 0.079. It is very close to being statistically significant. The correlation is positive as we hypothesised. It indicates that those who had visited examples and gained good conceptual understandings are those scored high in the Web-IRA task. This IP can therefore be regarded as a suitable one for detecting IRA of students.

16.2.2 Learning from Analogy

This IP is based on the MOT of ability to learn from analogy. The procedure of evaluating this IP is similar to that of generalisation from example discussed earilier in Section 16.2.1 . The only difference is to replace the HasExample relation by the Parallels relation.

In the PHP self-learning module, there are only two Parallels relations whereas there is only one Paralles relation in the IT-Infrastructure self-learning module. In our data, there are two students in the PHP self-learning module that had activated the Parallels relation, but they did not complete the evluation units. In the IT-Infrastructure self-learning module, no one activated the Parallels relation in their navigations. No data is avaiable for the analysis of this IP.

16.2.3 Hypothesis Generation

In chapter 7, we have discussed that hypothesis generation is an important step in inductive reasoning. The IP of hypothesis generation is based on HasExample and IsExampleOf relations. We hypothesised that once a student has visited an example of a concept through the HasExample relation, if the student generates a hypothesis, the student would want to test the hypothesis. Unlike the Web-RF task where a subject can enter triads of numbers to test hypothesises, i.e. active hypothesis testing, the only way to test a hypothesis after viewing an example in the learning systems is to go back to the concept node through the IsExampleOf relation. This is more of an act of hypothesis confirmation rather than hypothesis testing, nonetheless, it servers to check whether the generated hypothesis is correct or not.

In discordance what we have hypothesised, we could not find signs of effectiveness in this IP to predict IRA. We have calculated the number of occurrences of this IP, averaged it based on the total number of navigations. The average has very low correlation coefficient (-0.102, Pearson, 1 tailed, significance at 0.299) to *iraCorrect*.

When we used the mean score of 17.65 (see chapter 11) of Web-IRA to separate students into high inductive reasoning ability (HIRA) group and low inductive reasoning ability (LIRA) group, t-test resulted into a t-stat of -0.29. In the t-test, the P(T<=t) is 0.39 – no significant difference is found. We therefore have to conclude that the hypothesised IP is not an effective one in finding the IRA of students. More works will be needed in the future to find a suitable IP.

16.2.4 Domain Knowledge

In chapter 7, we have discussed about domain knowledge and IRA especially from the works of Hulshof (2001) and Heit (2000). Both Hulshof (2001) and Heit (2000) maintained that a positive relationship exists between domain knowledge and IRA. The domain knowledge serves as a reservoir that the functioning of IRA can draw on. We therefore would expect to see a positive relationship between domain knowledge and students' performances in the Web-IRA task.

In current evaluation, the level of domain knowledge is the average score of all the evaluation units that each student had done in the learning systems. The variable *average* is used to represent the averaged score. The correlation between *average* and *iraCorrect* is shown in Table 16-2.

Table 16-2: Correlation between average and iraCorrect

		average	iraCorrect
average	Pearson Correlation	1	.344
	Sig. (1-tailed)		.058
	N	22	22
iraCorrect	Pearson Correlation	.344	1
	Sig. (1-tailed)	.058	
	N	22	22

It can be seen in Table 16-2 that the correlation between *average* and *iraCorrect* is 0.344. Its significance level at 0.058 is very close to being significant. Using the mean score of 17.65 (see chapter 11) of Web-IRA to separate students into high inductive reasoning ability (HIRA) group and low inductive reasoning ability (LIRA) group, the score of HIRA group is a notable 1.56 times higher than the LIRA group. The positive correlation shown in Table 16-2 is also in accordance with our hypothesis. This IP can therefore be treated as a suitable one to infer students' inductive reasoning ability.

16.2.5 Working Memory Capacity

Working memory capacity (WMC) is identified as an influencing factor to IRA in chapter 7. We have hypothesised that those with high WMC would have high IRA. In chapter 13, we have presented detailed discussion of the relationship between IRA and WMC based on psychometric data. In this section, the relationship between IRA and WMC is examined again. But the WMC score (represented by the variable *wmc* in Table 16-3) is now from cognitive trait model whereas the IRA score (represented by the variable *iraCorrect* in Table 16-3) is of psychometric nature obtained from the Web-IRA task. Table 16-3 shows the correlation between *wmc* and *iraCorrect*.

Table 16-3: Correlation between wmc and iraCorrect

		wmc	iraCorrect
wmc	Pearson Correlation	1	.359
	Sig. (1-tailed)		.050
	N	22	22
iraCorrect	Pearson Correlation	.359	1
	Sig. (1-tailed)	.050	
	N	22	22

It can be seen in Table 16-3 that the correlation between *wmc* and *iraCorrect* is just at the significance level of 0.05. The correlation confirms our theoretical hypothesis that WMC and IRA are related. The positive correlation again indicates that the influence between WMC and IRA is positive. The data allows us to claim that the approximation of WMC obtained through cognitive trait modelling is an effective implementation pattern to infer IRA.

16.3 Combination of Selected Implementation Patterns

The implementation patterns (IPs) of inductive reasoning ability (IRA) have been evaluated individually. Among the 5 IPs, 1 is deemed unsuitable and 1 is not analysed because of sufficient data. The remaining 3 IPs, namely, generalisation from example, domain knowledge and working memory capacity, are selected for this combined evaluation.

In the combined evaluation, student navigational data are segmented into sessions by a special marker “Begin”. The segmentation process is the same as the one discussed in chapter 15. For each student, each of the sessions is then input into the Manifestation Detection Component which has the 3 selected IPs coded. If any of the implementation patterns is detected in a session, 1 point is attributed to either the high inductive reasoning ability (HIRA) group/category or the low inductive reasoning ability (LIRA) group depending on whether it is HIRA or LIRA the IP has detected.

The detection result is then output to the Multiple Portrayal Network which then decides whether the HIRA group or the LIRA group is the winning group. If HIRA group wins, the IRA score in the database is incremented. On the other hand, if LIRA group wins, the IRA score is decremented. The final IRA score (represented by *IRA* in Table 16-4) is then used to perform the correlation analysis with the student’s performance in Web-IRA (represented by *iraCorrect* in Table 16-4). The correlation table is displayed in Table 16-4.

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Table 16-4: Correlation between IRA and iraCorrect

			IRA	iraCorrect
Spearman's rho	IRA	Correlation Coefficient	1.000	.382(*)
		Sig. (1-tailed)	.	.020
		N	29	29

	iraCorrect	Correlation Coefficient	.382(*)	1.000
		Sig. (1-tailed)	.020	.
		N	29	29

* Correlation is significant at the 0.05 level (1-tailed).

Table 16-4 shows that the correlation coefficient between *IRA* and *iraCorrect* is 0.382 and is statistically significant. The implication of this correlation is two fold. Firstly, it implies the effectiveness of the selected 3 IPs. Secondly, the practical validity of cognitive trait modelling is again confirmed (previously done in chapter 15).

16.4 Summary

The five implementation patterns (IPs) evaluated in this chapter are translated from manifestation of traits (MOTs) of IRA. This chapter evaluates the effectiveness of the IPs against students' performances in the Web-IRA task.

The results rule out the IP of hypothesis generation from the list of suitable IPs for IRA. The IP of learning from analogy cannot be analysed because of insufficient data. The remaining 3 IPs, namely generalisation from example, domain knowledge and working memory capacity, are selected for a combined evaluation which evaluates cognitive trait modelling against psychometric data. The result has shown a positive, significant correlation between the approximation of IRA by cognitive trait modelling and the performances in the Web-IRA task. It confirms the effectiveness of the selected 3 IPs in inferring the IRA of students, and proves the practical validity of cognitive trait modelling.

This is the second chapter about empirical evaluations of cognitive trait modelling and IPs. Next chapter is the last one to do so and it evaluates divergent associative learning.

CHAPTER 17

Empirical Evaluation of Divergent Associative Learning

17.1 Introduction

In chapter 8, seven manifestations of trait (MOTs) of divergent associative learning (DAL) are listed and five of them are translated into implementation patterns (IPs). The five IPs are associative hierarchy, versatile navigation, working memory capacity, inducitive reasoning ability and domain knowledge. In this chapter, each of the five IPs is evaluated against students' performances in the Web-DAL task.

The Web-DAL task is discussed in details in chapter 12. There are three variables that are used to record students' performances in Web-DAL, namely *fluency, sumOrg* and *normOrg*. The total number of keywords that a student entered in Web-DAL is represented by *fluency*. Each keyword is assigned an originality score based on the reverse of its frequency of occurrence among all the keywords from the entire sample. The sum of the originality score for all the keywords is represented by the *sumOrg* variable. The varaible *normOrg* is calculated by dividing *sumOrg* by *fluency*. Both of *sumOrg* and *normOrg* have elements of originality in it. However, *sumOrg* represents the total amount of orignailtiy score; therefore this variable has facets for both the quality and the quanity of originality. On the other hand, the variable *normOrg* has only the quality factet in it because the quantity (*fluency*) has been removed.

In this chapter, the individual evalution of each IP is discussed in section 17.2 . After the individual evaluation, the IPs that are deem suitable are then selected for the combined evaluation. The combined evuation takes the form comparing the DAL value approximated by cognitive trait modelling with the peroformances in Web-DAL (i.e. *fluency*, *sumOrg*, and *normOrg*). The combined evaluation is presented in section 17.3 . Section 17.4 then summarises this chapter.

17.2 Implementation Patterns of Divergent Assocaitive Learning

17.2.1 Associative Hierarchy

Associative hierarchy refers to one's organisation of associations. The flatter the associative hierarchy is, the more divergent one's thinking is (Mednick, 1962). In chapter 8, we represent a student's associative hierarchy by the implementation pattern based on the ExcursesTo relations. The ExcursesTo relations lead students to excursion websites. Although the excursion websites are not curriculum-based, they contain information relevant to the curriculum.

We have hypothesised in chapter 8 that those students who took excursions had flatter associative hierarchy whereas those who did not (or were not interested in) taking excursions had steeper associative hierarchy. The following are the steps taken to prepare the data for this evaluation. First of all, the number of excursions that a student took is calculated and is represented by a variable called *excur*. The total number of navigations of the student is also calculated and is represented by a variable *totaNav*. The average percentage of excursions (*excurAvg*) is then calculated by dividing *excur* by *totalNav*. Correlations analysis is then performed on *exucr*, *excurAvg*, *sumOrg* and *fluency*. The correlations are shown in Table 17-1.

Table 17-1: Correlations between excur, excurAvg and sumOrg

		excur	excurAvg	sumOrg	fluency
excur	Pearson Correlation	1	.996(**)	.464(*)	.422
	Sig. (1-tailed)		.000	.047	.066
	N	14	14	14	14
excurAvg	Pearson Correlation	.996(**)	1	.498(*)	.449
	Sig. (1-tailed)	.000		.035	.054
	N	14	14	14	14
sumOrg	Pearson Correlation	.464(*)	.498(*)	1	.904(**)
	Sig. (1-tailed)	.047	.035		.000
	N	14	14	14	14
fluency	Pearson Correlation	.422	.449	.904(**)	1
	Sig. (1-tailed)	.066	.054	.000	
	N	14	14	14	14

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (1-tailed).

Table 17-1 shows that *excur*, *excurAvg,* and *sumOrg* are all significantly correlated to each other. The correlation between *excur* and *excurAvg* shows the consistency of excursion taking behaviour – students did not just happen to take an excursion. For those who did take excursions, they tended to do that, and took excursions often.

Fluency has close-to-significant correlations to both *excur* and *excurAvg*. The positive signs of these correlations are in line with our hypothesis. That is, the students who take more excursions are likely to generate more ideas/keywords.

The significant correlations between *excur* and *sumOrg, and between excurOrg and sumOrg* signify that those who took excursions were more likely to be more capable of divergent associative learning. The excursions one takes can increase the quantity of ideas likely because of the exposure to more ideas. Similarly, excursions can increase the quality/originality of ideas too because one is exposed to ideas that are outside of the curriculum. The two significant correlations are therefore supportive to our hypothesis because the variable *sumOrg* includes both the quality and quality facets of DAL. It can therefore be said that this IP is an effective one to infer students' DAL.

17.2.2 Versatile Navigation

In chapter 8, we have discussed about the relationship between versatile navigation and DAL through Eysenck's (1993) study about weak central coherence. We have therefore hypothesised that the level of versatility of a student's navigation would be related to the student's performance in the Web-DAL task.

The versatility of one's navigation is defined as the opposite to the linearity of one's navigation. Navigational linearity is one of the IP of WMC and is discussed in chapter 15. Navigational versatility is therefore the reverse value of navigational linearity. Navigational versatility is represented by the variable *vers* in Table 17-2, which also shows the correlation between *vers* and *normOrg*.

Table 17-2: Correlation between vers and normOrg

			vers	normOrg
Spearman's rho	vers	Correlation Coefficient	1.000	.459(*)
		Sig. (1-tailed)	.	.049
		N	14	14
	normOrg	Correlation Coefficient	.459(*)	1.000
		Sig. (1-tailed)	.049	.
		N	14	14

* Correlation is significant at the 0.05 level (1-tailed).

Table 17-2 shows that there is a significant correlation between *vers* and *normOrg*. The positive correlation indicates that those who are more likely to navigate in a versatile manner are better at divergent associative learning. The positive sign is in accordance to what we have hypothesised. That is, navigational versatility correlates performance in Web-DAL.

The correlation from *vers* to the qualitative aspect of DAL (i.e. *normOrg*) instead of to the quantitative aspect of DAL (i.e. *fluency* and *sumOrg*) can be explained by weak central coherence. Individuals with weak central coherence have different focus than other individuals: they have a tendency to pursue details rather than the overall meaning (Eysenck, 1993). The differences in focus would lead them to attend to concepts that others are less likely to pay attention to. This would result in "unusual" ideas that are accounted by the *normOrg* variable. In addition, because we have reasoned in chapter 8 that versatile navigation is a likely behaviour of individuals with weak central coherence, therefore it can be said that the IP of versatile navigation is an effective one to infer the quality of students' DAL.

17.2.3 Working Memory Capacity

Chapter 8 establishes the relationship between working memory capacity (WMC) and DAL by using the experiment results of Bahar and Hansell (2000) and Laumann (1999). The said relationship is a positive one – high WMC to high DAL and low WMC to low DAL. We therefore have hypothesised that the approximation of WMC by cognitive trait modelling should have a positive correlation to performance of Web-DAL, too.

The evaluation of this IP takes the approximated value of WMC (by CTM) from the database and represents it by the variable *wmc*. The correlation between *wmc* and *sumOrg* is then calculated and shown in Table 17-3.

Table 17-3: Correlation between wmc and sumOrg

			sumOrg	wmc
Spearman's rho	sumOrg	Correlation Coefficient	1.000	.388
		Sig. (1-tailed)	.	.085
		N	14	14
	wmc	Correlation Coefficient	.388	1.000
		Sig. (1-tailed)	.085	.
		N	14	14

The correlation coefficient between *wmc* and *sumOrg* is 0.388. The significance level of this correlation is 0.085 which is not far from being significant. The positive correlation is in accordance with what we have hypothesised. This IP can therefore be used to infer students' DAL.

17.2.4 Inductive Reasoning Ability

In chapter 9, we have hypothesised that inductive reasoning ability (IRA) can facilitate the generation of more associations and therefore should positively relate to DAL. Similar to the IP of WMC discussed earlier, we would also like to examine the relationship between the IRA approximated by cognitive trait modelling and performance of Web-DAL.

The approximation of IRA by CTM is extracted from database and represented by the variable *ira*. The correlation between *ira* and *sumOrg* is then calculated and shown in Table 17-4.

Table 17-4: Correlation between ira and sumOrg

			sumOrg	ira
Spearman's rho	sumOrg	Correlation Coefficient	1.000	.444
		Sig. (1-tailed)	.	.056
		N	14	14
	ira	Correlation Coefficient	.444	1.000
		Sig. (1-tailed)	.056	.
		N	14	14

Table 17-4 shows that the correlation coefficient between *ira* and *sumOrg* is 0.444. The significance of this correlation is 0.056 which is very close to being statistically significant. The positive correlation is the same as what we have hypothesised. This IP can also be used to infer students' DAL.

17.2.5 Domain Knowledge

In chapter 8, we have discussed the relationship between domain knowledge and DAL. We have hypothesised that high DAL facilitates learning comprehension which should result in better performance in the evaluations about domain knowledge.

Domain knowledge is also one of the IPs of inductive reasoning ability and the evaluation of it has been discussed in chapter 16. Current evaluation procedure follows that of the domain knowledge IP in chapter 16 except the variable representing the performances in Web-IRA is replaced by variables representing performances in Web-DAL. The variable *avg*, exactly the same as the one used in chapter 16, is the averaged score of the evaluation units in the learning systems. Correlations of *avg*, *sumOrg*, *fluency*, and *normOrg* are shown in Table 17-5.

Table 17-5: Correlations between avg, sumOrg, fluency, and normOrg

			avg	sumOrg	fluency	normOrg
Spearman's rho	avg	Correlation Coefficient	1.000	.627(**)	.470(*)	.435
		Sig. (1-tailed)	.	.008	.045	.060
		N	14	14	14	14
	sumOrg	Correlation Coefficient	.627(**)	1.000	.890(**)	.617(**)
		Sig. (1-tailed)	.008	.	.000	.009
		N	14	14	14	14
	fluency	Correlation Coefficient	.470(*)	.890(**)	1.000	.374
		Sig. (1-tailed)	.045	.000	.	.094
		N	14	14	14	14
	normOrg	Correlation Coefficient	.435	.617(**)	.374	1.000
		Sig. (1-tailed)	.060	.009	.094	.
		N	14	14	14	14

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (1-tailed).

We can see from Table 17-5 that the correlation between *avg* and *sumOrg* is very high and statistically significant. The correlation between *avg* and *normOrg* is also close to being statistically significant. This indicates that those who had highly-original/creative keywords also performed better in the evaluations of their domain knowledge.

The correlation between *avg* and *fluency* is also statistically significant. This implies that those who entered more keywords in the Web-DAL task are also performing better in the domain-related evaluations. Both this correlation and the correlation between *avg* and *sumOrg* support our hypothesis that DAL facilitates learning comprehension and the suitability of domain knowledge as an effective IP for DAL.

17.3 Combination of Selected Implementation Patterns

The five IPs of DAL have all been selected into the combined evaluation, although all of them have different degrees of correlations to the three variables of Web-DAL. Current combined evaluation follows the same procedure as that of the combined evaluations in chapters 15 and 16 – the approximation of DAL from cognitive trait modelling (represented by the variable *DALValue)* is compared to that of the performances in Web-DAL. The correlations are shown in Table 17-6.

Table 17-6: Correlations between sumOrg, fluency, normOrg and DALValue

			sumOrg	fluency	normOrg	DALValue
Spearman's rho	sumOrg	Correlation Coefficient	1.000	.890(**)	.617(**)	.653(**)

	Sig. (1-tailed)	.	.000	.009	.006
	N	14	14	14	14
fluency	Correlation Coefficient	.890(**)	1.000	.374	.499(*)
	Sig. (1-tailed)	.000	.	.094	.035
	N	14	14	14	14
normOrg	Correlation Coefficient	.617(**)	.374	1.000	.291
	Sig. (1-tailed)	.009	.094	.	.157
	N	14	14	14	14
DALValue	Correlation Coefficient	.653(**)	.499(*)	.291	1.000
	Sig. (1-tailed)	.006	.035	.157	.
	N	14	14	14	14

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (1-tailed).

It can be seen from Table 17-6 that although the correlation between *DALValue* and *normOrg* is not yet significant, *DALValue* is significantly correlated to both *sumOrg* and *fluency*.

The less-than-significant correlation between *DALValue* and *normOrg* can be explained by the following reason. There is more focus on the quantity aspect of DAL than the quality aspect in the IPs of DAL. Firstly, the reason that inductive reasoning ability (IRA) is related to DAL is because IRA helps to generate more associations – it is solely about quantity.

Secondly, the associative hierarchy IP is implemented as the detection of the average number of excursions. Excursions would undoubtedly enhance the quality of DAL because they expose the students to new and novel ideas, but in a way, they also increase the quantity of ideas. The high correlations between variables of associative hierarchy and *sumOrg* in Table 17-1 support this argument.

Thirdly, the IP of working memory capacity (WMC) is related to DAL because of Laumann's (1999) and Bahar and Hansell's (2000) empirical studies. The WMC-to-associative learning and WMC-to-divergent thinking relationships in Laumann (1999) and Bahar and Hansell (2000) respectively are both quantitative. That is, points were given based on the number, not the quality, of response items in their studies.

Among the five IPs, only versatile navigation is clearly oriented to the quality aspect of DAL, whereas three IPs, namely IRA, associative-hierarchy and WMC, are quantity-oriented. The IP of domain knowledge exists because of the causal relationships from DAL to learning comprehension and then from learning comprehension to domain performance. There is no clear quality- or quantity-orientation in the IP of domain knowledge. Quantity-oriented IPs outweigh quality-oriented IPs. Our reasoning in chapter 12 has also dictated that the quantity of students' performances in Web-DAL is to be the main criterion in determining DAL. The significant correlations of *DALValue* to *fluency* and to *sumOrg* are therefore in agreement with our reasoning as well. They also allow us to again confirm both the practical validity of cognitive trait modelling (previously done in chapters 15 and 16) and the suitability of the selected five IPs to infer students' DAL.

17.4 Summary

One of the aims of the current chapter is to evaluate the implementation patterns (IPs) of divergent associative learning (DAL). The evaluation results show that all the five IPs of DAL are suitable candidate IPs to infer students' DAL. The variables among all the five IPs have various degrees of correlations to the variables from the Web-DAL task.

Eysenck's (1993) study had shown the positive relation from weak central coherence to divergent thinking. Thereby, we have hypothesised that the behaviour of weak central coherence should also positively related to DAL and versatile navigation is a likely behaviour of weak central coherence. In our evaluation about the versatile navigation IP, data supports our hypothesis. Firstly, our data confirms that versatile navigation is a likely behaviour of weak central coherence. Furthermore, our data can also lend support to Eysenck's (1993) study about the relationship between weak central coherence and divergent thinking.

Most important of all, the significant correlations in the combine evaluation have again confirmed the practical validity of cognitive trait modelling. Together with the theoretical validation in chapter 9 and two practical validations from chapters 15 and 16, we can claim that cognitive trait modelling is both theoretically and practically valid and sound.

CHAPTER 18

Conclusion

18.1 Dissertation Summary

Cognitive trait model (CTM) is aimed at creating student profiles in which information about students' cognitive traits can be available for learning systems to use in order to help the students. The approach to create the said student profiles is called cognitive trait modelling.

In this dissertation, both CTM and cognitive trait modelling are presented and discussed. Specifically, the overall structure of CTM is presented in chapter 3. Two important components of cognitive trait modelling, namely the semantic relation analysis and multiple portrayal network, are addressed extensively in chapters 4 and 5 respectively.

Three cognitive traits are covered by this dissertation: working memory capacity (WMC), inductive reasoning ability (IRA) and divergent associative learning (DAL). WMC refers to the transient memory storage in human cognition. Researches about WMC have broadened the boundary of WMC – it is now quite popularly perceived as a cognitive construct that includes the transient memory and the capacity to process the content in the transient memory (Baddeley, 1992). IRA refers to the ability to generalise from the examples to reach a rule-based model that can be applied in different contexts. The third cognitive trait, DAL, is a construct of this study. It denotes the characteristic of learning that develops links between new and existing concepts. In chapters 6, 7 and 8, each one of the cognitive traits is studied in details.

Chapter 9 presented a theoretical validation of cognitive trait modelling. A computer simulation is employed to determine whether different portrayals/perspectives can be combined to form a representation that is more accurate than any single portrayal. The results from the computer simulation have been positive and show that cognitive trait modelling is theoretically sound and valid.

The empirical evaluations done in chapters 15, 16 and 17 reflect the findings in chapter 9. They show that what has been validated theoretically in chapter 9 can also be empirically validated.

Chapters 10, 11 and 12 introduced and discussed several web-based psychometric tools to measure WMC, IRA, and DAL. Chapter 13 then presented an analysis of the relationships between WMC, IRA and DAL from psychometric point of view. Chapter 14 presented a description of the learning systems that is used to collect student behaviour data and domain performance. The data gathered in chapter 14 is used as the behaviour data that were compared to the psychometric data obtained in chapters 10, 11 and 12. The comparisons constitute the empirical evaluations in chapters 15, 16 and 17.

The contributions and limitations of the research work presented in the chapters of this dissertation are summarised and discussed in section 18.2 Possible future research directions are also discussed in section 18.2 Some concluding remarks are presented at section 18.3 of this chapter to end this dissertation.

18.2 Contributions, Limitations, and Future Researches

One of the most important contributions of this dissertation is the concept of cognitive trait modelling. Cognitive trait modelling is a novel approach to create student cognitive trait profiles from student behaviours in learning systems.

Previously, various tools were used to measure cognitive traits; for example OSPAN (Turner and Engle, 1989) and GOSPAN (De Neys et al., 2002) to measure working memory capacity, and Wason's 2-4-6 task (Wason, 1960) and the Ball Aptitude Battery (Hall, 1985) to test inductive-reasoning related abilities. These psychometric tools however cannot be used to continuously monitor the dynamic changes of cognitive traits along the course of study (even if these changes happen rather very gradually, sometimes over decades). Research works in this dissertation have confirmed, together with evidences from other researchers (e.g. Hulshof, 2001; Harverty et al., 2000; Heit, 2000; Feldhusen, 2002), that some cognitive traits such as inductive reasoning ability and divergent associative learning, are influenced by domain knowledge. With the progress in the course, students' domain knowledge does not remain at static levels, so does the cognitive traits. From this line of argument, the static psychometric tests fall short of constantly reflecting accurate representations of cognitive traits.

However, the value of psychometric tests cannot be denied. Psychometric tests deliberately set up environments which facilitate the tests. The author proposed the combination of advantages of psychometric tests and cognitive trait modelling to achieve the best results. The psychometric tests, such as Web-OSPAN, Web-IRA and Web-DAL discussed in chapters 10, 11 and 12 respectively, can be used at the beginning of the course to initiate students' cognitive trait profiles. Cognitive trait modelling can then be used to continuously update the profiles to provide the most accurate *current-situation* information to the learning system. For example, a student might score high in Web-IRA at the beginning of a course. It is a sign of good general IRA. But for some reason, the student did not follow the course schedule well and therefore has low domain performances. At that moment, it is not helpful to the student if the cognitive trait profile still identifies this student as high-inductive-reasoning-ability because the learning system might give the student something too abstract and too hard. The student feels the material is too hard not because of the IRA of the student, but because of insufficient domain knowledge. Cognitive trait modelling would be able to pick up this problem because domain knowledge is one of the manifestations of trait (MOT) of IRA. The low domain knowledge would bring down the value the IRA in the CTM and therefore the adaptive learning system can provide materials suitable to the student.

18.2.1 Semantic Relation Analysis

Among the components required to perform cognitive trait modelling, *semantic relation analysis* (SRA) and *multiple portrayal network* (MPN) are two important innovative contributions introduced in this dissertation. They are both devised to solve issues of cognitive trait modelling but are each capable of being used independently outside of cognitive trait modelling. Their contributions are discussed in more details in this and the next sections.

SRA is an analysis method introduced in chapter 4 by using navigational patterns. SRA is a novel approach introduced in this research work that combines the strengths of content-less and content-based navigational pattern analysis (Mullier, 1999). SRA is tailor-made for information systems that are organised using semantic web structure to obtain useful user/learner information. After its introduction several years ago (Berners-Lee, 2003; Berners-Lee, Hendler and Lassila, 2001), semantic web has gained more and more popularity (see examples Amorim et al., 2006; Kiu and Lee, 2006). Koper (2006) listed the "use of ontologies and semantic web principles & tools" as one of the four main trends of researches in learning design. Information systems that are structured using semantic web concepts and technologies, no matter educational or commercial, are likely to be more and more widely used in the foreseeable future. There will be more needs to use SRA to find out information about users.

One important limitation for SRA, at the time of this writing, is the need to manually author the learning object relationships. Learning object relationships are the basic units of analysis in SRA. Without them, SRA cannot be applied in an information system. But we believe that the popularity of semantic web will 1) introduce other needs to specify the learning object relations during system development processes; and 2) promote the developments of more subject ontology (e.g. ontology for Java by Lee, Ye, and Wang, 2005). These developments will be able to help the creations of learning object relations automatically and greatly reduce the difficulty of employing SRA in the future.

18.2.2 Multiple Portrayal Network

MPN is a network structure capable of representing multiple different portrayals of an entity. The entities that MPN represents in this study are cognitive traits and different portrayals are different theories/perspectives about the cognitive traits. MPN has an Inclusion Resolution mechanism that is capable of discovering the relationships between different portrayals by using conditional probabilities. Even if there are no documented relationships between the portrayals, MPN is still capable of sorting out the relationships gradually.

Mary Midgley, a contemporary philosopher, used watching fish in a big aquarium as an analogy to human life – "Fish and other strange creatures constantly swim away from particular windows... reappearing where different lighting may make them hard to recognize... each of the peeholes or perspectives lends some additional insight, and that the important thing is to use them all" (Cohen, 2002, p.146). MPN offers a tool to combine perspectives to form a more accurate understanding about the object of study. The author believes that the application of MPN in this study is just an example of its application and other subjects/sciences, especially in Psychology, might also find MPN useful.

In chapter 5, there are only four types of relationship in MPN – inclusion, overlap, equivalent, and independent. These four types cover a broad range of combinations for any relationship between two two-dimensional geometric shapes. However, possibilities exist that there are more other types of relationships. In the future, research effort can be directed to the search for new types of relationships. Possible directions could be the relationships used in knowledge representation (e.g. Kim and Moldovan, 1993), or the relationships from fuzzy clustering research (e.g. Horng et al., 2005).

It should be mentioned that both SRA and MPN have not been used outside the study of CTM. Although they have been demonstrated as useful in CTM and the possibilities of their applications in other contexts have been foreseen through theoretical lens, independent studies are needed to find out more about how useful they are and their other possible application areas.

18.2.3 Perspective Differences and Individual Differences

The task of combining different theoretical perspectives (of cognitive trait) is not an easy one. Furthermore, the task using combined theoretical perspectives to cater for individual differences is an even complex one. The definitions given in chapter 3 about *perspective differences of cognitive traits* and *individual differences of students* serve to break the complex task into easier ones that can be addressed one-by-one. The author believes that the distinction of these two differences can be very useful for other researchers, who want to work on similar problems in the future.

18.2.4 Cognitive Traits, MOTs and IPs

It should be noted that 1) there are other possible ways of interpreting student behaviours than what the implementation patterns (IPs) try to detect; and 2) there are other possible ways of translating the manifestations of trait (MOTs) into IPs. Because of these two reasons, this dissertation separates its contributions into two layers, a theoretical layer and a practical layer. The MOTs are the contributions in the theoretical layer. They are extracted from extensive literature reviews on cognitive traits and are not affected by the two said reasons. The discussion in chapter 9 validates what we have proposed in the theoretical layer.

On the other hand, the IPs are the contributions in the practical layer. The IPs can only be regarded as an application of the theoretical layer in specific context – in the target-systems. The two said reasons are very true in the practical layer: there are other possible ways to translate the MOTs into IPs in the target-systems or in other systems; there are also other possible ways in which we can interpret student behaviours. The evaluations in chapters 15, 16 and 17 demonstrate that some IPs translated in this study are useful in finding the cognitive traits of students whereas some more research efforts are required to translate other IPs.

The separation of the theoretical and the practical layer also helps the adoption of CTM in other systems. Future research efforts should be directed to both searching for new MOTs and evaluating new translations of MOTs (i.e. IPs) in different contexts. The author believes that testing new IPs in different contexts can provide useful insights on how to improve the translation process from MOTs to IPs. The IPs used in this study may also be enhanced by experiences from other contexts.

Selection of the three cognitive traits was inspired by the information processing model of human cognition which takes the information processing device analogy about human cognitive functioning (Leahey, 1997). Working memory capacity (WMC) is a cognitive construct to process perceived information. Inductive reasoning ability (IRA) generalises patterns from perceived information to create knowledge. Information and knowledge are then associated to previously learned knowledge by divergent associative learning (DAL). The above describes a very simple scenario of learning that involves the three cognitive traits. In the future, we would like to explore more about new cognitive traits that are important in other accounts of learning such as collaborative learning (Okamoto, 2003; Kurhila, 2003).

18.2.5 Psychometric Tools

Another important contribution of this research study is the development of the three web-based psychometric tools, namely the Web-OSPAN, Web-IRA and Web-DAL. These tools 1) allow researchers to get larger number of participants who may be geographically dispersed; 2) free researchers from financial constraints; and 3) save the researchers' time by eliminating the tasks of supervising experiments, setting up experiment venue and manually processing the collected data. In addition to researchers, experiment subjects can also benefit from these tools. First of all, subjects can choose a time and place of convenience to partake in experiments. Secondly, when subjects are taking experiments in familiar environment, they do not feel anxieties incurred by the environments. Finally, subjects can get instant feedback of the experiment results.

Analysis of psychometric data in chapter 13 revealed many interesting findings. First of all, individual differences on WMC do not have an obvious effect on simple IRA tasks. The effect of WMC is most apparent when the IRA task is cognitively demanding. Secondly, a relationship exists between WMC and DAL. Moreover, data also points out a possible relationship between WMC and creativity. DAL is also found to have higher correlation to IRA when the IRA tasks are more cognitively demanding. It shows a possibility that WMC, IRA and DAL share a common underlying construct. Could WMC be a basis for the cognitive functions that we call IRA or DAL? Future research efforts are required to answer this question.

The inter-cognitive-trait relationships can also be studied from the data gathered in cognitive trait modelling. Do the relationships produced by cognitive trait modelling reflect that from psychometric data? Is there more we can learn about the three cognitive traits, or about human cognition in general, from the relationships produced by cognitive trait modelling? Certainly, many interesting questions and research directions about cognitive traits have sprung from this study.

In the future, larger scale experiments will be carried out, if possible, in order to find out normative (standardised) data for these three tools. The normative data will be very helpful for other researchers who wish to use these tools in the future. Collaborations will also be sought for researchers who can translate these tools into other languages. In addition to the wider user base, the effects of differences in languages and cultures can also be more formally studied.

Improvements on the psychometric tools have been made based on suggestions from other researchers. The author would like to make them freely available for other researchers and would like to improve on them by ourselves or in collaboration with others. The author believes that psychometric tests are valuable tools by which we can learn about the cognitive traits, and we need better tools if we wish to obtain better understanding about the cognitive traits.

18.2.6 Cognitive Capacities and Human Behaviour

It is also the author's interest to find out the relationships between human cognitive capacities and human behaviours. More particularly, the author would like to ask "Do the limitation and availability of cognitive capacities shape the human behaviours and produce something we call learning styles?"

Similar question had been addressed by Huai (2000) by looking at short term memory and serial learning style. In the future, we are interested to examine if this is a pattern that can be applied to other cognitive capacities and other learning styles.

18.2.7 Relationships between Perspectives of Cognitive Trait

The data gathered by cognitive trait modelling can also be a great resource to find out more about the relationships between different perspectives of a cognitive trait. Each of the MOTs represents a perspective/theoretical point of view about a cognitive trait. To our knowledge, inter-perspective studies are rare. The reason could be the recognised differences between these perspectives. On the other hand, the inclusive approach in this study about different perspectives provides a platform where these inter-perspectives relationships can be studied.

The author believes that these studies will greatly enhance our understanding about the cognitive traits. This would be an interesting and likely a rewarding future research direction.

18.2.8 Field Dependence/Independence and Working Memory

It has been noted in chapter 6 that even though there are generalisations of behaviour patterns, especially behaviour patterns in hypermedia-based learning systems, for field dependent/independent cognitive styles, there were however discrepancies among the scores in tests between measurement tools (Ford and Chen, 2000). The generalisations obtained by Ford and Chen (2000) could be particularly useful in this study because:

1. this study is looking for behaviour patterns in hypermedia-based learning systems, and
2. there are evidences showing the relationship between the cognitive style, field dependence/independence, and working memory (Miyake, Witzki, and Emerson, 2001; Kinshuk and Lin, 2005).

More investigation into the measurement tools used by Ford and Chen (2000) could be done in order to find out the reasons for the discrepancy which might not affect the usability of Ford and Chen's (2000) findings to infer students' working memory capacities.

18.2.9 Mental Imagery and Associative Learning

In the discussion about divergent associative learning in chapter 8, the use of mental imagery techniques to improve effectiveness of associative learning (such as de la Iglesia, 2004; Dunlosky, Hertzog, and Powell-Moman, 2005) has been mentioned. An example to learn an association between "car" and "rain" is to use the imagery of "many cars, each one of them is enclosed inside a water droplet, falling from sky". de la Iglesia (2004) postulated that when mental imagery techniques are used, greater interest and attention become apparent in associative learning. Although we agree that greater interest and attention are needs when using mental imagery techniques, we believe the term "interest" and "attention" did not sufficiently account for the observed improvement in memory recall. Instead, we speculate that it is more adequate to explain the increased associative learning performance by the increased number of associations developed during the formation of the mental imagery.

The reasons are:

1. A concept associated with more other concepts has higher possibility of getting activated (recalled) according to Anderson's (1983a, 1983b) views on how activation occurs.
2. Adler and Berkowitz's (1976) study showed that the group of children, who were shown a picture before starting to draw, produced drawings with no difference to the other group of children who were not shown a picture. The picture was shown passively, i.e. no active processing was required. Therefore, no associations were developed from the event of seeing the picture and therefore no differences were observed.

From Adler and Berkowitz's (1976) result, it is obvious that graphical representation alone does not account for changes in cognitive processing; it is the effects of using graphical representation, for example facilitation in increasing number of associations, that makes it a good tool to help associative learning.

However, validation of our speculation requires clarification of the relationship between "interest and attention" and "the number of associations". Dunlosky, Hertzog, and Powell-Moman's (2005) study about the mediators of associative learning might provide hint of answer to our speculation. This task, although interesting, is beyond the scope of current study.

18.2.10 Classification Ability: To Abstract or Identify

In the discussion about classification ability in chapter 8, speculation has been made about the difference in abstracting common characteristics to form a new class and identification of members of a class. Often these two different aspects of classification ability were not distinguished (e.g. in Sternberg, 1977, 1983; van de Vijver, 2002).

It is however speculated in this study that the processes of abstraction and identification are cognitively different: abstraction requires an extra step of concept formation and is used in inductive reasoning, whereas identification needs memory recall and is used in divergent associative learning. This speculation could lead to in-depth insight of the cognitive processes involved in the so-called classification ability, and may lead to the division of the abstraction- and identification-aspects of classification ability into separate abilities. However, investigation in this line remains to be done in the future.

18.2.11 Divergent Cognitive Style and IQ

Runco (1991) established a link between high divergent thinking ability and high IQ. This link is however contrary to the original definition of divergent "cognitive style" from Hudson (1966). Hudson defined divergers as those who score high in creativity tests but low in IQ tests. Although the relationship between the divergent cognitive style and IQ does not bear direct influence to the current study, it is nonetheless interesting to find out that maybe:

1. a difference exists between construct measured by the divergent cognitive style test, and divergent thinking test; or
2. the definition of IQ and tools to measure it have changed over time.

18.2.12 Definition of Task

One of the Manifestations of Trait (MOT) of working memory (WM) is the ability to perform simultaneous tasks. In order to determine the moment that a student is working on more than one task, task boundary has to be defined.

In current study, definition of task boundary is only by the hierarchical structure of the concepts - that is by using the hasPart and isPartOf relation. However, it is possible that there are other types of task structure. It could also be possible that the common perception of tasks, no matter hierarchical or other possible structures, does not reflect the underlying cognitive demand on WM, and therefore the meaning of task and task boundary should be further investigated.

18.2.13 Different Types of MOT

There are three different types of manifestations of trait (MOTs):

1. student behaviour patterns
2. student characteristics
3. cognitive trait

The mechanism developed in this study, especially the Multiple Portrayal Network (MPN) discussed in chapter 5, is designed for the first type of MOT, namely behaviour patterns.

Age is an example of the second type of MOT. This type could be easily catered for if this value is taken into consideration during the initialisation of cognitive trait model. For example, the initial value of WM capacity for a younger adult could be set higher because younger age in adulthood manifests higher WM. The influence of this MOT has already begun during the initialisation. But unlike the behaviour patterns which are continuously monitored, the MOT about younger age is relatively static. It should not pose continuous interference on the overall execution of the CTM because it will be overly weighted, i.e. the weight on the node representing younger age will be very great because it is always manifested, and therefore it will bias the CTM totally.

By setting a higher WM in the initialisation, we are acknowledging and taking into account those research results indicating the fact that younger age manifests higher WM, and at the same time safeguarding the representative-ness of CTM. In the future, we would also like to examine in more depth about the difference of these three types of MOTs.

18.2.14 Domain Independent Student Model

Student models have being closely related to the subject domains they situate. It has being long recognised the importance and value of re-usable student models (Brusilovsky, 2001). There are indeed some research efforts in developing domain-independent and reusable student modelling including Bontcheva and Wilks (2005).

Bontcheva and Wilks (2005) described a generic agent modelling framework called ViewGen. ViewGen is actually a model of a learner's believe system. It is very similar to an overlay student model that a learner's believes is a subset of the expert's believes. In Bontcheva and Wilks (2005), ViewGen was applied in a system teaching chemistry and computers. ViewGen however, has built-in reasoning mechanism that allows it to be used separately. Bontcheva and Wilks (2005) commented that ViewGen has being successfully applied in the context of first-order logic.

ViewGen's reusability sits in its representation of a believe system and the reasoning algorithm that operates on the set of believes. Its domain-independence and reusability is on the generic framework (model) itself, not the content of the student model – i.e. information about learners.

18.2.15 Bridge between Psychology and Learning Technology

It is the author's wish that the benefits of many great studies about human mind can be harvested and put into use in the area of e-learning. If all the contributions mentioned in this section are trivial, the fact that this research work tries to bridge the fields of Psychology and Learning Technology is worth some merit. It is also the author's wish that the said benefits can be more widely accessible through cognitive trait modelling even to students in poor countries.

18.3 Concluding Remarks

The famous Sophist Protagoras (approximately 490-420 B.C.) claimed: "Of all things, the measure is man" (Leahey, 1997). In the context of current research, I think what we wish to express is: "Of all things related to Education, the measure is student". Good technology, good learning design, good pedagogy and good educational psychology all aim to help students learn. The author believes that the most important step to help the students is to understand the students. Understanding the students is all what this dissertation is set out to do. The author hopes the works in this dissertation have slightly advanced human knowledge about how to better understand the students and their minds.

This dissertation identified three domain-transcending and persistent cognitive traits, namely working memory capacity, inductive reasoning ability and divergent associative learning, as the objects of study. In addition to the extensive literature reviews on the three traits so that we can understand them from others' works, three psychometric tools are developed in this study in order for us to study the cognitive traits in more details. Many interesting insights are found in the data from the psychometric tools, especially the inter-cognitive-trait relationships that were not documented elsewhere before.

The complexity of how to interpret human behaviour has once and still bewildered the author. The more we study about the cognitive traits and how to model them, the more we find how little we know about them.

A Chinese saying goes like this: Throw a stone to induce a jade. Its English counterpart is: To throw out a minnow to catch a whale. The author can only pose whatever presented in this dissertation as the stone – as a promotion of the importance of needs of cognitive support and successful evaluations of cognitive trait modelling as an encouragement for future talented researchers, that is, the jade.

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Appendix A: Information Sheet and Example

An information sheet is provided at the beginning of each research experiment. The information sheet includes introduction to the research, the researchers, participant involvement (including description of the task and estimated time), project procedure (include data handling) and statements of participant rights.

The following is an example of information sheet for the participants using Web-IRA.

Web-IRA: An web-based task for measuring Inductive Reasoning Ability

This research is part the Ph.D. study (Cognitive Trait Model for Adaptive Learning Environments) of Taiyu Lin, supervised by Dr. Kinshuk. Participation of this task is voluntary. Data collected in this task will be kept confidentially and only be used for research purpose.

This task consists of 30 questions and requires you to give correct answer to those 30 questions as soon as possible. 2 more subtasks are associated with Web-IRA, 1) Web-RF, a task for testing rule finding, and 2) Web-Sys, a task for testing systematic thinking.

Statement of Rights:

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

- decline to answer any particular question;
- withdraw from the study (specify timeframe);
- ask any questions about the study at any time during participation;
- provide information on the understanding that your name will not be used unless you give permission to the researcher;
- be given access to a summary of the project findings when it is concluded.

Note: This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher named above is responsible for the ethical conduct of this research.

If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher, please contact Professor Sylvia Rumball, Assistant to the Vice-Chancellor (Ethics & Enquiry), telephone 06 350 5249, email humanethicspn@massey.ac.nz.

Appendix B: Ethical Approval Application Form

Massey University

Te Kunenga ki Pürehuroa

NOTIFICATION OF LOW RISK RESEARCH/EVALUATION INVOLVING HUMAN PARTICIPANTS

(All notifications are to be typed)

SECTION A

1. **Project Title** Evaluation of Cognitive Trait Model

Projected start date 01 July 2003 – PhD commenced / 01 May 2006 – Evaluation part **Projected end date** 30 June 2007

2. **Applicant Details** *(Select the appropriate box and complete details)*

ACADEMIC STAFF NOTIFICATION

Full Name of Staff Applicant/s

School/Department/Institute

Region *(mark one only)* **Albany** [ ] **Palmerston North** [ ] **Wellington** [ ]

Telephone **Email Address**

STUDENT NOTIFICATION

Full Name of Student Applicant Taiyu Lin

Employer (if applicable) Massey University

Telephone *7643* **Email Address** t.lin@massey.ac.nz

Postal Address **Information Systems, Massey University, Palmerston North**

Full Name of Supervisor(s) A/Prof Kinshuk (Massey)
Prof. Tak-Wai Chan (National Central Uni., Taiwan)
A/Prof Demetrios Sampson (Uni. of Piraeus, Greece)

School/Department/Institute Information Systems
Human Resources Management

Region *(mark one only)* **Albany** [ ] **Palmerston North** [X] **Wellington** [ ]

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GENERAL STAFF NOTIFICATION

Full Name of Applicant

Section

Region *(mark one only)* **Albany** [ ] **Palmerston North** [ ] **Wellington** [ ]

Telephone **Email Address**

Full Name of Line Manager

Section

AB2

Telephone .... Email Address ....

3. **Type of Project** *(mark one only)*

Staff Research	[ ]	**Student Research:**			
		PhD Research	X	**Evaluation Programme**	[ ]
		Master's Research	[ ]	**Undergraduate Teaching Programme**	[ ]
		Honours Research	[ ]	**Other**	[ ]
		Undergraduate Research *(individual project)*	[ ]	**If Other, specify:**	

4. **Summary of Project**
Please outline in no more than 200 words in lay language why you have chosen this project, what you intend to do and the methods you will use.
(Note: all the information provided in the notification is potentially available if a request is made under the Official Information Act. In the event that a request is made, the University, in the first instance, would endeavour to satisfy that request by providing this summary. Please ensure that the language used is comprehensible to all)

Cognitive Trait Model tries to infer the cognitive capacity of a user from the user's online behaviour patterns. The hypothesis is that the user's online behaviour can be a source from which it gives indications of cognitive capacity of the user. In order to check the effectiveness of the Cognitive Trait Model, another mean to measure cognitive capacity is developed and it can be used without the information from the user's online behaviour pattern.

This project aims to evaluate the effectiveness of the Cognitive Trait Model by comparison of Cognitive Trait Model and the other measurement developed to measure cognitive capacity.

Please submit this Low Risk Notification (with the completed Screening Questionnaire) to:

The Ethics Administrator
Equity & Ethics, Old Main Building
Turitea, Palmerston North

SECTION B: DECLARATION *(Complete appropriate box)*

ACADEMIC STAFF RESEARCH

Declaration for Academic Staff Applicant

I have read the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants. I understand my obligations and the rights of the participants. I agree to undertake the research as set out in the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants. My Head of Department/School/Institute knows that I am undertaking this research. The information contained in this notification is to the very best of my knowledge accurate and not misleading.

Staff Applicant's Signature ______________________ Date: ____________

STUDENT RESEARCH

Declaration for Student Applicant

I have read the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants and discussed the ethical analysis with my Supervisor. I understand my obligations and the rights of the participants. I agree to undertake the research as set out in the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants. The information contained in this notification is to the very best of my knowledge accurate and not misleading.

Student Applicant's Signature 赵孝争 Date: 04/05/2006

Declaration for Supervisor

I have assisted the student in the ethical analysis of this project. As supervisor of this research I will ensure that the research is carried out according to the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants.

Supervisor's Signature ______________________ Date: 4/5/2006

Print Name KIN SHUK

GENERAL STAFF RESEARCH/EVALUATIONS

Declaration for General Staff Applicant

I have read the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants and discussed the ethical analysis with my Supervisor. I understand my obligations and the rights of the participants. I agree to undertake the research as set out in the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants. The information contained in this notification is to the very best of my knowledge accurate and not misleading.

General Staff Applicant's Signature ______________________ Date: ____________

Declaration for Line Manager

I declare that to the best of my knowledge, this notification complies with the Code of Ethical Conduct for Research, Teaching and Evaluations involving Human Participants and that I have approved its content and agreed that it can be submitted.

Line Manager's Signature ______________________ Date: ____________

Print Name ______________________

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