NEURAL NETWORK MODEL OF MEMORY REINFORCEMENT FOR TEXT-BASED INTELLIGENT TUTORING SYSTEM

By

FENG WANG, B.Eng., M.Eng.

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AUTHOR: Feng Wang, B.Eng. (Chengdu Science and Technology University, Chengdu, P.R. China), M.Eng. (Chongqing University, Chongqing, P.R. China).

SUPERVISOR: Professor Ali R. Montazemi

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Abstract

Information technology is generally believed to enhance learning processes. As a result, researchers are beginning to seek new theories and approaches towards developing information technology enabled learning environments. The focus of the research in this thesis is to provide the structure of an intelligent tutoring system (called MIS-Tutor) that we developed in support of mastery learning for students registered in a university-level management information system course. We adopted formative evaluation, spanning over 4 years and that included the participation of 1,328 students, to evaluate the effectiveness of the MIS-Tutor. An important component of this intelligent tutoring system is the ability to adapt its interaction to individual learning behaviour. This is achieved by means of neural network models to reinforce long-term memory retention and to assess the required time-on-task for each student. The results of our formative evaluation support the effectiveness of the proposed models in support of students' mastery learning.

Dedication

To my parents: Shuwo Liu and Guangying Wang,
and my Wife: Mei Lei

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Abbreviations

AI	-	Artificial Intelligence
CAI	-	Computer-Assisted Instruction
CBI	-	Computer-Based Instruction
CBT	-	Computer-Based Training
ICAI	-	Intelligent Computer Assisted Instruction
ITS	-	Intelligent Tutoring System
MIS	-	Management Information System
MIST	-	Management Information System Tutor
MIST-1	-	Management Information System Tutor Version 1 (used in 1993)
MIST-2	-	Management Information System Tutor Version 2 (used in 1994)
MIST-3	-	Management Information System Tutor Version 3 (used in 1995)
NRE	-	Neural Retention Estimator
NTE	-	Neural Time Estimator

1. Introduction

1.1 Introduction

Increasingly, it is expected that information technology will be used to enhance learning and teaching processes. This expectation is based on the notion that information technology, by supporting interactive instruction, will encourage students to become more responsible for their own learning. It is argued that information technology can help students learn the elementary and fundamental issues that underlie a course, thereby freeing faculty to work with them on the more complex and esoteric aspects of the course. Furthermore, information technology can facilitate assessment of learning more effectively and efficiently than traditional methods and improve feedback of assessment into educational design. In this endeavor, however, design of information technology should be based on well-grounded theories of learning processes (Leidner and Jarvenpaa, 1995). This is widely believed to be a challenging issue as evidenced in recent issues of Journal of Artificial Intelligence in Education (1996), MIS Quarterly (1995) and Communications of the ACM (1996). As a result, a variety of methodologies in support of computer-based tutoring (CBT) systems have been developed. Nonetheless, we still know little about the effectiveness of these proposed methodologies (Leidner and Jarvenpaa, 1995, Norman and Spohrer, 1996).

Thus the motivation for the research reported in this thesis was to develop an intelligent tutoring system in support of mastery learning and test its effectiveness.

1.2 On the Effectiveness of CBT

In the traditional education system, one teacher teaches a group of students. This style of teaching may neglect the unique capabilities of individual students. Each student has a different learning speed and different pre-existing long-term memories of facts and processes (Hudson, 1984). Therefore each student has a natural and effective learning speed. In addition, each person has his/her own unique attentiveness rhythm, which rises and falls regularly, every 90 minutes or so (Hudson, 1984). An ideal learning system should be able to pace itself to the requirements of individual students. In the traditional educational system, there is no way of achieving this ideal situation. No matter how carefully the instructor prepares his/her course of instruction, some of the more gifted students may feel they are wasting a proportion of their time spent in the classroom, while, at the same time, other less gifted students may be unable to keep up. This dichotomy has given rise to a consensus that suggests that tutorials, tailored to the needs of the individual students, provide the most effective form of learning processes in most domains (Nwana, 1990). Bloom (1984) in his comparison of group instruction with one-to-one tutoring found that 98% of those students provided with private tutors performed better than the average classroom students, even though all students spent the same amount of time learning the topic. Anderson et al. (1985) also found that students provided with private tutors spent less time than students provided only with classroom instruction to get to the same level of proficiency. A private human tutor, however, is rather too expensive for the average student and is not a viable alternative in a public education system. The promise of computer-based tutors is that they could make available the benefits of individualized instruction to all students at affordable costs (Anderson 1992).

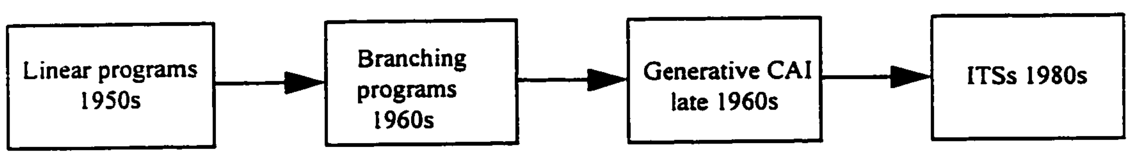
Current investigations indicate that, when compared to the traditional classroom approach, the use of CBT improves learning (Anderson et al., 1985; Burns and Bozeman, 1981; Corbett, 1990; Chambers and Sprecher, 1984; Deighan and Duncan, 1978; Eggert et al., 1992; Magidson, 1978; McKendree et al., 1992; Paden et al., 1977; Splittgerber, 1979). In addition, when compared to the traditional classroom approach, use of CBT reduces learning time (Anderson, 1985, 1992; Corbett et al., 1990; Chamber and Sprecher, 1984; Deighan and Duncan, 1978; Eggert et al., 1992; Kulik et al., 1980, Magidson, 1979). Furthermore, it is becoming clear that students develop more positive attitudes toward computers in general as a result of exposure to CBT (Chambers and Sprecher, 1984; Eggert et al., 1992; Kulik et al., 1980; Magidson, 1978; Splittgerber, 1979).

1.3 Literature Review of Computer-Based Tutoring Systems

Some major stages have accompanied the metamorphosis of the CBT (see Figure 1.1). The earliest application of the computer in education can be identified as computer-assisted instruction (CAI). Application of CAI, which was initiated in the early 1950s, was based on Skinner's theory of behaviour modification (1958). The overall architecture of a CAI tool can be described as follows: first the program output a frame of text, the intention of which was to take a student a small step towards the desired behaviour. The student then made a response based on what he/she already knew, or based on trial and error strategy! Finally the program informed the student whether he/she had selected the correct response to the questions posed by the system. A stream of such steps formed what is known as a "linear program". The student worked through the materials at his/her own pace, and his/her correct replies were rewarded immediately (Yazdani, 1987).

Figure 1.1

CAI to ITS Metamorphosis



During 1960s, another architecture emerged - this time in the form of branch programs. Branch programs presented some materials to the student. After the student responded to these materials, the system checked the student's response, and based on its evaluation of the response, the student received feedback, usually in the form of a request for the student to repeat the section or to move on to another section in a predetermined sequence. Two students would not in general receive the same feedback. Less able students would receive materials that were more explanatory than materials presented to more able students. But to build such a system is a time-consuming and wearisome exercise for the builder, because all the materials and possible branches need to be coded into the system in advance; the only way to make the system adequately adaptive is to add extensive materials and a complex and subtle branching test. Although special programming languages (authoring language) have been developed to help build such systems it is by no means a trivial programming task to ensure that all possible paths through the materials are complete and sensible (Yazdani, 1987).

Despite significant evolution in the development of CAI, the systems just described had no ability to perform inferencing (i.e., they merely stored information and could not answer "why" and "how" questions, if they were to be posed by the student). Carbonell defined branching systems as ad hoc-frame-oriented (AFO) CAI systems (Carbonell, 1970) because the teaching materials were stored in different frames. To improve the effectiveness of CAI, Carbonell proposed use of artificial intelligence (AI) in the CAI and constructed SCHOLAR. Carbonell's introduction of AI into CAI marked the beginning of the era of ITS (Nwana, 1990). For historical reasons, the ITS is sometimes referred to as Intelligent Computer Assisted Instruction (ICAI) by some researchers (Self, 1988). Many researchers, however, prefer the name intelligent tutoring system (ITS) (e.g. Nwana, 1990; Wenger, 1987). This preference is motivated by a claim that, in many ways, the significance of the shift in research methodology goes beyond the addition of an "I" to CAI (Wenger, 1987).

The field of ITS is dominated by two schools of thought. One school believes that, rather than merely pump the teacher's knowledge into the student, the learning process should help the student to build his/her own knowledge model. The process is based on the transformation of the factual knowledge into experiential knowledge (Schank and Edelson, 1989/90; Sleeman and Brown, 1982). The other school of thought believes that students should be guided by tutoring systems (Nwana, 1990). In this latter case, the student learns largely by receiving feedback about what is wrong with his/her choices (selection). This is appropriate for mastery learning environments. As a result, our proposed methodologies for the development of ITS, which we report in this thesis, follow the second school of thought. A literature review of the structure of ITS is now provided.

1.3.1 Architecture of an ITS

A variety of architectures for the development of an ITS are available. For example, LISP tutor (Anderson 1985) consists of four components as follows:

(1) Domain expert: The module, also referred to as the "ideal student" model, that has the capability of solving a variety of problem in a particular domain.

(2) Bug catalogue: An extensive library of common misconceptions and errors in a particular domain.

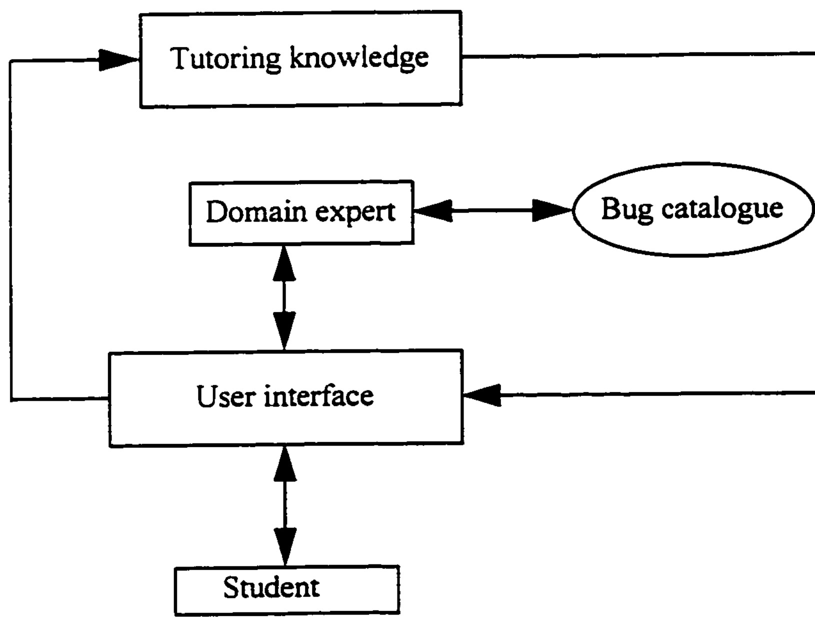
(3) Tutoring knowledge: The module that contains those strategies necessary to teach the domain knowledge.

(4) User interface: The module that administers the interaction between the tutor and the student.

The relationships among these components are depicted in Figure 1.2.

Figure 1.2

ITS Architecture Adopted from Anderson (1985)



Another ITS architecture proposed by Hartley and Sleeman (1973) consists of the following modules:

(1) Domain expert: A representation of the teaching task that includes not only specific objects, but also a task analysis that identifies the structure of the teaching materials.

(2) Student model: The representation of the student through his/her performance data.

(3) Teaching knowledge: The set of teaching operations that enables the instruction to proceed.

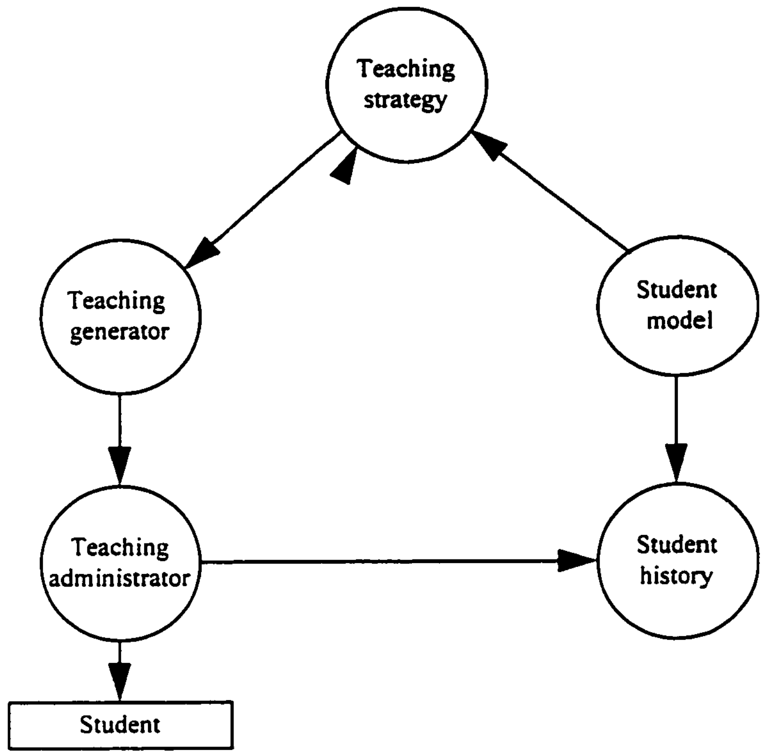
(4) A set of mean-ends guidance rules: Decision rules that state the conditions under which the teaching operations should be used for individual students.

Hartley and Sleeman's architecture differs from Anderson's LISP tutor (1985) inasmuch as it does not give primary importance to the representation of misconceptions in the domain (the bug catalogue). Instead, it introduces the student model as the primary component of the system (Yazdani 1987).

O'Shea et al.(1984) proposed a five-ring model, which includes the following: (1) Student history; (2) student model; (3) teaching strategy; (4) teaching generator; and (5) Teaching administrator. Here, the importance of domain knowledge and misconcepts are undermined in favour of an emphasis on the importance of various teaching skills (see Figure 1.3).

Figure 1.3

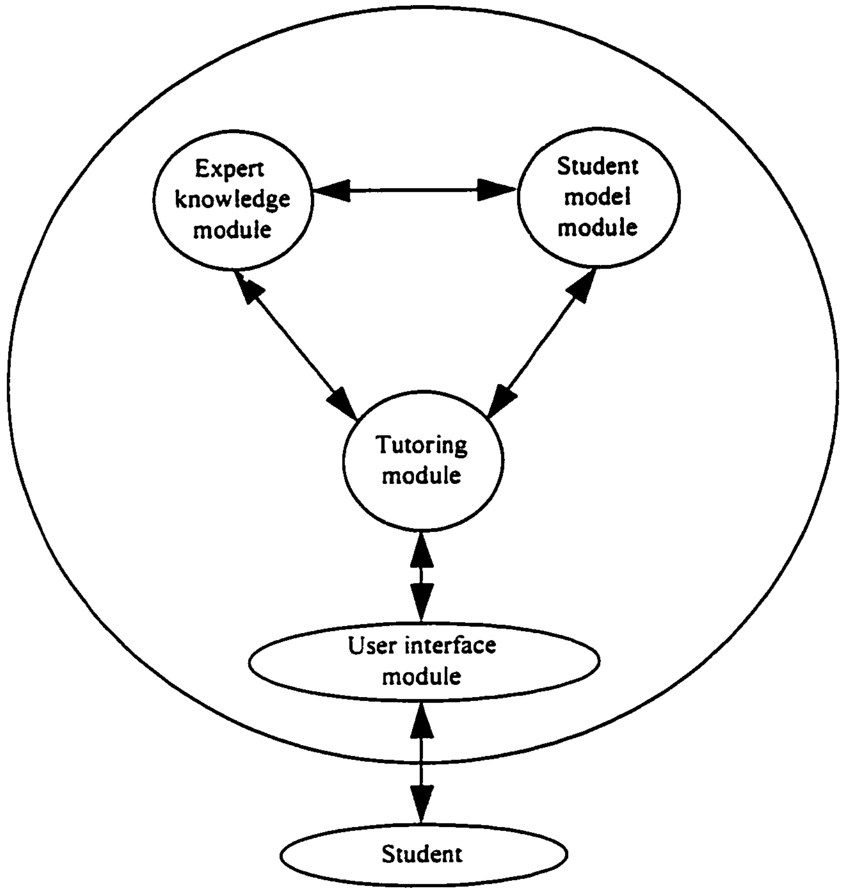
ITS Architecture Adopted from O'Shea et al. (1984)



Although it is rare to find two ITSs based on the same architecture (Nwana 1990), a considerable consensus in the literature suggests that an ITS should consist of four basic components as depicted in Figure 1.4 (Wenger 1987; Burn & Capps 1988; Barr & Feigenbaum 1982).

Figure 1.4

A General Architecture for ITS



Expert knowledge modules are used to solve problem and make inferences. The main promise of computer tutors lies in their potential for moment-by-moment adaptation of instructional content and their ability to conform to the changing cognitive needs of individual learners (Ohlsson, 1987). To fulfill this goal, in order to set up a dynamic student model (a cognitive diagnosis), the ITSs must be aware of an individual student's cognitive state. The Student model is utilized by diagnosis procedures to make an approximation of the student's state of knowledge and learning ability. Since a student may not possess the same knowledge as the expert, the tutoring module should embody the strategies necessary to reduce the difference between the student's and the expert's performance. Whereas the tutoring module decides on issues relating to timeliness and content, the interface module takes care of interaction (communication) with the student. The user interface, which acts as a translator between the system and the student, affects communication in two ways. First, when the ITS presents a topic, the interface makes its presentation more or less understandable. Also, because the interface is the final form in which a system presents itself to a student, ease of use is crucial. Second, progress in media technology is providing increasingly sophisticated tools, whose communicative power can drive the design of the entire system (Wenger, 1987). The interface, of course, should be built with the student in mind so that he/she integrates well into the ITS.

1.4 Objective of This Research

A frequent charge leveled against the CBT systems is that they often seem to be designed to exploit the capabilities of technology rather than to meet instructional needs; that is, that they are technology based rather than theory based (Clancy, 1993; Koschmann, 1994; Ohlsson, 1991; Livergood, 1991). For example, Ohlsson (1991) states that

> The evaluation of an instructional system should focus on the pedagogical hypothesis that informed the design of the system, not on the system itself. Most instructional systems developed by researchers never leave the laboratory, so their usefulness is not an issue. We do not primarily want to know whether such a system works in the sense that students can learn from it, but whether the underlying hypothesis is true. Empirical data should be collected in such a way that they allow us to evaluate the empirical adequacy of that research. (p.13)

The question raised is how might we apply instructional theories relating to the design of CBT systems to promote effective learning. The goal of the research reported in this thesis, is to apply formative evaluation to assess the effectiveness of application of two adaptive neural network models designed to reinforce long-term memory retention of students in a management information system (MIS) course. To this end, we performed a longitudinal investigation that spanned 4 years and that included the participation of 1,328 students.

This dissertation is organized as follows: Chapter two provides a rationale in support of mastery learning and long-term retention of learning materials; chapter three evaluates the basic theories on the effect of reinforcing the long-term retention of information with a view to proposing two adaptive neural network models and proposes six hypotheses on the effectiveness of the proposed models in support of mastery learning; chapter four outlines the methodology adopted to assess the stated hypotheses; and chapter five analyzes the stated hypotheses. A discussion and an overview of the implication for practice and future research close the thesis.

2. Mastery Learning and Memory Retention

2.1 Introduction

The goal of this research was to design and develop a methodology in support of long-term memory enhancement of text-based mastery learning. Therefore, we first present an overview of factors affecting mastery learning. This provides a context to portray the importance of long-term retention of learning materials. Section 2.3 provides a literature review of findings related to long-term retention of learning materials and CBT support in the ACT model. This review provides the bases for our investigational goal which is described in section 2.4.

2.2 Factors Affecting Mastery Learning

Learning is a change in human disposition or capabilities that persists over a period of time and that is not simply ascribable to processes of growth (Gagne, 1985). This kind of change called learning exhibits itself as a change in behaviour. The inference of learning is made by comparing what behaviour was possible before the individual was placed in a learning situation and what behaviour is exhibited afterwards. The change may be, and often is, an increased capability for some type of performance. Learning may also be an altered disposition, of the sort called attitude, interest, or value.

Instruction can be viewed as a set of events external to the learner, which are designed to support the internal process of learning (Gagne, 1977). Specifically, events that make up the process of learning are believed to take place in an approximately ordered sequence as follows (Gagne and Dick, 1983): (a) gaining attention, (b) informing the learner of the objective, (c) stimulating recall of prerequisites, (d) presenting the stimulus material, (e) providing feedback, (f) assessing the performance, and (g) enhancing retention of learning materials. The goal of this research is to develop a methodology for the development of an intelligent tutoring system (ITS) to enhance retention of text-based learning materials in support of mastery learning. To this end, we elaborate on the issues affecting long-term retention of learning materials in the next section.

2.3 Long-Term Retention of Learning Materials

Only a portion of the information we acquire becomes part of permanent knowledge. Knowledge is acquired over extended periods of time, during which actual practice is limited to relatively short periods, spaced at intervals. Practice sessions may be more or less clearly defined, but in most instances, intervals intercede between sessions. Without repeated exposure to the same information, only a small portion of the information acquired during the original exposure remains directly recallable on a permanent basis (Bahrick, 1979). Research findings show that the effect of repetition is greater when memory for an earlier presentation of the repeated item is less accessible

(Cuddy and Jacoby, 1982). We adopt the J. Anderson's (1976) ACT model to elaborate on the problem of long-term retention of information.

The ACT model proposes that human cognition is made up of two systems: a propositional network and a set of productions. A propositional network is a set of nodes connected by links. The nodes generally represent ideas, and the links represent some sort of relationship between these ideas. The propositional network is likened by Anderson to declarative knowledge. Productions, on the other hand, represent procedural knowledge. Sets of productions can be represented formally as computer programs. Two assumptions of ACT are especially relevant to a discussion of long-term retention of information as follows:

1. All nodes, links, and productions, once created, are non-erasable. This implies that failures in memory are due to failures in retrieval, rather than to absolute loss of previously stored information.
2. Every time a link is used to activate a production (i.e., every time it matches the condition of a production), its strength is increased incrementally by one unit. This suggests that use is an important determinant in the ability to retrieve knowledge.

The act of testing long-term retention would be viewed in the ACT model in the following manner: Some probe stimulus (often a question) is given to the learner to stimulate recall. The learner has a standard set of productions that parses and encodes the probe stimulus into the propositional network. Activation proceeds from this part of the network to closely related parts. From any one node, activation is distributed down all links emanating from it, in proportion to their relative strengths. The process is terminated when either the appropriate information has been retrieved or a certain amount of time has passed without successful retrieval. A major performance limitation of ACT is that it encodes association in memory with a predetermined probability for retention of information (J. Anderson, 1976), thereby, making it difficult to dynamically adapt to idiosyncrasies of individual students. The question arises how might we develop an adaptive model of long-term retention of information, and it was this question that provided the motivation for our investigation.

2.4 Investigational Goal

Our goal was to develop and to assess the effectiveness of an adaptive neural-network model for reinforcing the long-term retention of information learned from text-based materials. Repeated reading is a recognized method of improving a learner's memory (Anderson, 1980; Barnett and Seefeldt, 1989; Durgunoglu, et al., 1993). The process of repetition can be massed or spaced/distributed (Wickelgren, 1977). In massed repetition, no time interval occurs between two presentations of the same material. Spaced repetition, however, provides an elapsed time between repetitions of the same material. Evidence suggests that spaced repetition is superior to massed repetition (Cuddy and Jacoby, 1982; Greene, 1989; Krug et al., 1990). For example, Cuddy and Jacoby (1982) stated that "we believe that repeated processing of an item can enhance memory performance but that processing will only be repeated if memory for a prior presentation of an item is not readily accessible" (p.464).

The total knowledge acquisition process can therefore be conceived of as a cycle of acquisition, loss, and reacquisition of knowledge (Bahrick, 1979). Effective use of spaced repetition toward enhancing knowledge acquisition requires a model to predict the course of the decay of learning materials over time as a function of the cognitive demands of learning task and the individual learner's ability (Farr, 1987). Five factors affect a learner's long-term retention of learning materials as follows (Farr, 1987):

1. Degree of original learning/mastery;
2. Instructional strategies/conditions of learning;
3. Methods of testing retention/condition of retrieval;
4. Task characteristics that consist of task type and task complexity/difficulty; and
5. Retention interval (elapsed time).

As can be noted, to enhance students' long-term retention of learning materials, we need to assess students' degree of original learning/mastery (i.e., factor 1 in the above list). It is believed that the amount a student learns is a direct result of the amount of time he/she spends learning (time-on-task). Therefore, an optimal amount of time spent by the student to learn a subject matter has a direct effect on enhancing his/her long-term retention of learning materials. Justification for this is given next.

2.4.1 On the Effectiveness of Time-on-Task

In both educational and psychological research, instructional time, in relation to learning, is conventionally regarded as a dependent variable (L. Anderson, 1976; Gettinger, 1985). In cognitive terms, process learning time is viewed as a direct measure of a student's mental processing effort (Anderson, 1978), or as a measure of efficiency to test optimization schemes in adaptive instructional strategies (Belland et al., 1985; Scandura, 1977; Tennyson and Park, 1984). Evidence also suggests that learning time is a stronger correlate of school learning than is IQ (Gettinger and White, 1979). Thus, instructional programs should be designed to allow variations in the instructional time made available to students. In design of CBI systems, two strategies have been adopted to allow this variation: self-pacing and externally controlled pacing. Research into the effectiveness of these two types of pacing has produced equivocal results (Reiser, 1984). For example, Belland et al. (1985) found that moderate external pacing of CBI increases learner attention, and as a result, allows the learner to acquire more information in less time than he/she would have done in a self-paced instructional program. However, the problem with external pacing is its effect on a student's motivation to learn (Hannafin and Sullivan, 1995). It is the self-determined form of motivation that positively predicts high quality learning and personal adjustment in school (Deci and Ryan, 1985 & 1994). A recent meta-analysis, in fact, provides evidence for the effectiveness of learner control (Goforth, 1994). Previous conflicting findings, makes the development of a system that allows an optimal allocation of control between the learner and tutoring system a necessity

(Goforth, 1994). This provided the motivation for developing a methodology for an optimal allocation of control between the learner and tutoring system.

3. Proposed Methodologies for ITS

3.1 Introduction

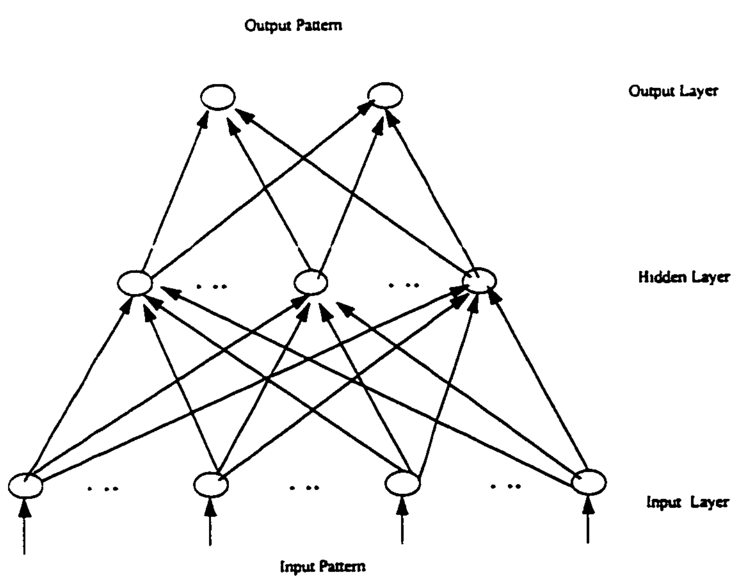
The goal of this research was to develop a methodology for an ITS to enhance retention of text-based learning materials in support of mastery learning. To this end, neural network technology was adopted to develop a methodology to assess the students' optimal time-on-task. Next, this model of time-on-task was used in conjunction with another neural network model to assess the students' retention of long-term prerequisite learning materials. In this chapter, we first provide a brief description of the neural network technology used in this research. Next, the neural network model of time-on-task, and long-term decay of learning materials by individual students is presented. In section 3.4, we postulate six hypotheses toward the goal of this research. Moderating effect of personal factors on the stated hypotheses is presented in section 3.5.

3.2 Neural Network Technology for Estimating Time-on-Task

Interest is growing in the application of neural network technology to the design and development of ITS (e.g., See Mengel and Lively, 1990/91; Papa et al., 1994; Russell, 1992; Shankam and Cooley, 1991). A neural network is an information processing system that is nonalgorithmic, nondigital, and intensely parallel (Caudill and Butler, 1992). Basically, a neural network consists of a number of very simple and highly interconnected processors called neurons; these are analogous of the biological neurons of the human brain (See Figure 3.1). In a neural network, neurons are connected by a large number of links over which signals pass. Each neuron is associated with a number, referred to as the neuron's activation. Similarly, each link in a network also has a number associated with it, called its weight. A neuron in a neural network receives input stimuli along its input connections and translates those stimuli into an output response through an activation function.

Figure 3.1

Structure of a Neural Network



Learning and training are fundamental to almost all models of neural network. Training is the procedure by which the network learns; learning is the end result of that procedure. A neural network can be trained in two ways: supervised and unsupervised. In this research, we use supervised training. To this end, the network is provided with an input stimulus pattern along with the corresponding desired output pattern. The learning rule for such a network typically computes an error that is the difference between the desired output and the output computed by the network. This error is then used to modify the weights on the interconnections between the neurons.

Many paradigms can be used to construct and train a neural network. One of the first major feedforward paradigms was perceptron proposed by Rosenblatt (1958). Backpropagation was derived from this paradigm. Backpropagation allows a network to memorize far more patterns than the number of neurons in its network. In this research, we used a fully connected backpropagation paradigm to construct and train our neural network to estimate the time-on-task required by individual students to successfully complete learning lessons (called neural time estimator), and to estimate the long-term decay of learning materials by individual students (called neural retention estimator). The models of neural time estimator (NTE) and neural retention estimator (NRE) are presented below.

3.3 The Models of NTE and NRE

The input pattern of NTE consisted of learning contents dependent factors (LC_i) and the student's learning rate (LR) (See Figure 3.2). The former included two variables -- the degree of difficulty of the learning-lesson i (D_i) and the size of the learning-lesson i (S_i). The value of D_i was based on students' performance in phase two of the study, and the value of S_i was based on the number of words in the learning-lesson i. The student's learning rate was computed as a function of the time required to master previous learning-lessons (T_p). The output of NTE had one neuron to represent the required time-on-task for each student.

We contemplated measurement of the input pattern of NRE by means of the following three factors: (1) individual retention ability (measured in form of response to questions in retention test) (Q_p); (2) task complexity (measured in form of complexity of each learning-lesson) (D_i); and (3) retention interval (measured as elapsed time since the learning-lesson was learned) (E_i). The output of the NRE had two neurons to represent the strength of a student's long-term memory of the prerequisite learning lesson: one neuron represented "forgotten" (F_i), the other neuron represented "not forgotten" (R_i) (See Figure 3.3). The methodology used to train the NTE and NRE is presented in Chapter 4.

Figure 3.2

Neural Network Model of Neural Time Estimator (NTE)

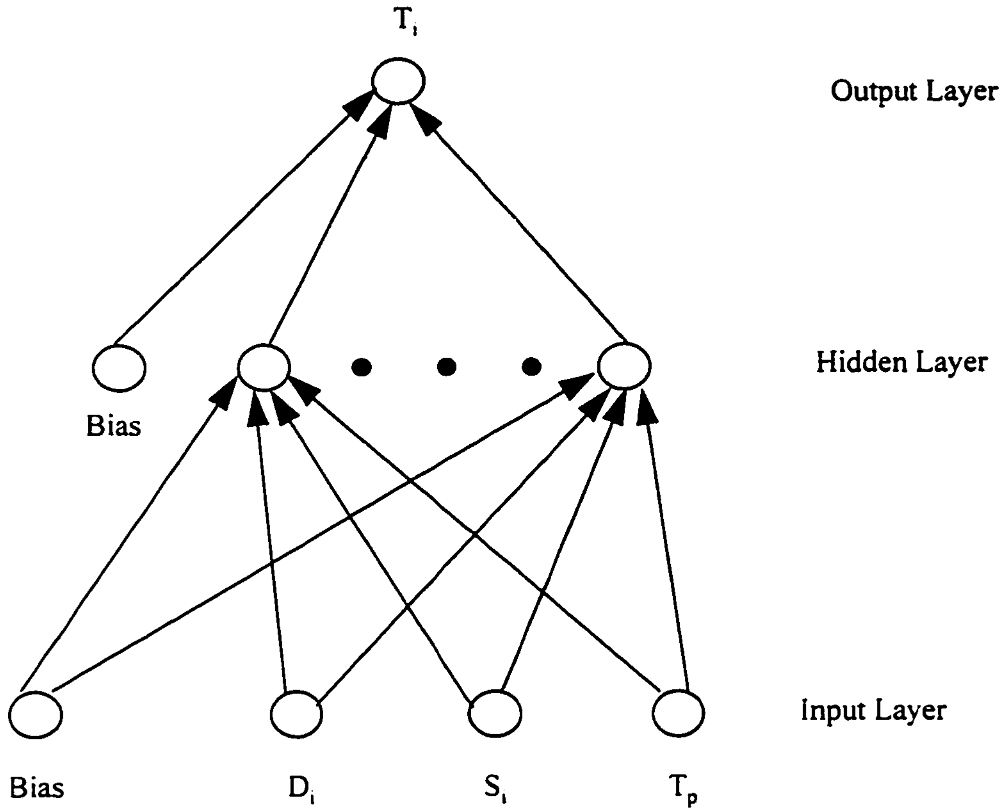
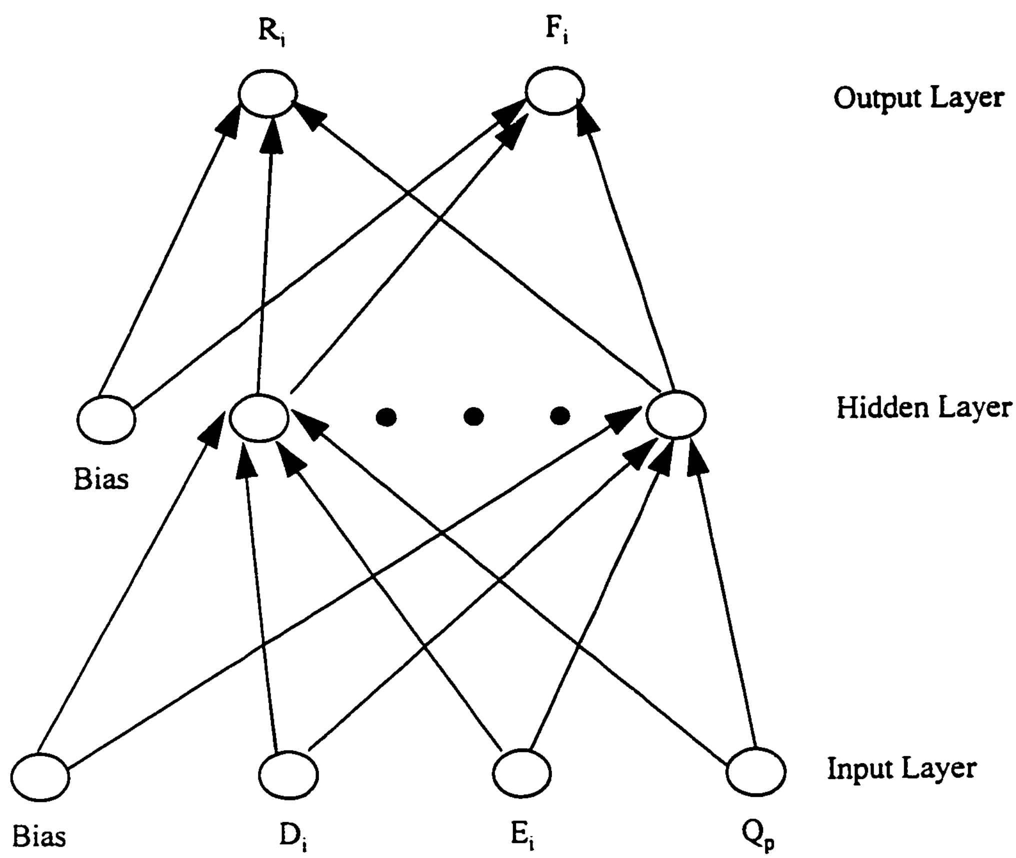


Figure 3.3

Neural Network Model of Neural Retention Estimator (NRE)



3.4 Investigational Hypotheses

The question raised in this research is whether CBT systems can be effective in their support of mastery learning. Bloom (1971, 1976) contends that the amount a student learns is a direct result of the amount of time he/she spends learning (i.e., time-on-task).

It is assumed that in the initial stages of a learning sequence, extra time will be needed by some students. The result is a considerable degree of time variability vis-à-vis individual students. However, it is postulated that mastery of prerequisite learning material enables all students to approach new material with similar motivation and similar relevant knowledge. Consequently, all students will be able to learn at similar, efficient learning rates. Slower students will gradually become similar to faster students until a "vanishing point" of individual differences is reached (L. Anderson, 1976; Bloom, 1976, 1974, 1971).

Based on previous findings in mastery learning, we can postulate the following three hypotheses.

Hypothesis 1. The amount a student learns is a direct result of the amount of time he/she spends learning (time-on-task).

Hypothesis 2. The difference among the students on the amount of time spent on a task diminishes as they progress through the lessons.

Hypothesis 3. The difference in performance among students diminishes as they progress through the lessons.

The three stated hypotheses are based on findings gleaned from the literature on mastery learning in which student learning was supported by human tutors. Starting from this base, our investigation moves beyond reliance on the human tutor. Underpinning our research is the implicit assumption that a one-to-one learning environment, supported by

CBI, results in achieving all benefits related to mastery learning (Nwana, 1990). There are limited empirical findings in support of this assumption (Niemiec and Walberg, 1987).

Furthermore, we expect that the added functionality of NTE and NRE, based on the above discussion, improves students' mastery learning. We postulate the following three hypotheses as follows: when a student is involved in learning text-based materials

Hypothesis 4. Inclusion of NTE in MIST improves student's mastery learning.

Hypothesis 5. Inclusion of NRE in MIST improves student's mastery learning.

Hypothesis 6. Spaced repetition is superior to massed repetition with respect to the student's mastery learning.

We contemplated possible effect of personal factors in testing the above hypotheses. Justification for the choice of personal factors adopted in this research is presented next.

3.5 Moderating Effect of Personal Factors

As noted before, NTE and NRE were incorporated into a CBI system called MIST to test the stated hypotheses. However, the effectiveness of computerized systems such as MIST can be compromised because of the personal factors such as negative emotional reaction towards the use of computers. In addition, students' metacognition strategies towards self-regulated learning and motivation to learn can affect the usefulness of the MIST. Therefore, we contemplated the moderating effect of two categories of personal factors on the assessment of the stated hypotheses. The first category included two factors to measure the students' attitude towards computer use. The second category of personal factors consisted of five factors to measure the students' motivational and self-regulated learning components of classroom performance.

Research findings show that attitude (personal factors) can influence how an application system is used by an individual (e.g., Carlson and Wright, 1993; Campeau and Higgins, 1995; Gardner et al., 1993; Howard et al., 1993). Attitudes can be defined as internal states that moderate the personal action choices made by an individual (Gagne, 1985). Generally, attitudes are considered to have affective (emotional) components, cognitive aspects, and behavioral consequences. Here, we emphasize the behavioral consequences of attitude and their relationship to choices of action made by an individual. The internal states that influence these actions may possess both intellectual and emotional aspects. However, it is their outcome in human performance that provides the point of reference for our description of attitude as learned disposition. Therefore, to control any extraneous variance due to personal factors, we partial them out of the dependent variable (i.e., mastery learning performance). If the variance of individual differences is not isolated, it becomes part of the error term that leads to a less precise analysis of a stated hypothesis.

3.5.1 Moderating Effect of Personal Factors on Computer Use

The personal factors, affecting computer use, considered in this investigation were computer anxiety and computer efficacy. Most definitions of computer anxiety focus on negative emotional reactions towards the use, or anticipated use, of computers, which are perceived as personally threatening to the user (Gardner et al., 1993). Individuals who experience computer anxiety exhibit behavior such as avoiding contact with computers, minimizing the amount of time they spend operating them, and being excessively cautious while using them (Maurer and Simonson, 1984).

Self-efficacy is defined as one's belief in one's ability to perform a specific task (Bandura, 1977). Several recent studies have examined the relationship between self-efficacy with respect to using computers and a variety of computer behavior (e.g., Campeau and Higgins, 1995; Gist et al., 1989; Hill et al., 1987). These studies evidence a relationship between self-efficacy and registration in university computer courses (Hill et al., 1987) and performance in software training (Campeau and Higgins, 1995; Gist et al., 1989).

3.5.2 Moderating Effect of Motivation and Self-Regulated Learning

Self-regulated learning and motivation are important aspects of student learning and academic performance (Corno and Mandinach, 1983; Corno and Rohrkemper, 1985). Self-regulated learning includes students' metacognitive strategies for planning, monitoring, and modifying their cognition (Corno, 1986; Zimmerman and Pons, 1986). Self-regulated learning consists of two components: (a) cognitive strategy and (b) self-regulation. Different cognitive strategies have been found to foster active cognitive engagement in learning and result in higher levels of achievement (Weinstein and Mayer, 1986). While, self-regulation is the students' management and control of their effort on classroom academic tasks. For example, capable students who persist at a difficult task or block out distracters (i.e., noisy classmates) maintain their cognitive engagement in the task, enabling them to perform better (Corno, 1986; Corno and Rohrkemper, 1985).

Students must be motivated to use strategies to regulate their cognition and effort (Pintrich, 1988, 1989). Research findings suggests that students with a motivational orientation involving goals of mastery, learning, and challenge, as well as beliefs that the task is interesting and important, will engage in more metacognitive activity, more cognitive strategy use, and more effective effort management (Ames and Archer, 1988; Meece et. al., 1988; Nolen, 1988). The theoretical framework for conceptualizing student motivation is an adaptation of a general expectancy-value model of motivation (Pintrich, 1988, 1989). The model proposes that there are three motivational components that can be linked to the components of self-regulated learning: (a) an expectancy component, which includes students' beliefs about their ability to perform a task (i.e., self-efficacy), (b) a value component, which includes students' goals and beliefs about the importance and interest of the task (i.e., intrinsic value), and (c) an affective component, which includes students' emotional reactions to the task (i.e., test anxiety).

4. Empirical Evaluation Methodology

4.1 Introduction

Formative evaluation was adopted for assessing the stated hypotheses. This evaluation strategy is based on the notion that the development of an instructional system should be informed by successive evaluation along the way to a completed design. The systematic integration of various strategies, through repeated studies and the addition of one strategy at a time, holds the promise to lead to the point where the characteristics of an effective instructional program can be defined in a generalizable manner (Seidel and Park, 1994; Winne, 1993).

Our experiment was performed in four phases of a university level management information system (MIS) course. First, the performance of 454 undergraduates, who had registered in the course in the Fall of 1992, was tested with human tutors. In phase two, a CBI system (called MIS Tutor version one "MIST-1"), which incorporated a self-pacing procedure, was introduced, and the performance of 333 students, who had registered in the Fall term of 1993, was assessed (Montazemi and Wang, 1995a). The data collected in this second phase were used to develop a neural network (called neural time estimator "NTE") for external-pacing. The NTE was embedded in the MIST (called MIST-2), and its effect on the performance of 273 students was measured in the

Fall of 1994 (Montazemi and Wang, 1995b). The data collected in this third phase were used to develop a neural network (called neural retention estimator "NRE") for assessing a learner's long-term retention of learning materials. The NRE was embedded in the MIST-2 (called MIST-3), and its effect on the performance of 268 students was measured in the Fall of 1995. A detailed description of the methodology used in this research follows.

4.2 Environment

The MIS course, in which our students had registered, covers a wide range of topics fundamental to an understanding of the subject matter (e.g., See Zwass, 1992). One objective in the course was to ensure that students learned basic concepts, facts, and methodologies (i.e., achieved mastery learning). The second objective was to enable students to discover the myriad of complexities that impact on the application of information technology in an organization. Mastery learning was supported by means of MIST. This enabled us to devote class-time toward the second objective of the course. To this end, based on basic knowledge, students used case studies and became involved in projects and class discussions to discover issues that affect the implementation and use of information technology.

4.3 Instrument

Access to the MIST system could be gained at will from microcomputers located in two micro-labs. During the first week of the term, students attended a tutorial session held in a micro-lab so that they could familiarize themselves with MIST system. This was achieved by walking students through different functions embedded in MIST. Before using MIST, students completed three questionnaires to assess their levels of computer anxiety and computer efficacy, self-regulated learning and motivation. To reflect a fear of using computers, the fourteen items identified by Kernan and Howard (1990) were adopted to measure computer anxiety (See Appendix 1-A). Computer efficacy was measured using the four-item questionnaire developed by Hill et al. (1987) (See Appendix 1-B). Self-regulated learning and motivation were measured using the 44-item questionnaire developed by Pintrich and De Groot (1990) (See Appendix 1-C).

4.3.1 MIST System Structure

Four levels of conscious processing, over which a learner can exercise deliberate control, are postulated to exist (Merrill, 1984): content selection, display selection, conscious cognition, and meta-cognition. Merrill contends

> Content selection refers to a decision by the learner about what objective (segment, lesson or unit) to study next. Display selection refers to a decision by the learner about what type of presentation s/he wishes to study next. Conscious cognition refers to the mental processes the student uses to encode the information presented by the given display. Meta-cognition refers to the "how to study" model which the student

> uses to guide her/his interaction with the instructional system being used (p.223).

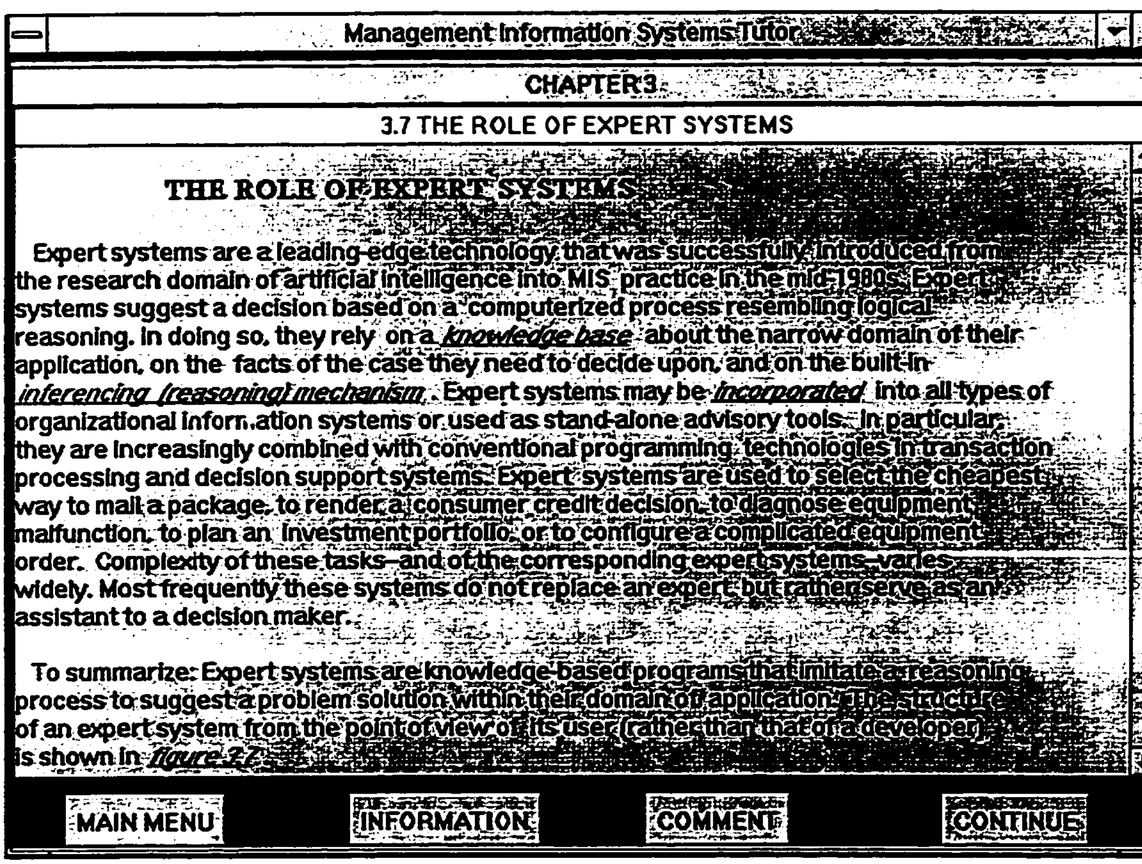
An overlay model of CBI (Ohlsson, 1993) was adopted for the development of the MIST (See 4.3.3.1 for a detailed description of overlay model). This model made possible the control of content selection, display selection, and the metacognition rules used by students to select content or displays. Consequently, any variation in learning and performance among the students could be attributed to conscious cognition, including the student's goal orientation toward the course material.

Student goals can have both intrinsic and extrinsic orientation (Pintrich and Garcia, 1991). Intrinsic reasons for performing in a classroom setting include rationales such as wanting to learn more, being challenged, being curious, and attempting to understand the course material in depth. Simultaneously, students may have extrinsic reasons for attempting class work, and these include achieving good grades, proving they are more intelligent than their fellow students, and seeking approval from others, such as family or friends.

To support a learner's extrinsic goals, a learner-control advisement condition was incorporated into the design of the MIST. Tennyson (1981) found that a learner-control condition can be a valuable CBI management strategy, if the students receive sufficient information about their progress -- information that continuously demonstrates what progress they are making toward mastery of the objective and that provides meaningful advice on the appropriate stimuli necessary to obtain it (See Figure 4.1).

Figure 4.1

A Learning-Lesson with Hyper-Bottons (Underlined)
The Information Button, at the Buttom of the Screen, Informs the Student of His/Her Progress through the Lessons



To support a learner's intrinsic goal, hypermedia technology was used in the development of MIST (McGraw, 1994). Hypermedia technology enabled the learner to control his/her path through the material in each learning-lesson (within the limit created by the instructional designer in the form of hyper-button). The learner could match his/her style to the hypermedia product and browse as interest demanded. Kearsely (1988) contends that hypermedia links facilitate remembering, concept formation, and understanding. The hypermedia links were similar in structure to those in the instructional hypertext design reported by Kelly and O'Donnell (1994). The screen design of the MIST corresponded to guidelines suggested by Jeiven (1994).

4.3.2 MIST's Instructional Structure

The intellectual skills to be taught in a particular instructional program should always be identified (Torshen, 1977). Teaching these skills should be sequenced so that students master basic skills before they attempt to learn the more advanced ones (Resnick, 1981). MIST's teaching style was adopted from the pre-structured teaching materials as laid out in a MIS text book authored by Zwass (1992). The structure of material in this text follows closely the elaboration theory of instruction (Reigeluth, 1979; Reigeluth et al., 1978). The text begins with a wide-angle view of MIS, which gradually increases the detail and complexity of its parts by zooming in on them. The wide angle view is revisited once more to integrate specific information with the larger whole and to review previous instruction. This structure is believed to enhance learning, retention, and learning transfer (Gagne and Dick, 1983). The Zwass text comprised twenty chapters (See Appendix 2), each being divided into sections, with each section consisting of several learning-lessons and which included text materials.

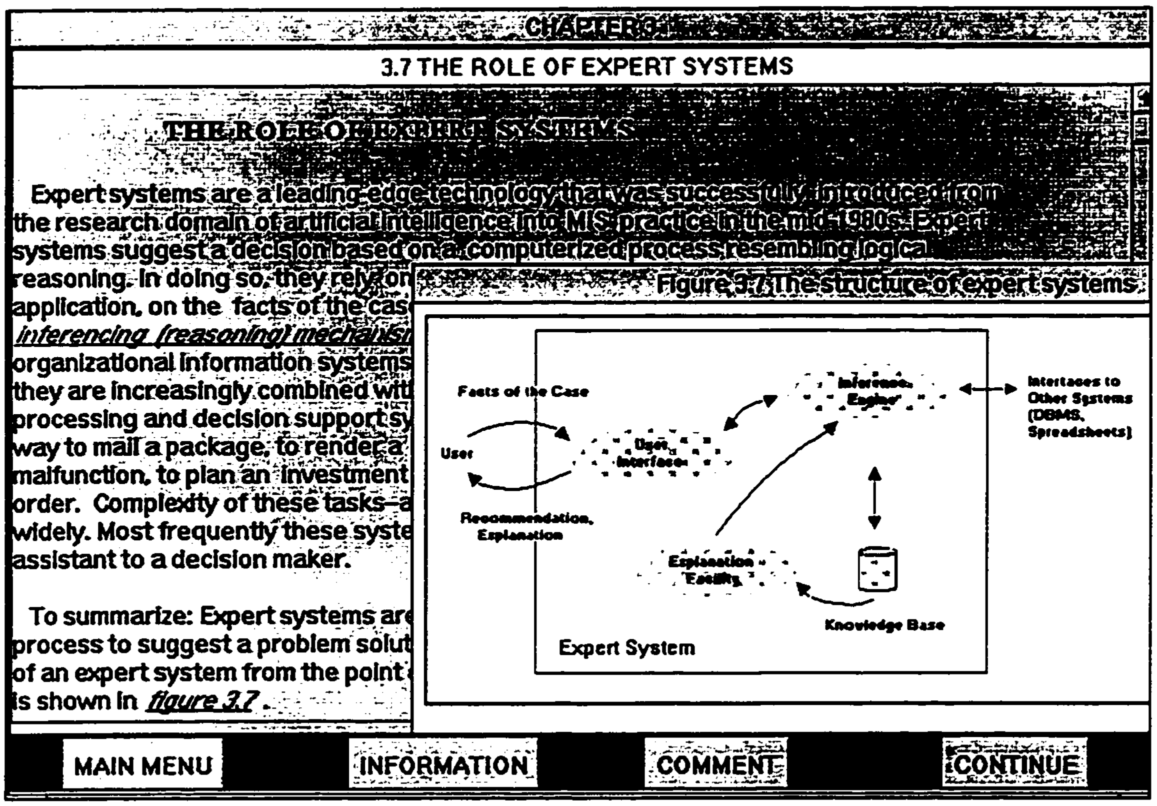
4.3.3 Overview of the Attributes of the Three Versions of MIST

4.3.3.1 Attributes Common to All Three Versions of MIST

1. The sequence of the learning-lessons was pre-specified: All learning-lessons within a section had to be successfully completed before a student was allowed to move on to the next. Hyper-buttons in each learning-lesson provided additional information in form of texts, figures, graphs, and pictures (See Figure 4.2). Selection of hyper-buttons was at the discretion of the individual students. The content of all sections of a chapter had to be mastered before a student could go on to the next.

Figure 4.2

An Example of the Content of a Hyper-Button in the Form of a Figure

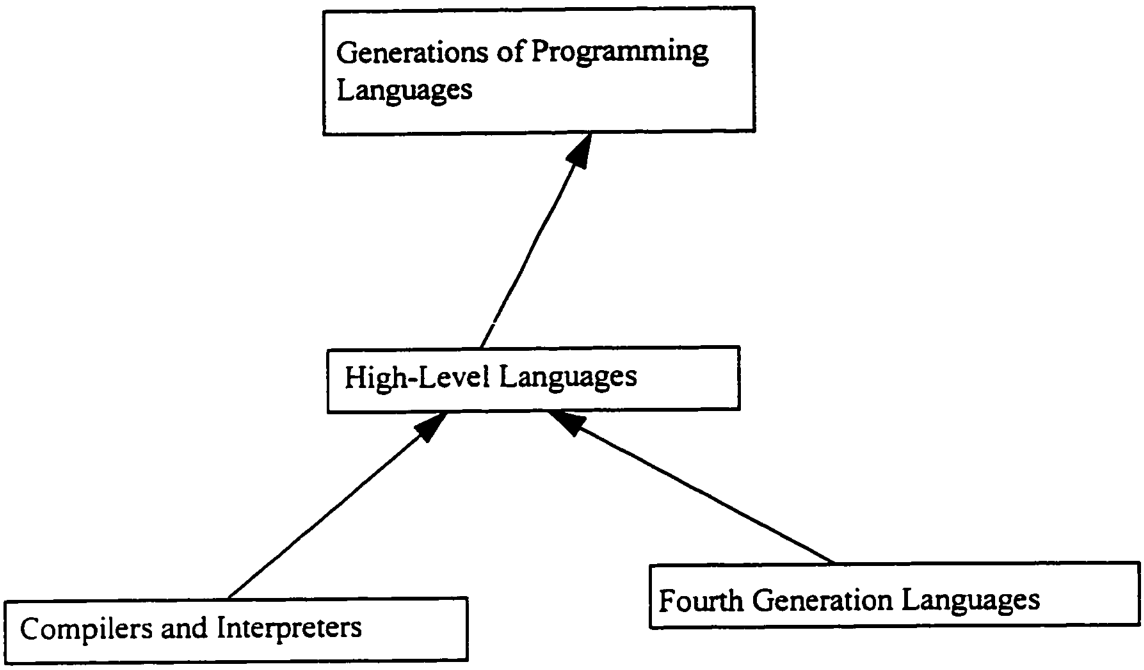


2. An overlay model of computer-based instruction was adopted for the development of the MIST to control the learning materials presented to the students. Overlay model consists of three software components. First, the subject matter must be organized into a set of learning lessons (knowledge items) (see Figure 4.3). The criterion for distinguishing two learning lessons X and Y (e.g., "*Compilers and Interpreters*" and "*Fourth generation Languages*") is that it is possible to learn X without acquiring Y, or vice versa. The items are then connected by prerequisite relations. A learning lesson X (e.g., "*Generations of Programming Languages*") is a prerequisite of another learning lesson Z (e.g., lesson "*High-Level Languages*") if X must be mastered before the learner is ready to learn Z.

The second component of an overlay model is a procedure for inferring which learning-lesson a particular learner has mastered at a particular point in time. The required inference is as follows: If mastery of learning lesson X (e.g., "Generations of the Programming Languages") is necessary for success on task of Y (e.g., correctly responding to a question in regard to "High-Level Languages"), and if the learner succeeds on Y, then mark learning-lesson X as learned.

Figure 4.3

Prerequisites Structure for Section 8 of Chapter 6



The third component of an overlay model is the rule to avoid teaching what the student already knows and to teach only those learning-lessons which he/she is ready to learn. The procedure for this is to select the next learning-lesson to teach, such that (a) it has not been acquired already, but (b) its prerequisites have all been mastered. For example, if the learner already learned lesson "Generations of Programming Languages" but has not learned the lessons "High-Level Languages", "Compilers and Interpreters" and "Fourth Generation Languages", then the next learning lesson he/she should learn is lesson "High-

Level Languages". Only after he/she learned the lesson "High-Level Languages", can he/she start to learn lesson "Compilers and Interpreters" or "Fourth Generation Languages".

3. MIST's teaching style was adopted from the pre-structured teaching materials as laid out in MIST text book authored by Zwass (1992) that comprised twenty chapters (See Appendix 2). Each chapter being divided into sections, with each section consisting of several learning-lessons. MIST consisted of 365 learning lessons. All students started from chapter one. Upon mastering each chapter, the student was able to continue to the next chapter.

4. Student mastery in MIST was assessed as follows. A set of questions tested student knowledge of the learning-lessons in one section of the text. Upon an incorrect response to a question, the related learning-lesson was presented to the student. The student could then spend as much time as he/she felt necessary to learn the content of the learning-lesson. After exiting the learning-lesson, a question was randomly selected and presented to the student. Questions were either of the multiple choice or true/false format. A wrong answer triggered feedback, and the content of the learning-lesson was displayed once more on the screen. To facilitate retention, this feedback did not provide the correct answer.

4.3.3.2 The Differences Between the Three Versions of MIST

1. First version of MIST (MIST-1) enabled the students to have complete control over the amount of time spent (i.e., self-paced) studying each learning-lesson (See Figure 4.4).

2. The second version of MIST (i.e., MIST-2) used a neural network model (called NTE) to estimate the required time for mastering a learning-lesson by a student. Students had control over the time spent on each learning-lesson. However, if they made repeated mistakes in responding to pertinent questions, then MIST-2 locked them for a specific amount of time (generated by NTE) to study the relevant learning lesson (See Figure 4.5).

3. The third version of MIST (i.e., MIST-3) incorporated an adaptive neural network model (called NRE) for assessing the prerequisite learning-lessons that a student had forgotten, into MIST-2 (See Figure 4.6). The added functionality of NRE enabled MIST-3 to assess whether or not a student had forgotten a prerequisite learning-lesson. Thus making it possible to relearn a prerequisite learning-lesson if NRE assessed it to have been forgotten.

Figure 4.4

Flow Chart for Mastery Learning of a Section in MIST-1

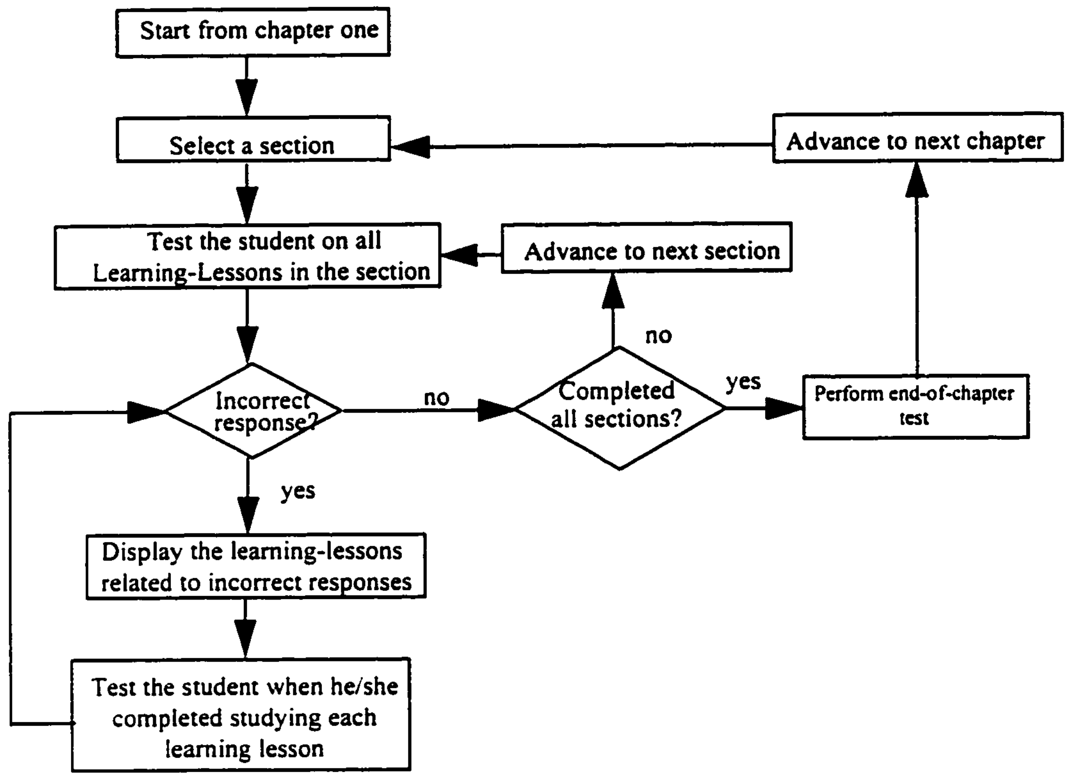


Figure 4.5

Flow Chart for Mastery Learning of a Section in MIST-2

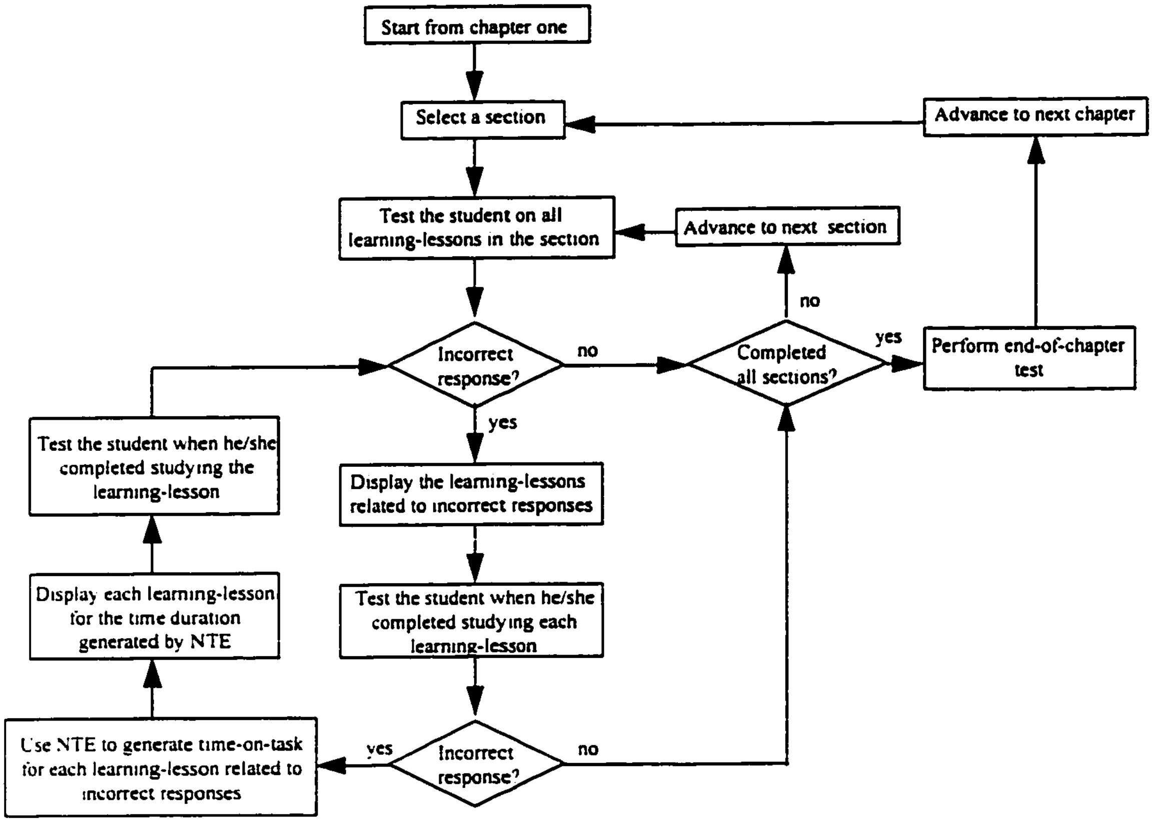
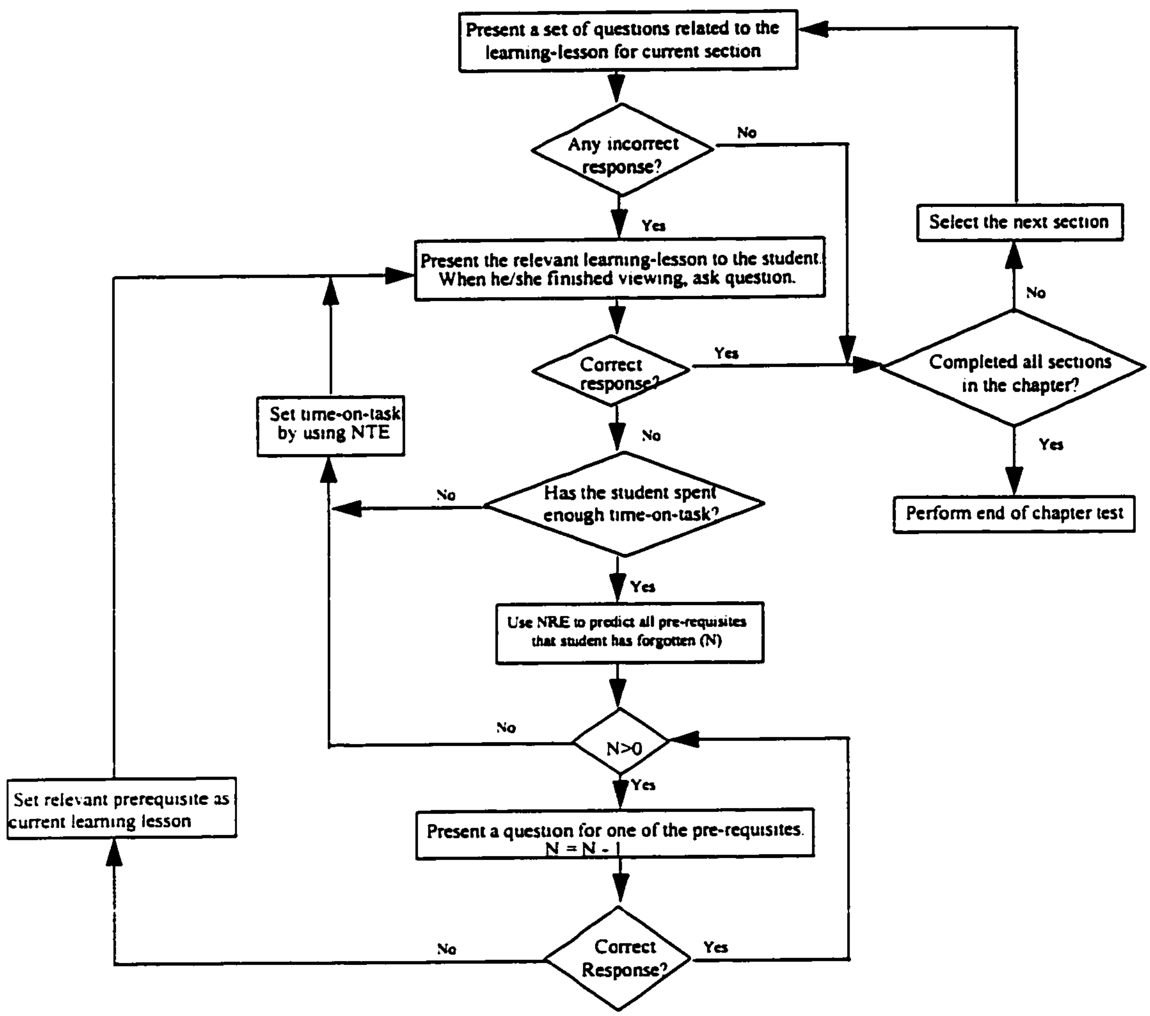


Figure 4.6

Flow Chart for Mastery Learning of a Section in MIST-3



4.3.3.3 MIST-1's Instructional Path

Student mastery in MIST-1 was assessed as follows (see Figure 4.4 for an overview. A detailed flow chart of MIST is presented in the Appendix 3). A set of questions tested student knowledge of the learning-lessons in one section of the text. Upon an incorrect response to a question, the related learning-lesson was presented to the student. The student could then spend as much time as he/she felt necessary to learn the content of a learning-lesson. After exiting a learning-lesson, a question was randomly selected and presented to the student. Questions were either of the multiple choice or true/false format. A wrong answer triggered feedback, and the content of the learning-lesson was displayed once more on the screen. To facilitate retention, this feedback did not provide the correct answer (Surber and Anderson, 1975). Students could leave the learning-lesson and respond to another randomly generated question. An incorrect response to this question indicated that the student has not spent enough time on the relevant learning lesson. Therefore, and the content of the learning-lesson was displayed once more on the screen. The above process was repeated until the student correctly responded to the question.

4.3.3.4 MIST-2's Instructional Path

Student mastery in MIST-2 was assessed as follows (see Figure 4.5 for an overview. A detailed flow chart of MIST is presented in the Appendix 3). A set of questions tested student knowledge of the learning-lessons in one section of the text.

Upon an incorrect response to a question, the related learning-lesson was presented to the student. The student could then spend as much time as he/she felt necessary to learn the content of a learning-lesson. After exiting a learning-lesson, a question was randomly selected and presented to the student. Questions were either of the multiple choice or true/false format. A wrong answer triggered feedback, and the content of the learning-lesson was displayed once more on the screen. To facilitate retention, this feedback did not provide the correct answer (Surber and Anderson, 1975). At this point, external pacing was enforced. The time required to learn the learning-lesson was computed by the neural network time estimator (NTE). After the allotted time elapsed, students could leave the learning-lesson and respond to another randomly generated question. An incorrect response to this question indicated that the student requires a longer time-on-task to study the learning-lesson.

4.3.3.5 MIST-3's Instructional Path

Student mastery in MIST-3 was assessed as follows (see Figure 4.6 for an overview. A detailed flow chart of MIST is presented in the Appendix 3). A set of questions tested student knowledge of the learning-lessons in one section of the text. Upon an incorrect response to a question, the related learning-lesson was presented to the student. The student could then spend as much time as he/she felt necessary to learn the content of a learning-lesson. After exiting a learning-lesson, a question was randomly selected and presented to the student. Questions were either of the multiple choice or true/false format. A wrong answer triggered feedback, and the content of the learning-lesson was displayed once more on the screen. To facilitate retention, this feedback did not provide the correct answer (Surber and Anderson, 1975). At this point, external pacing was enforced. The time required to learn the learning-lesson was computed by the neural network time estimator (NTE developed for the MIST-2). After the allotted time elapsed, students could leave the learning-lesson and respond to another randomly generated question. An incorrect response to this question indicated that the student might have forgotten a subset of prerequisite materials for understanding the learning-lesson. The challenge for the NRE was to identify the most probable prerequisite learning-lessons that had been forgotten by individual students.

Two versions of MIST-3 were developed to present the prerequisites to the students. The first version (MIST-3a), used by one group of students (group 3a), tested individual students on all prerequisite lessons. This made possible identification of the relevant prerequisite learning-lessons that individual students had forgotten, and allowed comparison of these to those that the NRE would have suggested. This enabled us, in turn, to assess the performance of the NRE in identifying the prerequisites that had been forgotten by students. The second version of MIST-3 (MIST-3b) used the NRE to assess the prerequisite learning-lessons that the second group of students (group 3b) might have forgotten. The performance of the two groups (i.e., groups 3a and 3b) of students in nine weekly laboratory-tests and a final-exam made it possible to compare the effectiveness of the two versions of MIST-3 in their support of mastery learning.

4.3.4 Neural Network Time Estimator Development

4.3.4.1 Data Collection

The data collected from the 333 students who used MIST-1 was used in the design and development of the neural network time estimator (NTE) utilized in MIST-2. A total of 100,000 data for time-on-task spent by students on the learning-lessons in MIST-1 were collected. Analysis of data from the second phase of our investigation showed a significant correlation between student performance and time-on-task expended. In fact, two significantly different clusters of students' emerged -- high and low performers. Our goal for MIST-2 was to enable low performers to improve their learning to the level of high performers. To this end, the NTE was developed based on the data collected from the high performing group.

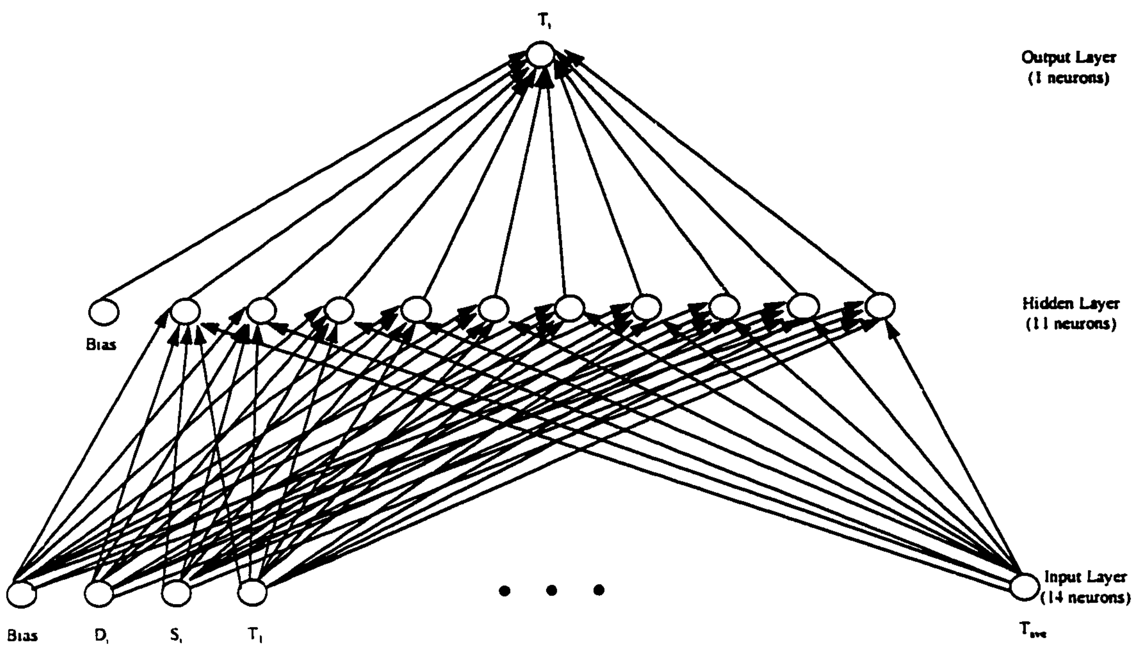
4.3.4.2 NTE Training Procedure

The training of a neural network toward a generalized model is influenced by three factors (Haykin, 1994): the size of the training set, the structure of the network, and the complexity of the problem at hand. Obviously, we had no control over the latter factor. The input pattern of NTE consisted of learning contents dependent factors (LC_i) and the student's learning rate (LR). The former included two variables -- the degree of difficulty of the learning-lesson i (D_i) and the size of the learning-lesson i (S_i). The value of D_i was based on student performance in phase two of the study, and the value of S_i was based on the number of words in the learning-lesson i. The student's learning rate was computed as a function of the time required to master previous learning-lessons. Based on a series of tests we found that, selection of the latest 10 value of the student's time-on-task for learning lessons and their average enabled the NTE to converge with a mean square error of 0.080. Therefore, our NTE had 13 input neurons. A series of tests determined the number of neurons for the hidden layer. Test results showed that with ten neurons in the hidden layer, the means square error was the lowest (i.e., 0.0804) and produced the highest percent of correct output (i.e., 81.3%). Since the NTE was a fully connected network, it comprised 151 connections with synaptic weights (See Figure 4.7). We adopted logistic activation function with a range of 0 to 10 minutes for NTE. The upper limit of 10 minutes was based on the maximum time-on-task spent by the students in MIST-1.

The size of a training set must be large enough to allow good generalization of the neural network model. Based on heuristics recommended in the literature, the size of the training set (N) is governed by the total number of synaptic weights in the network (W) and mean square error (e), such that $N > W/e$. We found that with sample size $N=5000$, the mean square error for 151 synaptic weights converged to 0.080. This means that by selecting 5000 random samples, the network could be trained to compute the required time for a learning-lesson, with an expected error of less than 5 seconds. Therefore, we used 5000 random samples to train the network and another 1000 random samples to test it.

Figure 4.7

Neural Network Structure of Neural Time Estimator (NTE)



Where:

T_i - Estimated required time-on-task for learning lesson i (output of NTE);

D_i - Degree of difficulty of learning lesson i;

S_i - Size of learning lesson i (computed as the number of words embedded in the learning lesson);

Bias - Bias neuron with -1 as input;

T_k - Time-on-task for the latest 10 learning lessons ($k = 1$ to 10);

T_{ave} - Average of T_k $k = 1$ to 10.

4.3.4.3 Operationalization of NTE in MIST-2

To begin, the inputs of the NTE were set at a default value of zero so as to minimize control of student's time-on-task. After viewing the first ten learning-lessons, the NTE adjusted its parameters to fit the learning behavior of the student. From learning-lesson 11 onward, the inputs of NTE were adjusted after viewing each new learning lesson. In addition, the test performance (P) at the end of each chapter provided the means to assess a student's mastery learning. Mastery level was set at 85%. If the student did not reach the mastery level, time-on-task was increased proportional to the mark scored on the test: $R = 85/P$.

4.3.5 Neural Network Retention Estimator Development

4.3.5.1 Data Collection

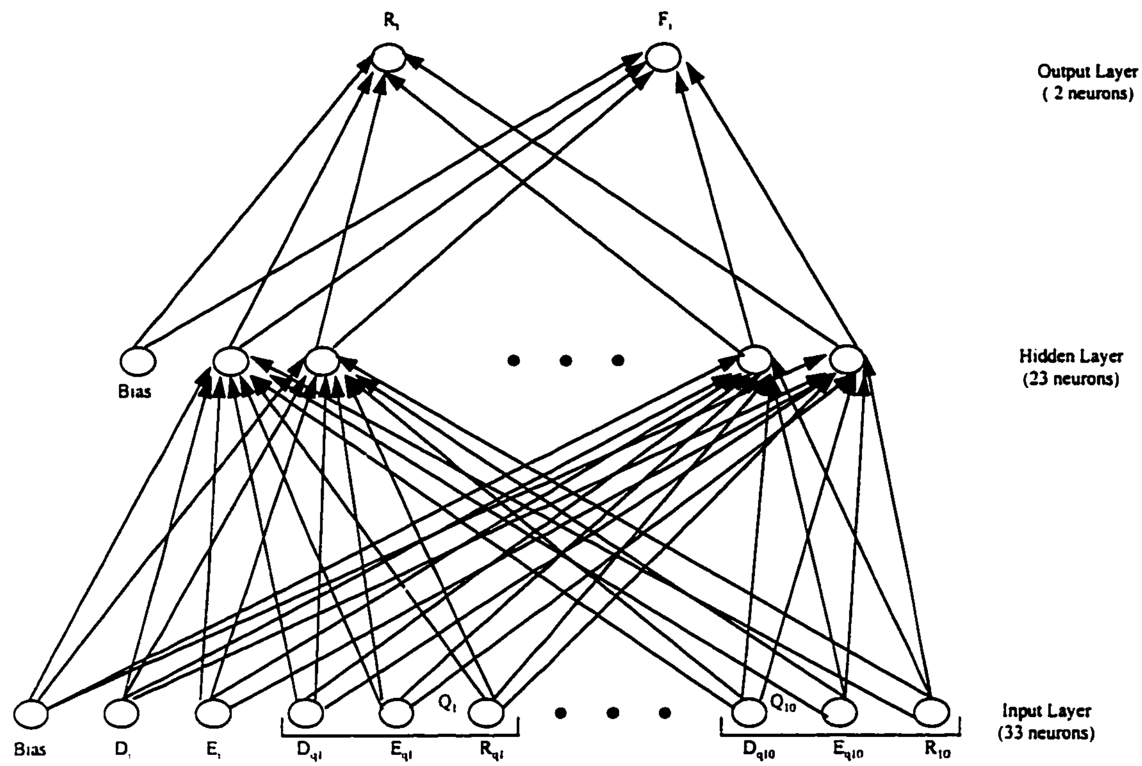
The data collected from the 273 students who used MIST-2 were used in the design and development of the neural network retention estimator (NRE) utilized in MIST-3. A total of 10,000 data were collected for students on the learning-lessons in MIST-2.

4.3.5.2 NRE Training Procedure

To predict whether the prerequisite learning lesson i is forgotten by the student, the input pattern of NRE consisted of three factors: (1) the degree of difficulty of the learning-lesson i (D_i) (i.e., task characteristic), (2) the elapsed time (retention interval) E_i, and (3) a recent history of the student's retention ability Q_k (k=1 to 10). The value of D_i was based on the students' performance in phase two of the study. The value of E_i was based on the elapsed time (i.e., lag) since the last occasion during which the student had been tested for learning lesson i. The individual retention ability was measured by means of 10 sets of data (see Figure 4.8). Each set contained three related data about a recent response of the student to a test question (from end of chapter test and lab-test). The three related data consisted of (a) the question difficulty, (b) the elapsed time between the time that the pertinent learning lesson was tested during the tutorials and end of chapter test (or lab-test), and (c) the student's response (i.e., correct or incorrect). To measure the retention ability of the student, our bias was toward the questions to which the student had incorrectly responded. This bias was used for selecting the 10 most recent set of data.

Figure 4.8

Neural Network Structure of Neural Retention Estimator (NRE)



where:

R_i - The neuron representing state of "not forgotten" for the learning lesson i. The value of R_i can be between 0 to 1, representing the possibility that the student still remembers the content of learning lesson i;

F_i - The neuron representing state of "forgotten" for the learning lesson; i. The value of F_i can be between 0 to 1, representing the possibility that the student has forgotten the content of learning lesson i.

Bias - Bias neuron with -1 as input;

D_i - Degree of difficulty of learning lesson i;

E_i - Elapse time since last time that the student learned the learning lesson i;

Response of the student to 10 questions was used for assessing his/her memory retention ability as follows (See Figure 4.9). A set of questions at the end of each chapter as well as weekly lab-tests was used to assess the students' mastery learning performance. Ten questions from these tests was selected by the MIST with one qualifying condition that the student had already been tested on the related subject matter (learning lesson) during MIST's tutorial. The bias was on the selection of questions that the student had responded incorrectly in the end of chapter tests and/or lab-tests (i.e. the bias was in capturing the "forgetting" behaviour of the student). These ten questions were updated continuously to revise retention ability of the student. Three attributes for each of these 10 questions was used to define input patter for NRE, as follow:

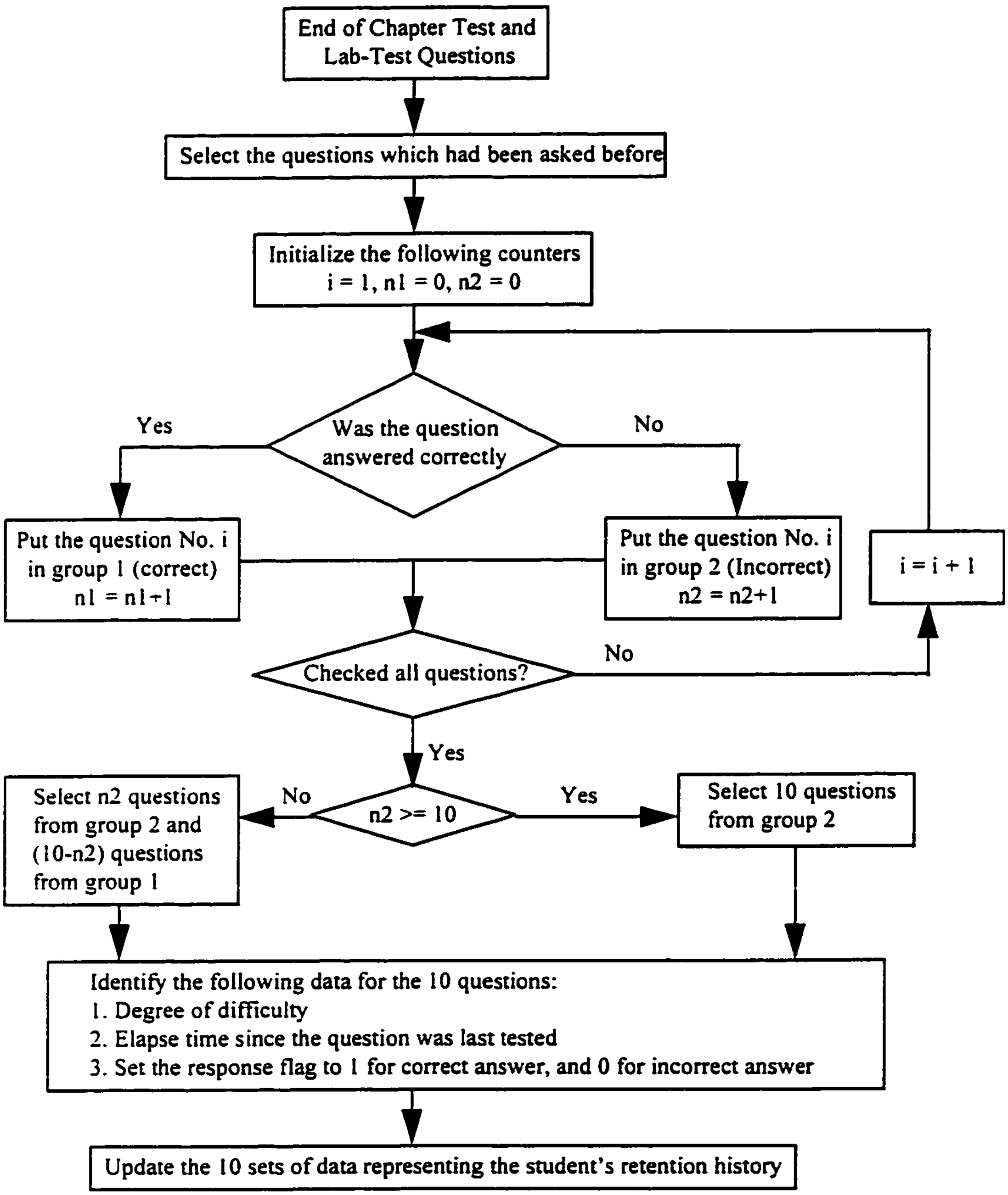
D_{qk} - Degree of difficulty for the questions (k = 1 to 10);

E_{qk} - The elapsed time since the student was tested on the related learning lesson during the tutorials (k = 1 to 10);

R_{qk} - Student's response to the question for the end of chapter test or lab-test (k = 1 to 10). This attribute had a binary value: 1 indicating that the student responded correctly to the question in the test, and 0 for an incorrect response.

Figure 4.9

The Operation of NRE Model



Based on the above architecture, the NRE had 32 input neurons. Decision criteria for assessing the size of hidden layer is a problem in backpropagation neural network models (Hrycej, 1992). The neural network may not be able to learn with too few hidden neurons. However, more hidden units may enhance the performance on the training set but the test set performance may deteriorate (Hrycej, 1992). In order to decide the proper size for NRE, different numbers of hidden neurons were tested in this research. We found that with 22 neurons in the hidden layer, the means square error for test set was the lowest (i.e., 0.0927) and produced the highest percentage of correct output (i.e., 81.5%) (See Table 4.1).

Table 4.1

Selection of the Most Appropriate Size of Hidden Layer

Hidden Size	Training Mean Square Error	Test Mean Square Error	Test Cor. Rate
10	0.4782	N/A	N/A
15	0.1147	0.2143	66.5%
20	0.0903	0.1758	71.2%
21	0.0901	0.1311	77.4%
22	0.0871	0.0927	81.5%
23	0.0850	0.0930	81.5%
25	0.0853	0.0941	79.9%
30	0.0847	0.0957	75.5%
40	0.0821	0.0964	72.2%

For the output layer, both one-neuron and two-neurons were tested. The correct rate of classification with one neuron to represent the output was 75.9%, and when output was represented by means of two neurons, the correct classification rate was 81.5%. Therefore, two neurons were adopted to represent the output classification of the NRE. Since the NRE was a fully connected network, it comprised 772 connections with synaptic weights.

The size of a training set must be large enough to allow good generalization of the neural network model. Based on the heuristics recommended in the literature, the size of the training set (N) is governed by the total number of synaptic weights in the network (W) and mean square error (e), such that $N > W/e$. We found that with sample size $N=8000$, the mean square error for 772 synaptic weights converged to 0.09. Therefore, we used 8000 random samples to train the network and another 2000 random samples to test it. Application of two neurons to represent the output of the NRE made it necessary to correctly classify them as "forgotten" and "not forgotten". To this end, a discriminate statistical method was used with the 2000 test sample to develop a classification function. The resulting function was as follows:

$$D=0.03158 + 2.89026*Output_R - 2.957096*Output_F \qquad .... (1)$$

where:

$D>0$ represents "not-forgotten" and $D<0$ represents "forgotten".

$Output_R$ is one of the output neurons R that represents "not-forgotten", and

$Output_F$ is the other output neuron F that represents "forgotten".

Output of the NRE was used in equation (1) to assess whether or not the student had forgotten a prerequisite learning lesson.

4.3.5.3 Operationalization of NRE in MIST-3

To start, the retention performance of the student for input to NRE was unknown. Therefore, the 10 sets of data representing retention performance were set at a default value of zero. After completed the end of chapter test for Chapter 1, the NRE adjusted its parameters to fit the learning behavior of the student. From Chapter 2 onward, the parameters of the NRE were adjusted after completing each end of chapter test or lab test.

4.3.5.4 MIST Student Files

The responses of each student to the questions, and the time spent on each subsection (learning-lesson), were saved in a student file. Students could use icons at the bottom of the screen to determine how much of the material they had covered and to assess their performance on each chapter, on weekly tests, and their class average.

4.4 Subjects

The first group of 454 students were registered in seven sections of the same course taught by three instructors; the second group of 333 students were registered in six sections taught by two instructors; the third group of 273 students were registered in six sections taught by two instructors; and the fourth group of 268 students were registered in four sections taught by one instructor. The second, third, and fourth groups used MIST-1, MIST-2, and MIST-3, respectively. Students in group 4 were randomly assigned to two sub-groups (i.e., group 3a and 3b) had access to MIST-3a and MIST-3b, respectively.

Because the second group were required to use MIST-1, it was possible to gather enough information to develop the NTE for MIST-2. Use of MIST-2 and MIST-3, however, was optional. All students had already completed an introductory computer course that covered popular software such as spreadsheet and BASIC programming language; however, students had not previously taken MIS course. It was reasonable, therefore, to assume a common background knowledge of course material among the students. Nonetheless, we tested for student levels of computer anxiety, computer efficacy, motivation, and self-regulated learning. The point was to assess these levels for their moderating effect on MIST system use.

4.5 Test

The 200 multiple choice and true/false questions on the final exam, which was taken by all students, covered materials from all 20 chapters of the text book. In addition, group two, three, and four were subjected to weekly lab-tests. Each test contained 50 questions that covered a set of prescheduled chapters. The questions used in the weekly lab-tests, and administered in a micro-lab, were similar to those used in the MIST tutorials. To enhance learning and to reduce possible cumulative effects of errors, students were prompted with the correct answer when an incorrect answer was entered (Foos and Fisher, 1988).

One-way ANOVA test of the final exam for each group of students showed no significant difference between sections taught by different instructors (See Table 4.2). Therefore, we can be confident that no significant difference in student learning existed due to the instructor effect.

Table 4.2

ANOVA Test of Students' Performance on the Final Exam
Among Students Taught by Different Instructors

Group	Number of Students	Number of Sections	Number of Instructors	F-value	Significance of F
1	454	7	3	0.094	0.910
2	333	6	2	1.318	0.212
3	273	6	2	2.666	0.104

4.6 Questionnaire Reliability and Validity

Reliability of a questionnaire refers to its stability under a variety of conditions (Thorndike, 1982). The Cronbach alpha reliability score for the two questionnaires was 0.69 to 0.97 (See Table 4.3). These scores confirmed the questionnaires as acceptable instruments, because little variance in response was due to measurement error (Nunnally, 1978).

Construct validity is the extent to which a measure relates to the measure of other constructs consistent with a theoretically derived hypothesis concerning the constructs being measured. In this context, the measure of construct validity is the extent to which each item of a questionnaire correlates with the total score (Kerlinger, 1973). The correlation between the score for each item (question) and the total score was between 0.46 to 0.89 (See Table 4.3). Based on these findings, the overall scores relating to computer anxiety, computer efficacy self-efficacy, intrinsic value, test anxiety, cognitive strategy use, and self-regulation, and the score for each item of the questionnaire, can be used as a meaningful measure of these constructs.

Table 4.3

Reliability and Validity of the Questionnaires

Questionnaire	**Reliability (Cronbach Alpha)**		**Validity (Correlation (Min., Max.))**	
	MIST-2	**MIST-3**	**MIST-2***	**MIST-3***
Computer Anxiety	0.94	0.97	(0.64,0.89)	(0.65,0.74)
Computer Efficacy	0.75	0.80	(0.71,0.80)	(0.72,0.84)
Self-Efficacy	0.92	0.93	(0.64, 0.85)	(0.66, 0.86)
Intrinsic Value	0.81	0.70	(0.61, 0.83)	(056, 0.86)
Test Anxiety	0.97	0.96	(0.86, 0.88)	(0.79, 90)
Cognitive Strategy Use	0.74	0.69	(0.46, 0.72)	(0.48, 0.72)
Self Regulation	0.76	0.71	(0.54, 0.69)	(0.49, 0.71)

Note: * All $p < 0.001$

5. Analysis

5.1 Hypothesis H1

The first hypothesis (H1) states that the amount a student learns is a direct result of the amount of time he/she spends in learning (time-on-task). In the MIST system, the 20 chapters of the text book were split into 87 sections. Correlation between student performance for each section, and the time spent studying its content was computed to assess this first hypothesis. The results of this analysis for the three versions of MIST are as follows.

5.1.1 Analysis of H1 for MIST-1

Among the 87 sections in MIST, only 3 sections, the correlations between time-on-task and performance were not significant ($r < 0.18$, $p > 0.05$). The remaining 83 correlations were all significant (see Table 5.1). This result suggests that hypothesis H1 cannot be rejected, thereby confirming previous findings gleaned from mastery learning research: there is a significant relationship between time-on-task and performance.

Table 5.1

Correlation of Time-on-Task and Performance in Tutorial Tests of 87 Sections for MIST-1

No. of Sections	Range of Correlation Coefficients
3	0.06 to 0.18
6	0.2 to 0.3*
9	0.3 to 0.4*
14	0.4 to 0.5*
17	0.5 to 0.6*
19	0.6 to 0.7*
16	0.7 to 0.8*
2	0.8 to 0.9*
1	0.9 to 1.0*

* Significant at $p < 0.01$

5.1.2 Analysis of H1 for MIST-2 and MIST-3

Correlation between student performance for each section, and the time spent studying its content was computed for students using MIST-2 (see Table 5.2) and MIST-3 (see Table 5.3). As can be noted, the results of these analyses are similar to those found for MIST-1: there is a significant relationship between time-on-task and performance. Therefore, there is a strong evidence in support of hypothesis H1.

Table 5.2

Correlation of Time-on-Task and Performance in Tutorial Tests of 87 Sections for MIST-2

No. of Sections	Range of Correlation Coefficients
7	0.01 to 0.09
13	0.1 to 0.2*
15	0.2 to 0.3*
21	0.3 to 0.4**
12	0.4 to 0.5**
8	0.5 to 0.6**
7	0.6 to 0.7**
4	0.7 to 0.8**

* Significant at $p < 0.05$
** Significant at $p < 0.01$

Table 5.3

Correlation of Time-on-Task and Performance in Tutorial Tests of 87 Sections for MIST-3

No. of Sections	Range of Correlation Coefficients
8	0.011 to 0.09
17	0.1 to 0.2*
22	0.2 to 0.3*
16	0.3 to 0.4**
13	0.4 to 0.5**
7	0.5 to 0.6**
3	0.6 to 0.7**
1	0.7 to 0.8**

* Significant at $p < 0.05$
** Significant at $p < 0.01$

5.2 Hypothesis H2

The second hypothesis (H2) states that difference among the students spent on the amount of time spent on task diminishes as they progress through the lessons. To capture this variation, the amount of time spent by the students in chapter one was divided into four equal percentiles. This strategy grouped the students into four types. Next, multivariate analysis of variance (MANOVA) with repeated measures, was adopted to test both within subject and between subject (i.e., among the four types of students) difference for time on task spent in each of the 20 chapters. Therefore, the factor time on task had four factor levels (treatments): the four types of students. An index for time was generated to allow for the variation due to size and complexity among the chapters. For each student, this index was computed as the time spent on each chapter divided by the average time spent by all students on the same chapter. This time index was assigned as a response variable.

As noted, the effect of variance due to personal factors on the response variable had to be accounted for in the analysis of the second hypothesis. Personal factors in our experimental design were indirectly controlled by including them, as covariates, in the statistical model. In this research, these covariates comprise motivation, learning strategies, computer efficacy and computer anxiety. The respective analysis for the students using the three versions of the MIST are as follows.

5.2.1 Analysis of H2 for MIST-1

The result of MANOVA analysis suggested that none of the covariates had a significant effect on the response variable (See Table 5.4). No significant difference was noted for time on task within subjects across the 20 chapters. However, a significant difference was noted for time on task among the four types of students. This suggests that time on task for each student type, compared with the rest of the students, remained the same across the 20 chapters. Therefore, the second hypothesis cannot be supported because the difference among the students for the time spent on task did not diminish as they progressed through the chapters.

Table 5.4

MANOVA Test of Variation of Time-on-Task During Tutorial
Across 20 Chapters for MIST-1

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	2397.73	330	8.47		
Regression	0.09	1	0.09	0.01	0.916
Constant	729.44	1	729.44	86.09	0.000
Four Types of students	635.93	3	211.98	25.02	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	3132.35	5396	0.58		
Chapter	1.30	19	0.07	0.12	1.000
Four Types By Chapter	136.27	57	2.39	4.12	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.00024	-0.00624	0.002	-0.105	0.916
Computer Efficacy	0.00798	0.05085	0.009	0.857	0.392

Mauchly Sphericity Test W = 0.00011
Chi-Square Approx. = 2525.435474 with 189 D.F.
Significance = 0.000

5.2.2 Analysis of H2 for MIST-2 and MIST-3

MANOVA tests of variation of time-on-task during tutorial across 20 chapters for the students who used MIST-2 and MIST-3 are depicted in Tables 5.5 and 5.6 respectively. As can be noted, the results of these analyses are the same as those described in section 5.2.1 (i.e., for MIST-1). This show that there is a significant evidence that the second hypothesis cannot be supported. Therefore, the second hypothesis cannot be supported because the difference among the students for the time spent on task did not diminish as they progressed through the chapters.

Table 5.5

MANOVA Test of Variation of Time-on-Task During Tutorial
Across 20 Chapters for MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	1327.35	100	8.23		
Regression	0.17	1	0.17	0.04	0.882
Constant	548.53	1	548.53	63.78	0.000
Four Types of students	357.38	3	115.56	18.34	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	2262.93	3832	0.60		
Chapter	4.27	19	0.38	0.22	1.000
Four Types By Chapter	84.597	57	1.62	4.63	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.00029	-0.01321	0.003	-0.126	0.895
Computer Efficacy	-0.00923	-0.08577	0.011	-0.853	0.313
Self-Efficacy	-0.00329	-0.05091	0.004	-0.735	0.463
Intrinsic Value	-0.00230	-0.03990	0.004	-0.576	0.565
Test Anxiety	-0.00009	-0.00111	0.005	-0.016	0.987
Cognitive Strategy Use	-0.00245	-0.06059	0.003	-0.875	0.382
Self Regulation	-0.00642	-0.10661	0.004	-1.546	0.124

Mauchly Sphericity Test W = 0.00008
Chi-Square Approx. = 1135.852804 with 189 D.F.
Significance = 0.000

Table 5.6

MANOVA Test of Variation of Time-on-Task During Tutorial
Across 20 Chapters for MIST-3

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	592.47	80	7.41		
Regression	0.23	1	0.23	0.03	0.860
Constant	307.93	1	307.93	41.58	0.000
Four Types of students	129.38	3	43.13	5.82	0.001
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	1032.35	1539	0.67		
Chapter	6.64	19	0.35	0.52	0.955
Four Types By Chapter	62.39	57	1.09	1.63	0.002
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.00059	-0.01972	0.003	-0.176	0.860
Computer Efficacy	-0.01193	-0.10592	0.013	-0.953	0.344
Self-Efficacy	-0.00077	-0.00836	0.007	-0.115	0.909
Intrinsic Value	0.00488	0.04863	0.008	0.648	0.519
Test Anxiety	-0.00097	-0.00913	0.008	-0.121	0.903
Cognitive Strategy Use	-0.00442	-0.07109	0.005	-0.948	0.344
Self Regulation	-0.00074	-0.00802	0.007	-0.107	0.915

Mauchly Sphericity Test W = 0.00002
Chi-Square Approx. = 806.95966 with 189 D.F.
Significance = 0.000

5.3 Hypothesis H3

The third hypothesis (H3) states that the difference in performance among the students diminishes as they progress through the lessons. Two different measurements were used to assess student performance: (1) performance based on tutorial tests for each of 20 chapters and (2) performance based on each of the nine lab-tests. Next, for each measurement, students were grouped into two types according to their performance on chapter one of the tutorial tests and the first lab-test: those who reached mastery performance (i.e., scored 85% or more) were labelled "high-performers", and those who did not reach mastery performance were labelled "low-performers". Therefore, factor performance had two levels (treatments): the two types of students were contingent on their performance. We used a MANOVA model with repeated measure similar to the one used for the second hypothesis (H2), except that for (H3) the response variable was replaced with two independent test performances. The respective analyses for the three versions of MIST are as follows.

5.3.1 Analysis of H3 for MIST-1

The results of MANOVA tests for the students' performance on each chapter during the tutorials are presented in Table 5.7 and for the lab-tests in Table 5.8. It should be noted that none of the covariates had a significant effect on the response variable. However, a significant difference was noted among the two student types. Therefore, the third hypothesis cannot be supported, because the difference between the performance of the two types of students did not diminish as they progressed through the chapters. In addition, the results of within-subject analysis show a significant effect due to tests and a significant interaction between tests and the two types of students. Test scores in Tables 5.9 and 5.10 show variations in performance across tests. We can interpret these variations in light of the relationship between the students' goals and feedback on their performance.

Table 5.7

MANOVA Test of Variation of Performance in Tutorial-Tests
Across 20 Chapters for MIST-1

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	41.27	330	0.14		
Regression	0.01	1	0.01	0.04	0.837
Constant	416.93	1	416.93	2878.90	0.000
Two Types of Students	4.10	1	4.10	28.28	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	108.22	5434	0.02		
Chapter	17.30	19	0.91	45.73	0.000
Two Student Type by Chapter	1.37	19	0.07	3.61	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.000	0.01218	0.000	0.205	0.837
Computer Efficacy	0.000	0.04661	0.001	0.788	0.433

Mauchly Sphericity Test W = 0.0068
Chi-Square Approx. = 1394.8969 with 189 D.F.
Significance = 0.000

Table 5.8

MANOVA Test of Variation of Performance in 9 Lab-Tests for MIST-1

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	14.27	330	0.04		
Regression	0.13	1	0.13	3.03	0.082
Constant	279.02	1	279.02	6450.87	0.000
Two Student Types	2.80	1	2.80	64.08	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	21.77	2648	0.01		
Lab-Test	13.29	8	1.66	202.08	0.000
Two Student Types by Lab-Test	0.96	8	0.12	14.63	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.000	-0.030	0.000	-0.553	0.581
Computer Efficacy	-0.001	-0.044	0.001	-0.798	0.426

Mauchly Sphericity Test W = 0.35437
Chi-Square Approx. = 340.40106 with 35 D.F.
Significance = 0.000

Table 5.9

Students' Performance for Tutorial Tests for MIST-1

	Type 1 (Low-Performers)		Type 2 (High-Performers)	
Chapter	Mean (%)	S.D.	Mean(%)	S.D.
1	75.35	7.10	91.86	4.40
2	79.84	12.20	84.38	13.20
3	82.75	11.90	87.75	10.60
4	82.23	12.70	84.75	1.00
5	80.48	12.20	84.31	10.00
6	75.54	12.70	79.06	0.90
7	81.25	13.60	83.76	1.50
8	66.27	26.70	71.77	26.10
9	75.49	12.20	79.64	11.10
10	70.92	17.40	76.32	15.90
11	78.59	23.00	79.46	23.30
12	81.42	18.80	82.58	18.00
13	73.73	16.80	78.19	15.00
14	73.68	16.60	78.38	15.00
15	69.98	15.20	75.41	13.90
16	74.64	16.10	79.32	15.80
17	70.38	18.90	77.16	16.60
18	60.86	16.30	65.67	15.70
19	66.31	18.60	75.19	17.90
20	64.35	18.70	74.52	16.40

Table 5.10

Students' Performance for Lab Tests for MIST-1

	Type 1 (Low-Performers)		Type 2 (High-Performers)	
Lab-Test	Mean(%)	S.D.	Mean(%)	S.D.
1	73.06	11.90	90.25	3.50
2	86.13	9.40	91.18	5.40
3	83.15	11.10	86.45	7.80
4	71.56	12.10	77.11	8.40
5	70.97	10.10	77.16	8.40
6	83.10	9.20	88.32	7.90
7	80.67	11.80	85.61	1.10
8	71.88	12.20	76.85	11.40
9	76.88	13.30	81.93	10.00

The relation between goals and feedback can be defined as follows (Lock and Latham, 1990):

> Feedback tells people what is; goals tell them what is desired. Feedback involves information; goals involve evaluation. Goals inform individuals as to what type or level of performance is to be attained so that they can direct and evaluate their actions and efforts accordingly. Feedback allows them to set reasonable goals and to track their performance in relation to their goals, so that adjustments in effort, direction, and even strategy can be made as needed. Goals and feedback can be considered a paradigm case of the joint effect of motivation and cognition controlling action. (p.197)

The variations of performance among the different tests suggest that the discrepancy between the students' goals and feedback on their most recent performances led to an adjustment of the amount effort expended to ensure reaching the desired goal in the next test.

Extraneous demands on students' time and effort to do other tasks seemed in both tests to have had a negative effect on performance in both tests. A point to consider the is low performance for lab-tests 4, 5, 8, and 9. A possible reason for the low performance is that students were engaged in writing midterm examinations for other courses during the 2 weeks allotted to lab-tests 4 and 5 (i.e., chapters 8, 9, and 10). Also, lab-tests 8 and 9 (i.e., from chapter 13 onward) coincided with a period in which students had to hand in two major computer assignments for the MIS course and several assignments for other courses. This suggests that the effectiveness of any CBT system should be assessed in relation to both external environmental factors and internal learner factors. Therefore, the overall design of an effective CBT system becomes an integrative process with many competing voices concerning the social, physical, and information-processing environments (Clancy, 1993).

5.3.2 Analysis of H3 for MIST-2 and MIST-3

To assess the third hypothesis for the students who used MIS-2 and MIST-3, we replicated the same set of analysis reported in section 5.3.1 for MIST-1. The results of MANOVA tests of performance in tutorial tests (see Table 5.11) and lab-tests (see Table

5.12), for students who used MIST-2 showed that the difference of the performance between the two types of students (i.e., low performers and high-performers) did not diminish as they progressed through chapters. However, the same analysis for the students who used MIST-3 showed that the difference of the students' performance diminished as they progressed through the chapters (see Table 5.13 and Table 5.14). The methodology embedded in MIST-3 to reinforce long-term memory retention of the students enabled all of them to reach mastery learning. Therefore, based on the above analysis, the third hypothesis is supported only for the students who used MIST-3. This indicates that long-term memory support of students is an important component of mastery learning.

Table 5.11

MANOVA Test of Variation of Performance in Tutorial-Tests
Across 20 Chapters for MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	1686.32	102	31.41		
Regression	3.74	1	3.74	0.10	0.753
Constant	9834.83	1	9834.83	41.58	0.000
Two Types of Students	127.58	1	127.58	9.47	0.034
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	9317.74	2663	15.39		
Chapter	361.33	19	83.78	11.25	0.000
Two Student Type by Chapter	492.79	19	102.63	3.57	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.00074	0.02278	0.009	0.229	0.803
Computer Efficacy	0.00418	0.08853	0.021	0.943	0.322
Self-Efficacy	0.02274	0.03863	0.041	0.560	0.576
Intrinsic Value	0.01334	0.02490	0.037	0.361	0.719
Test Anxiety	-0.02701	-0.03864	0.048	-0.560	0.576
Cognitive Strategy Use	0.01421	0.03824	0.026	0.555	0.580
Self Regulation	0.02567	0.04661	0.038	0.676	0.500

Mauchly Sphericity Test W = 0.00702
Chi-Square Approx. = 629.79532 with 189 D.F.
Significance = 0.000

Table 5.12

MANOVA Test of Variation of Performance in 9 Lab-Tests for MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	0.74	46	0.02		
Regression	0.05	1	0.05	3.27	0.077
Constant	69.41	1	69.41	4329.94	0.000
Two Types of Students	0.23	1	0.23	14.65	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	1.75	423	0.00		
Lab-Test	0.00	8	0.00	0.12	0.999
Two Student Types by Lab-Test	0.09	8	0.01	2.50	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.00057	-0.25775	0.000	-1.809	0.077
Computer Efficacy	-0.00144	-0.14930	0.001	-1.024	0.311
Self-Efficacy	-0.00001	-0.00165	0.001	-0.025	0.980
Intrinsic Value	0.00000	-0.00047	0.000	-0.007	0.994
Test Anxiety	-0.00025	-0.02647	0.001	-0.403	0.687
Cognitive Strategy Use	0.00025	0.05219	0.000	0.796	0.427
Self Regulation	0.00038	0.05268	0.000	0.804	0.422

Mauchly Sphericity Test W = 0.13672
Chi-Square Approx. = 87.14627 with 35 D.F.
Significance = 0.000

Table 5.13

MANOVA Test of Variation of Performance in Tutorial-Tests
Across 20 Chapters for MIST-3

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	16816.32	82	205.08		
Regression	20.51	1	20.51	0.10	0.753
Constant	2232960.83	1	2232960.83	2903.47	0.000
Two Types of Students	587.02	1	587.02	5.82	0.094
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	81262.15	1577	51.53		
Chapter	3109.23	19	163.64	3.18	0.000
Two Student Types by Chapter	4191.56	19	220.61	4.28	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.00552	0.0349	0.017	0.316	0.753
Computer Efficacy	0.08480	0.1422	0.065	1.301	0.197
Self-Efficacy	0.02796	0.0722	0.029	0.969	0.334
Intrinsic Value	0.04833	0.1114	0.032	1.499	0.136
Test Anxiety	-0.02588	-0.056	0.035	-0.749	0.455
Cognitive Strategy Use	0.02292	0.0859	0.020	1.153	0.250
Self Regulation	0.03122	0.0775	0.030	1.040	0.300

Mauchly Sphericity Test W = 0.00754
Chi-Square Approx. = 373.85333 with 189 D.F.
Significance = 0.000

Table 5.14

MANOVA Test of Variation of Performance in 9 Lab-Tests for MIST-3

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	0.21	19	0.01		
Regression	0.00	1	0.00	0.02	0.901
Constant	31.78	1	31.78	2903.47	0.000
Two Types of Students	0.04	1	0.04	3.95	0.062
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	0.69	200	0.00		
Lab-Test	0.20	8	0.02	5.68	0.000
Two Student Types by Lab-Test	0.12	8	0.01	3.52	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.00005	0.02897	0.000	0.126	0.901
Computer Efficacy	-0.00070	-0.10842	0.001	-0.475	0.640
Self-Efficacy	0.00041	0.05041	0.001	0.728	0.468
Intrinsic Value	0.00008	0.00916	0.001	0.132	0.895
Test Anxiety	-0.00037	-0.03646	0.001	0.526	0.599
Cognitive Strategy Use	0.00035	0.06057	0.000	0.875	0.382
Self Regulation	-0.00021	-0.2642	0.001	-0.381	0.704

Mauchly Sphericity Test W = 0.00152
Chi-Square Approx. = 106.84957 with 35 D.F.
Significance = 0.000

5.4 Hypothesis H4

The fourth hypothesis states that inclusion of NTE improves student's mastery learning. Test of this hypothesis was based on data collected from students' performance in phase one (i.e., with human tutor), phase two (i.e., with MIST-1), and phase three (i.e., with MIST-2).

Student performance in the final exam differed among the three groups of students (See Table 5.15). The ANOVA test for the final exam of the three groups showed a significant difference among them ($F=114.93$, $p<0.0001$) and the covariates of personal factors (i.e., motivation, self-regulated learning, computer anxiety and computer efficacy) had no significant effect in this analysis. Tukey test revealed that the performance of third group was significantly better than that of the second group, and the second group performed significantly better than the first. This shows that MIST was instrumental in improving student learning of subject matter. In support of students' mastery learning, MIST-2 was more effective than MIST-1. Therefore, the difference in student performance on the final exam could be attributed to the difference in the architecture of MIST-1 and MIST-2 (i.e., self-paced versus adaptable external control). Improved performance was also evident in weekly lab-test performance (See Table 5.16). To assess this, we performed MANOVA test for lab-tests between the two groups with covariates of computer anxiety and computer efficacy. The results showed that the group using MIST-2 performed significantly better than the second group (who used MIST-1) in all weekly lab-tests and that the two covariates had no significant effect on the performance (Table

5.16). These results clearly show that MIST-2 better supported mastery learning than did MIST-1.

Table 5.15

Comparison of Performance for Final Exam of the Three Groups of Students

Performance (%)			**ANOVA***	
N0-MIST (92)	**MIST-1 (93)**	**MIST-2 (94)**	**F-value**	**Significance of F ($p<$)**
71.43	81.81	84.16	114.93	0.0001

Note: * Covariates of motivation, self-regulated learning, computer anxiety and computer efficacy were insignificant at $p > 0.50$.

Table 5.16

MANOVA Test of Variation of Performance in 9 Lab-Tests for the Students Using MIST-1 and MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	253.53	538	0.47		
Regression	0.13	1	0.13	0.28	0.753
Constant	5359.93	1	5359.93	11373.74	0.000
MIST-1 & MIST-2	64.62	1	64.62	137.13	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	355.35	4312	0.08		
Lab-Test	2045.23	8	255.65	3102.20	0.000
MIST-1 & MIST-2 by Lab-Test	37.38	8	4.67	57.70	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.00029	0.02291	0.001	0.532	0.595
Computer Efficacy	0.00152	0.02941	0.002	0.682	0.495

Mauchly Sphericity Test W = 0.18918
Chi-Square Approx. = 892.67078 with 35 D.F.
Significance = 0.000

As noted before, we found significant correlation between time-on-task and performance with MIST-1 (see section 5.1). Therefore, the difference of performance between the MIST-1 group and the MIST-2 group could be attributed to the time-on-task (i.e., MIST-2 students might have spent more time-on-task than MIST-1 students). To explore this further, we performed MANOVA test for time-on-task for each chapter between the two groups with covariates of computer anxiety and computer efficacy. The results showed a significant difference between the two groups (see Tables 5.17). The time-on-task for MIST-1 was significantly higher than for MIST-2 (see Table 5.18). This is contrary to traditional findings about mastery learning. This intriguing finding can be rationalized in light of students' motivation. We will return to this phenomenon later.

Table 5.17

MANOVA Test of Variation of Time-on-Task for the Students Using MIST-1 and MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	709055557	293	26993364		
Regression	9835244.11	1	9835244.11	0.61	0.436
Constant	930754845	1	930754845	34.48	0.000
MIST-1 & MIST-2	403424175	1	403424175	14.95	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	9739889575	5567	1749576.0		
Chapter	66213292.7	19	8148068.0	5.00	0.000
MIST-1 & MIST-2 by Chapter	67764543.8	19	3566554.9	2.04	0.005
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	2.50764	0.03499	2.219	0.779	0.436
Computer Efficacy	18.77309	0.06381	13.197	1.423	0.155

Mauchly Sphericity Test W = 8.011721E-07
Chi-Square Approx. = 4021.4087 35 D.F.
Significance = 0.000

Table 5.18
Average Time-on-Task in Seconds

Chapter	MIST-1	MIST-2 (With NTE)	MIST-2 (Fixed-time)
1	1540.33	738.46	546.57
2	949.50	468.92	486.91
3	1206.31	474.21	309.77
4	769.05	234.01	207.71
5	2183.29	287.36	286.53
6	2042.52	593.10	528.88
7	2096.75	354.00	398.51
8	1266.01	502.08	658.65
9	1626.31	303.52	533.41
10	910.39	177.73	307.19
11	643.39	109.54	305.62
12	1048.91	179.59	365.91
13	1095.12	155.84	416.49
14	1213.76	213.42	579.62
15	1466.16	220.52	509.95
16	1214.72	115.93	410.41
17	1365.19	176.65	462.66
18	1053.09	222.85	588.14
19	1005.52	196.22	357.00
20	1245.23	135.75	226.58

The methodology we used for external control allowed adaptation to each student's learning behavior. The question to be asked now is whether a fixed external control for all students would have resulted in the same amount of time-on-task as those obtained with MIST-2. Although we did not assess the effect of fixed external pacing on students' performance, it is possible to compare time-on-task for the two methodologies (i.e., NTE and fixed time). To assess this, we computed the externally paced time-on-task proposed by the Belland et al. (1985) as follows:

> (a) 1 second per line, plus 1 second; so for 5 lines, 6 seconds for reading were given (this approximated an average of 300 words per minute); (b) 7 seconds cognitive processing were given (p.190).

Table 5.18 presents the average time-on-task for the two types of external pacing. MANOVA analysis shows that the fixed external pacing is significantly less than the adaptive methodology we used for Chapters one and three of the text (see Table 5.19). However, from Chapter eight onward, the time-on-task in our adaptive methodology becomes significantly less than fixed external pacing. This is evidence that our adaptive external pacing saves student time expended toward mastery learning.

Table 5.19

MANOVA Test of Variation of Time-on-Task for NTE versus Fixed External Pacing

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	140066264	102	339966.66		
Regression	212944.92	1	212944.92	0.63	0.429
Constant	98569676.37	1	98569676.40	289.94	0.000
Two Pacing Types	6326857.85	1	6326857.80	18.61	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	252205890.1	3717	67852.00		
Chapter	6388239.34	19	6265359.90	92.34	0.000
Two Pacing Types by Chapter	29711779.83	19	3301308.90	48.65	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	1.08293	0.02780	1.918	0.585	0.573
Computer Efficacy	0.38103	0.03896	0.481	0.791	0.429
Self-Efficacy	0.12548	0.00449	1.470	0.085	0.932
Intrinsic Value	1.25255	0.03989	1.651	0.759	0.449
Test Anxiety	2.34432	0.06999	1.759	1.333	0.183
Cognitive Strategy Use	-0.10569	-0.00547	1.016	-0.104	0.917
Self Regulation	0.53444	0.01827	1.539	0.347	0.729

Mauchly Sphericity Test W = 0.10068
Chi-Square Approx. = 940.82453 with 189 D.F.
Significance = 0.000

5.4.1 Discussion of Findings Related to H4

The adaptive nature of the MIST-2(NTE) provided challenge for a student (i.e., intrinsic motivation) to reduce external control by the system. This conjecture can be justified as follows: First, visual observation during tutorials with MIST system, showed that students were excited at the prospect of being in control of their interaction with the system. As a result, students were careful to provide correct responses to questions. In case of an incorrect response, they read with care the content of the learning-lesson presented on the screen. They wanted to avoid making another mistake and thereby being locked by the system for the period required to reread the learning-lesson. In part, this intrinsic motivation could be attributed to their superior performance when compared to the second group MIST-1 users.

Our second justification is based on the current literature on human-computer interaction. In general, an inverse relationship between the response time and error rate is found (Shneiderman, 1992). This relationship can be attributed to our finding that the time-on-task for MIST-1 (with immediate response time) was significantly higher than for MIST-2. When using MIST-1, students were careless when responding to question, and as a result, they had to revisit a learning-lesson more often than students using MIST-2. Furthermore, Shneiderman (1992) contends that "there appears to be an optimal pace for each user-task situation -- response times that are shorter or longer than this pace lead to increased error rate (p. 293)". Our analysis shows that students adjust their learning behavior to minimize time-on-task. The comparison between time-on-task for MIST-

2(NTE) and MIST-2(fixed) makes this apparent -- the required time for MIST-2(NTE) was significantly lower than MIST-2(fixed) as students progressed through the lessons.

A comparison of weekly lab-tests between MIST-2 users and students who did not use MIST-2 revealed that the performance of the latter was significantly poorer (see Table 5.20). Further analysis showed no significant difference between the two types of students regarding their time-on-task (for chapters completed in MIST-2), computer anxiety, computer efficacy, motivation, and self-regulated learning. Therefore, we can attribute use of MIST-2 to the extrinsic motivation of the students to prepare for lab-tests.

Table 5.20

MANOVA Test of Performance for Lab-Tests between the Students Who Used MIST-2 and the Students Who did not

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	29.77	111	0.27		
Regression	0.01	1	0.01	0.02	0.877
Constant	1257.05	1	1257.05	4686.93	0.000
Two Student Groups	9.70	1	9.70	36.18	0.000
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	53.73	896	0.06		
Lab-Test	178.80	8	22.35	362.67	0.000
Two Student Groups by Lab-Test	1.96	8	0.24	4.08	0.000
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	-0.00012	-0.01478	0.001	-0.156	0.877
Computer Efficacy	-0.00002	-0.00055	0.003	-0.006	0.995
Self-Efficacy	0.00042	0.05285	0.001	0.521	0.603
Intrinsic Value	0.00058	0.09861	0.001	0.976	0.332
Test Anxiety	-0.00065	-0.08577	0.001	-0.848	0.399
Cognitive Strategy Use	0.00021	0.05303	0.000	0.523	0.602
Self Regulation	0.00051	0.08709	0.001	0.861	0.391

Mauchly Sphericity Test W = 0.14398
Chi-Square Approx. = 311.49664 with 35 D.F.
Significance = 0.000

5.5 Hypothesis H5

The fifth hypothesis states that the inclusion of NRE in MIST improves student's mastery learning. NRE was embedded in the third version of MIST (i.e., MIST-3) and was used by students in our phase four of the investigation. To start, we assess the effectiveness of NRE in identifying the prerequisite learning-lessons that the students had forgotten. Next, the effectiveness of NRE in support of mastery learning (i.e., hypothesis H5) will be analyzed.

5.5.1 Effectiveness of NRE in Assessing Prerequisites

As noted before, MIST-3a used all pertinent pre-requisites to assess whether a student had forgotten a learning lesson. Therefore, responses of the students to all pre-requisites in group 3a were used as a measure of correct prediction rate of NRE (see Table 5.21). The NRE required 10 sets of questions the student's answered in the end of chapter test or lab-test to adjust its output to the memory retention ability of the students. Therefore, as shown in Table 5.21, the correct prediction rate of the NRE was low for the first two chapters, improving to a satisfactory level thereafter. Motivation for the use of the NRE was to reduce the number of questions related to the pre-requisites. Therefore, it was necessary to determine whether the NRE asked significantly fewer questions than when the brute-force method of asking all prerequisite questions was used. To this end, the Chi-Square test was used to assess the difference between the average number of pre-requisites in each chapter and the average number of pre-requisites that would have been selected by the NRE for group 3b (see Table 5.22). This analysis showed that the NRE would have suggested significantly fewer pre-requisites.

Group 3a was presented with all the pre-requisites, and the NRE was used to predict a subset of pre-requisites for the students in group 3b. The question arises whether assessment of a significantly lower number of pre-requisites compromised the students' performance when using MIST-3b. To this end, MANOVA was used to assess the variation between the performance of group 3a and 3b. The results showed no significant difference in weekly lab-tests between the two groups (see Table 5.23). We also tested the performance of these two groups of students in the final exam. To do this analysis, the students who had used MIST-3 to complete all 20 chapters were selected. The ANOVA test of the performance of these students showed no significant difference between the two groups, 3a and 3b ($F=0.320$, $p=0.573$). Based on these findings, we can be confident that student performance is not compromised as a result of the significantly lower prediction of pre-requisites by the NRE.

Table 5.21
Correct Predication Rate of the NRE

Chapter	**Correct Prediction Rate(%)**
1	54.2
2	62.0
3	77.6
4	78.7
5	79.2
6	80.3
7	77.0
8	76.2
9	78.7
10	78.2
11	77.1
12	79.3
13	77.7
14	78.6
15	78.8
16	77.7
17	79.1
18	81.4
19	79.3
20	79.4

Table 5.22

Chi-Square Test of Ave. # of Possible Prerequisites with Ave. # of NRE Selected Prerequisites

Chapter	Ave.# of Possible Prerequisites	Ave. # of NRE Selected Prerequisites	Pearson -Value	Likelihood Ratio Value	Significance (p<)
1	16.33	9.77	345.67	395.19	0.001
2	16.65	9.09	597.57	627.10	0.001
3	19.15	11.56	531.17	596.76	0.001
4	18.05	11.00	444.52	503.05	0.001
5	17.89	10.74	475.21	536.55	0.001
6	16.79	10.90	624.32	519.98	0.001
7	20.94	12.54	395.77	445.81	0.001
8	24.08	14.61	425.12	491.83	0.001
9	27.56	17.37	561.75	635.92	0.001
10	23.22	14.06	579.07	641.93	0.001
11	25.58	15.21	593.11	666.99	0.001
12	20.60	13.00	454.84	518.74	0.001
13	24.19	14.66	592.69	670.24	0.001
14	23.80	14.40	548.58	642.73	0.001
15	23.01	13.76	530.60	613.33	0.001
16	21.07	13.34	431.43	493.38	0.001
17	32.06	20.06	101.65	118.45	0.001
18	25.18	14.18	36.53	43.72	0.001
19	38.21	22.48	341.14	386.16	0.001
20	26.93	15.73	224.43	245.62	0.001

Table 5.23

MANOVA Test of Performance for Lab-Tests Between the two Groups of Students Using MIST-3a and MIST-3b

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	10.04	205	0.05		
Regression	0.27	1	0.27	5.48	0.020
Constant	291.08	1	291.08	5945.37	0.000
MIST-3a & MIST-3b	0.02	1	0.02	0.49	0.485
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	11.50	1648	0.01		
Lab-Test	0.20	8	0.03	3.65	0.000
MIST-3a & MIST-3b By Lab-Tests	0.04	8	0.01	0.77	0.635
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.0021	0.2035	0.001	1.967	0.078
Computer Efficacy	0.0015	0.1124	0.001	1.619	0.107
Self-Efficacy	0.0003	0.0262	0.001	0.378	0.706
Intrinsic Value	-0.0005	-0.0437	0.001	-0.630	0.529
Test Anxiety	-0.0005	-0.0403	0.001	-0.582	0.561
Cognitive Strategy Use	0.0002	0.0338	0.000	0.488	0.626
Self Regulation	-0.0001	-0.0113	0.001	-0.162	0.871

Mauchly Sphericity Test W = 0.21170
Chi - Square Approx. = 315.366 with 35 D.F.
Significance = 0.000

5.5.2 Effectiveness of NRE in Improving Mastery Learning

The effectiveness of MIST-3 can be measured in two ways. First, by comparison of the performance of students who used it versus those who did not. Second, by comparison of students who used MIST-3 versus those who used earlier versions of MIST (i.e., MIST-1 and MIST-2). This latter comparison enabled us to assess the added functionality of the NRE embedded in MIST-3.

The student's performance for each lab test was divided by their average performance to remove variation due to test difficulty. MANOVA test of the performance between these two groups showed significant difference for all lab-tests: students who used MIST-3 performed significantly better than those who did not (See Table 5.24).

Table 5.24
MANOVA Test of Performance for Lab-Tests Between the two Groups of Students Who Used MIST-3 and Those Who did not Use MIST-3

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	2.76	90	0.03		
Regression	0.00	1	0.00	0.02	0.891
Constant	140.92	1	140.92	4587.67	0.000
Group who used MIST-3 vs. Group who did not use MIST-3	0.37	1	0.37	12.20	0.001
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	4.41	728	0.01		
Lab-Test	0.10	8	0.01	2.15	0.029
Group who used MIST-3 vs. Group who did not use MIST-3 By Lab-Tests	0.12	8	0.01	2.43	0.014
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.0004	0.10616	0.000	1.536	0.126
Computer Efficacy	0.0016	0.10668	0.001	1.544	0.124
Self-Efficacy	0.0010	0.13529	0.001	1.190	0.238
Intrinsic Value	0.0003	0.03269	0.001	0.285	0.776
Test Anxiety	-0.0012	-0.12614	0.001	-1.109	0.271
Cognitive Strategy Use	0.0011	0.20072	0.001	1.786	0.078
Self Regulation	0.0011	0.13931	0.001	1.226	0.224

Mauchly Sphericity Test W = 0.14540
Chi - Square Approx. = 395.531 with 35 D.F.
Significance = 0.000

The average performance of students in the final exam who used MIST-3 to complete all 20 chapters was 90% and the performance of those students who did not use MIST-3 at all was 78%. The ANOVA test of performance between these two groups also showed that MIST-3 enabled students to significantly improve their performance ($F=120.93$, $p<0.0001$). The difference in performance between those who used MIST-3, and those who did not, could be attributed to other factors, such as to difference in their knowledge of the subject matter. This possibility was ruled out because the Tukey-test test showed that the performance of students who used MIST-3 for a lab-test was significantly higher than when the same student discontinued its use for later lab-tests. These findings show that improved student performance can be attributed to the use of MIST-3.

The next set of analyses was performed to assess the effectiveness of the added functionality of MIST-3. Student performance in the final exam differed between the two groups of students (the average mark for the first group who used MIST-2 was 84.16 and for the second group who used MIST-3 was 89.94). The ANOVA test for the final exam of the two groups revealed that the performance of the students who used MIST-3 was significantly better than the MIST-2 users ($F=57.585$, $p<0.001$). This shows that the added functionality of MIST was instrumental in improving a student's learning of the subject matter. Improved performance was also evident in their weekly lab-test performance (See Table 5.25). To assess this improvement, we performed MANOVA test for lab-tests between the two groups with covariates of computer anxiety, computer efficacy, motivation, and self-regulated learning. The results showed that group who used MIST-3 had a significant higher performance than the group who used MIST-2 and that the covariates had no significant effect on performance (Table 5.26). In addition, Tukey test revealed that the performance of the students who used MIST-3 was significantly higher than group who used MIST-2 in seven lab-tests, and equal in two of them.

Table 5.25

Tukey-Test of Performance for the Students Who Used MIST-2 and Who Used MIST-3

Lab-test	Performance (%)		Tukey-Test
	MIST-2	MIST-3	$p<0.05$
1	85	87	MIST-2<MIST-3
2	95	97	MIST-2<MIST-3
3	89	93	MIST-2<MIST-3
4	79	84	MIST-2<MIST-3
5	87	90	MIST-2=MIST-3
6	86	89	MIST-2<MIST-3
7	86	87	MIST-2=MIST-3
8	87	90	MIST-2<MIST-3
9	78	86	MIST-2<MIST-3

Table 5.26

MANOVA Test of Performance for Lab-Tests Between the two Groups of Students Who Used MIST-3 and Those Who Used MIST-2

Between-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	10.37	207	0.05		
Regression	0.11	1	0.11	2.36	0.126
Constant	187.69	1	187.69	4036.9	0.000
MIST-2 & MIST-3	0.19	1	0.19	4.12	0.044
Within-Subjects Effect					
Source of Variation	SS	DF	MS	F	Sig.of F
Within Cells	15.09	1664	0.01		
Lab-Test	0.25	8	0.03	3.46	0.001
MIST-2 & MIST-3 By Lab-Test	0.04	8	0.01	0.53	0.835
Covariates					
	B	Beta	Std. Err	t-value	Sig.of t
Computer Anxiety	0.835	0.1062	0.000	1.536	0.126
Computer Efficacy	0.0016	0.1067	0.001	1.544	0.124
Self-Efficacy	0.0001	0.0098	0.001	0.136	0.892
Intrinsic Value	0.0003	0.0417	0.001	0.578	0.564
Test Anxiety	-0.0009	-0.0841	0.001	-1.170	0.244
Cognitive Strategy Use	0.0001	0.0078	0.000	0.109	0.914
Self Regulation	0.0003	0.0330	0.001	0.458	0.648

Mauchly Sphericity Test W = 0.1454
Chi - Square Approx. = 395.531 with 35 D.F.
Significance = 0.000

5.6 Hypothesis H6

The sixth hypothesis states that spaced repetition is superior to massed repetition with respect to the student's mastery learning. Information is better remembered if it is presented at widely spaced intervals than if it is repeated in massed fashion (Glenberg and Lehmann, 1980; Green, 1989). As a general rule, as the spacing between the presentations of repeated information is increased, memory performance also increases (Glenberg and Lehmann, 1980). This phenomenon is called the spacing or lag effect. For example, Glenberg and Lehmann (1980) found that spacing repetitions over 1 day or 1 week facilitates performance relative to spacing of just a few minutes. Therefore, the most effective strategy to use MIST-3 in support of mastery learning was to study the required chapters at widely spaced intervals (e.g., complete the required chapters daily for 5 days).

The lag between two lab-tests was 6 days. However, we found that use of MIST-3 tutorials varied between 1 to 5 days. This means some students completed their study of relevant chapters daily over a five day period and some students used MIST-3 only one day to prepare for the lab-test (see Table 5.27). The former learning strategy made use of widely spaced intervals which was superior to the latter strategy of massed fashion. As can be noted from Table 5.27, the relative performance of students who used MIST-3 for 1 or 2 days is lower compared with 3 to 5 days of study duration. We analyzed group 4 students' performance in light of the spacing effect on memory reinforcement. Students who used MIST-3 for 1 or 2 days (group 4I) to prepare for a lab-test were selected, and their performance was compared to those who used MIST-3 for more than 2 days (group 4II) (See Table 5.28). Tukey-testing showed that the performance of those students who used MIST-3 more than two days was significantly better than that of the group 4I for all lab-tests. These findings demonstrate that spaced repetition has a positive effect on mastery learning. Thus, hypothesis H6 is supported.

Table 5.27

Variation of Performance due to the Number of Days that MIST-3 was used Prior to a Lab-Test

Lab -Test	**The Relative Performance for different Time Duration*, (Number of Students)**				
	1	**2**	**3**	**4**	**5**
1	0.951 (34)	0.957 (29)	1.037 (56)	1.030 (37)	1.041 (13)
2	0.990 (20)	1.005 (28)	1.006 (64)	1.009 (68)	1.020 (14)
3	0.960 (32)	0.988 (30)	1.008 (60)	1.011 (66)	1.023 (12)
4	0.956 (30)	0.987 (54)	1.023 (37)	1.031 (11)	--- (0)
5	0.967 (21)	0.986 (26)	1.009 (40)	1.009 (48)	1.047 (10)
6	0.960 (10)	0.976 (27)	1.010 (43)	1.021 (45)	1.043 (9)
7	0.934 (14)	0.980 (40)	1.018 (37)	1.024 (32)	1.038 (10)
8	0.959 (15)	0.978 (25)	1.003 (43)	1.019 (36)	1.048 (7)
9	0.925 (35)	0.982 (36)	1.080 (22)	1.097 (10)	1.208 (2)

Note: * The relative performance is the students' performance divided by the average performance of all students who used MIST-3 for the lab-test

Table 5.28

Improved Performance due to Increased Spacing Effect on the Use of MIST-3

Labt-test	Performance (%)		Tukey-Test
	Duration <= 2 days* (Group 4I)	Duration > 2 days** (Group 4II)	$p<0.05$
1	87	90	Group 4I < Group 4II
2	94	98	Group 4I < Group 4II
3	90	94	Group 4I < Group 4II
4	81	86	Group 4I < Group 4II
5	86	92	Group 4I < Group 4II
6	85	91	Group 4I < Group 4II
7	86	89	Group 4I < Group 4II
8	86	91	Group 4I < Group 4II
9	82	93	Group 4I < Group 4II

Note: * Performance of students used MIST-3 for one or two days to prepare for a lab-test.
** Performance of students used MIST-3 for more than two days to prepare for a lab-test.

6. Discussion

We believe, as others do (Koschmann et al., 1994; Leidner and Jarvenpaa, 1995; Ohlsson, 1991; Scardamalia and Bereiter, 1994; Seidel and Park, 1994; Self, 1990) that system "hacking" is not an effective means of improving the computer-based instruction (CBI) state of art. Instead, well-grounded learning theories need to be empirically tested in CBI environments. Such an approach should progress through four steps (Koschmann et al., 1994): (a) making explicit the instructional requirements that serve as design goals for the project, (b) performing a detailed study of current educational practice with regard to these goals, (c) developing a specification based on the identified requirements/limitations of the instructional setting and the known capabilities of the technology, and (d) producing an implementation that allows for local adaptation to instructional practice. Our research endeavor in the design, development, and formative evaluation of MIS-Tutor is based on these four steps.

A primary advantage of computer-based instruction is its ability to provide improved performance by means of one-to-one tutoring. The results of our formative evaluation of the MIS-Tutor support this notion. The proposed neural network models of adaptive external pacing and reinforcing long-term memory retention of students for text-based learning, improved mastery learning.

6.1 Implication For Practice

Application of MIST in educational institutions can help students learn fundamental issues, thereby freeing faculty to work with them on discovery of the more complex aspects of the course (e.g., creating a virtual learning environment (Leidner and Jarvenpaa, 1995)). The structure of MIST can be adopted in support of mastery learning for text-based materials. This includes company training manuals for operational procedures. Thereby, making it possible to update the knowledge of employees continuously.

We can also use the structure of NRE in support of tasks that can be enhanced by recalling previous events. It is well-established findings in memory research that we can recognize materials far more easily than we can recall it from memory (Norman, 1988; Preece et al., 1994). NRE can help us recall events that we have forgotten. The structure of the NRE was based on findings from cognitive psychology in support of reinforcing memory retention, and neural network technology enabled us to effectively operationalize the underlying model of reinforcement for text-based mastery learning. Therefore, it is possible to apply the structure of the NRE to other learning environments, such as in the provision of context-dependent case-based reasoning systems, fashioned to particular situations and user difficulties or experiences (Gupta and Montazemi, forthcoming; Maes, 1994; Montazemi and Gupta, 1996).

6.2. Implication For Research

While the results of our empirical tests are encouraging, we acknowledge that its context is limited to the overlaying technique for text-based mastery learning. It is our hope that this work will generate fruitful discussion and provoke further research. Application of hypermedia in the MIST enabled a learner to control his/her path through materials in each learning-lesson. Nonetheless, our adopted overlaying structure was restrictive. The question arises as to whether the restrictive structure of overlaying has a negative effect on students' mastery learning. The goal of the mastery approach to learning is to disseminate knowledge from guru to a learner. This approach of learning is effective when used to teach the core of basic skills, concepts, and facts. However, we need to empower students toward more complex knowledge creation processes. Thus, the second research question is "how might we apply ITS to empower learners to discover new knowledge on their own?" This is a challenging task and may require a combination of ITS and other learning technologies, such as computer support for cooperative work (Alavi et al., 1995; Edelson et al., 1996; Koschmann, 1994; Scardamalia and Bereiter, 1996).

Optimal use of MIST-3 required students to work with it on an ongoing basis, at least 3 days prior to a lab-test. Students were encouraged verbally to adopt this study behavior. However, at times (e.g., lab-test 4, which coincided with mid-term examination for other courses) the majority of students opted to use MIST-3 for only 1 or 2 days prior to the lab-test. As a result, their performance was negatively affected because of the reduced time lag. Future research should consider models of ITS that encourage students develop optimal study behavior.

There is no doubt that information technology can provide much needed support to enhance our learning environments. Hardware and software are not a limiting factor toward this endeavor. The limiting factor is lack of knowledge of learning models that would allow courseware designers make optimal use of information technology. It is only through well-grounded research that we can effectively utilize technology in support of improved learning ability.

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Appendix 1

Instrument used to assess computer anxiety and computer efficacy. All the items were assessed on the following 7 point Likert-type scale:

	3	2	1	0	-1	-2	-3	
Agree	extremely	quite	slightly	neither	slightly	quite	extremely	Disagree

Part A

Computer Anxiety

1. Computers intimidate and threaten me.
2. Even though computers are valuable and necessary, I still have a fear of them.
3. I am confident that I could learn computer skills.
4. I am unsure of my ability to learn a computer programming language.
5. I feel apprehensive about using a computer terminal.
6. I have avoided computers because they are unfamiliar to me.
7. I hesitate to use a computer for fear of making mistakes I cannot correct.
8. I am unsure of my ability to interpret a computer printout.
9. I have difficulty in understanding most technical matters.
10. Computer terminology sounds like confusing jargon to me.
11. Computers are kind of strange and frightening.

12. There's a computer revolution going on, and I don't feel like I'm part of it.
13. Other people are learning about and using computers, and I am being left out of that group.
14. I feel like a technological outcast because I don't use computers very much, if at all.

Part B

Computer Efficacy

1. I will never understand how to use a computer
2. Only a few experts really understand how computers work.
3. It is extremely difficult to learn a computer language.
4. Computer errors are very difficult to fix.

Part C

The following 44 items represent the Motivated Strategies for Learning Questionnaire (MSLQ) that was used in this study to measure students' motivational beliefs and self-regulated learning. The number next to the items reflect the item's actual position on the questionnaire. All the items were assessed on the following 7 point Likert-type scale:

	1	2	3	4	5	6	7	
not at all true of me								Very true of me

Motivational Beliefs

I. Self-Efficacy

2. Compared with other students in this class I expect to do well.
6. I'm certain I can understand the ideas taught in this course.
8. I expect to do very well in this class.
9. Compared with other students in this class, I think I am good student.
11. I am sure I can do an excellent job on the problems and tasks assigned for this class.
13. I think I will receive a good grade in this class.
16. My study skills are excellent compared with others in this class.
18. Compared with other students in this class I think I know a great deal about the subject.
19. I know that I will be able to learn the material for this class.

II. Intrinsic Value

1. I prefer class work that is challenging so I can learn new things.
4. It is important for me to learn what is being taught in this class.
5. I like what I am learning in this class.
7. I think I will be able to use what I learn in this class in other classes.
10. I often choose paper topics I will learn something from even if they require more work.
14. Even when I do poorly on a test I try to learn from my mistakes.

15. I think that what I am learning in this class is useful for me to know.

17. I think that what we are learning in this class is interesting.

21. Understanding this subject is important to me.

III. Test Anxiety

3. I am so nervous during a test that I cannot remember facts I have learned.

12. I have an uneasy, upset feeling when I take a test.

20. I worry a great deal about test.

22. When I take a test I think about how poorly I am doing.

Self-Regulated Learning Strategies

IV. Cognitive Strategy Use

23. When I study for a test, I try to put together the information from class and from the book.

24. When I do homework, I try to remember what the teacher said in class so I can answer the questions correctly.

26. It is hard for me to decide what the main ideas are in what I read.

28. When I study I put important ideas into my own words.

29. I always try to understand what the teacher is saying even if it does not make sense.

30. When I study for a test I try to remember as many facts as I can.

31. When studying, I copy my notes over to help me remember material.

32. When I study for a test I practice saying the important facts over and over to myself.
36. I use what I have learned from old homework assignments and the textbook to do new assignments.
39. When I am studying a topic, I try to make everything fit together.
41. When I read material for this class, I say the words over and over to myself to help me remember.
42. I outline the chapters in my book to help me study.
44. When reading I try to connect the things I am reading about with what I already know.

V. Self-Regulation

25. I ask myself questions to make sure I know the material I have been studying.
27. When work is hard I either give up or study only the easy parts.
32. I work on practice exercise and answer end of chapter questions even when I do not have to.
33. Even when study materials are dull and uninteresting, I keep working until I finish.
35. Before I begin studying I think about the things I will need to do to learn.
37. I often find that I have been reading for class but do not know what it is all about.

38. I find that when the teacher is talking I think of other things and do not really listen to what is being said.

40. When I'm reading I stop once in a while and go over what I have read.

43. I work hard to get a good grade even when I do not like a class.

Appendix 2

Title of 20 Chapters of Zwass Text Book

1 Introduction to management information systems

2 Informational needs of organizations in an information society

3 Structure of management information systems

4 Transaction processing systems

5 Information systems for competitive advantage: Strategic use of information

6 Computer systems: Hardware and software

7 Distributed processing systems, telecommunications, and computer networks

8 Databases

9 End-user computing

10 Systems concepts

11 Management concepts: Planning and control

12 Organizations: Innovating with information technology

13 Manager and decision maker

14 Decision support systems and executive information systems

15 Applied artificial intelligence: Expert systems

16 Office information systems

17 The MIS function and information systems planning

18 Development and implementation of information systems

19 Techniques and tools for structured systems development

20 Operation, control, and maintenance of information systems

Appendix 3

Figure A.1

Detailed Flow Chart of MIST

Part 1

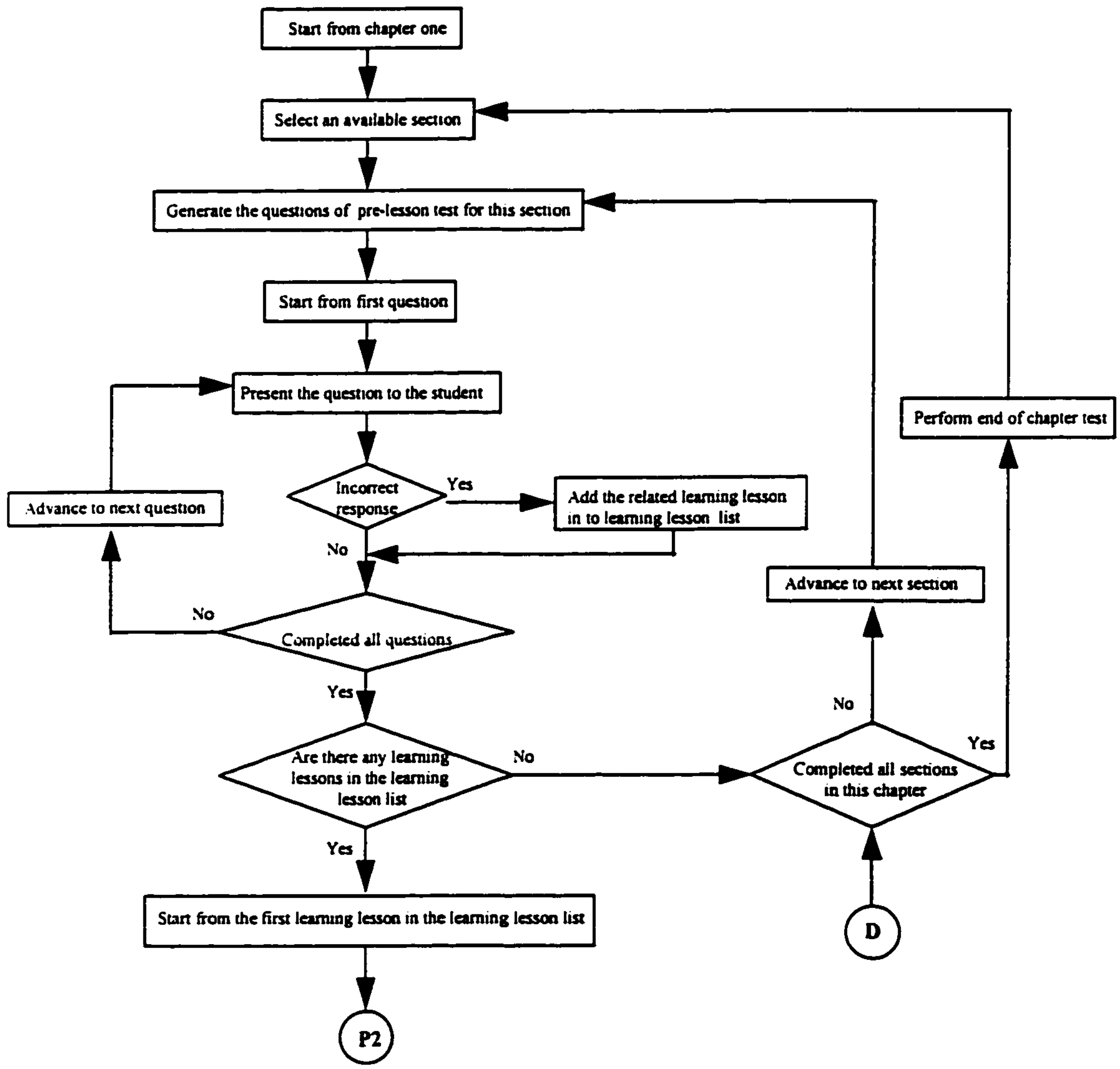


Figure A.2

Detailed Flow Chart of MIST

Part 2

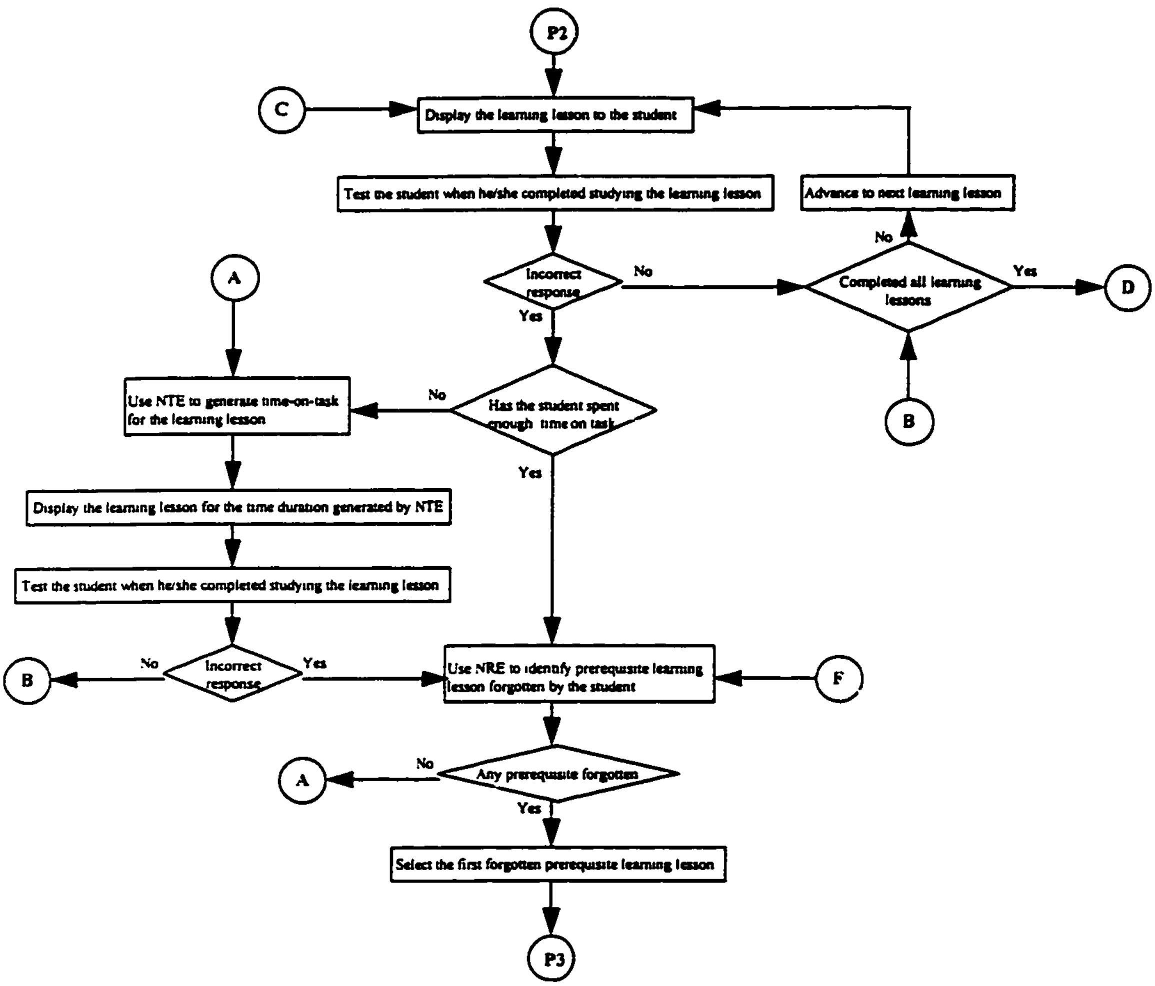


Figure A.3

Detailed Flow Chart of MIST

Part 3

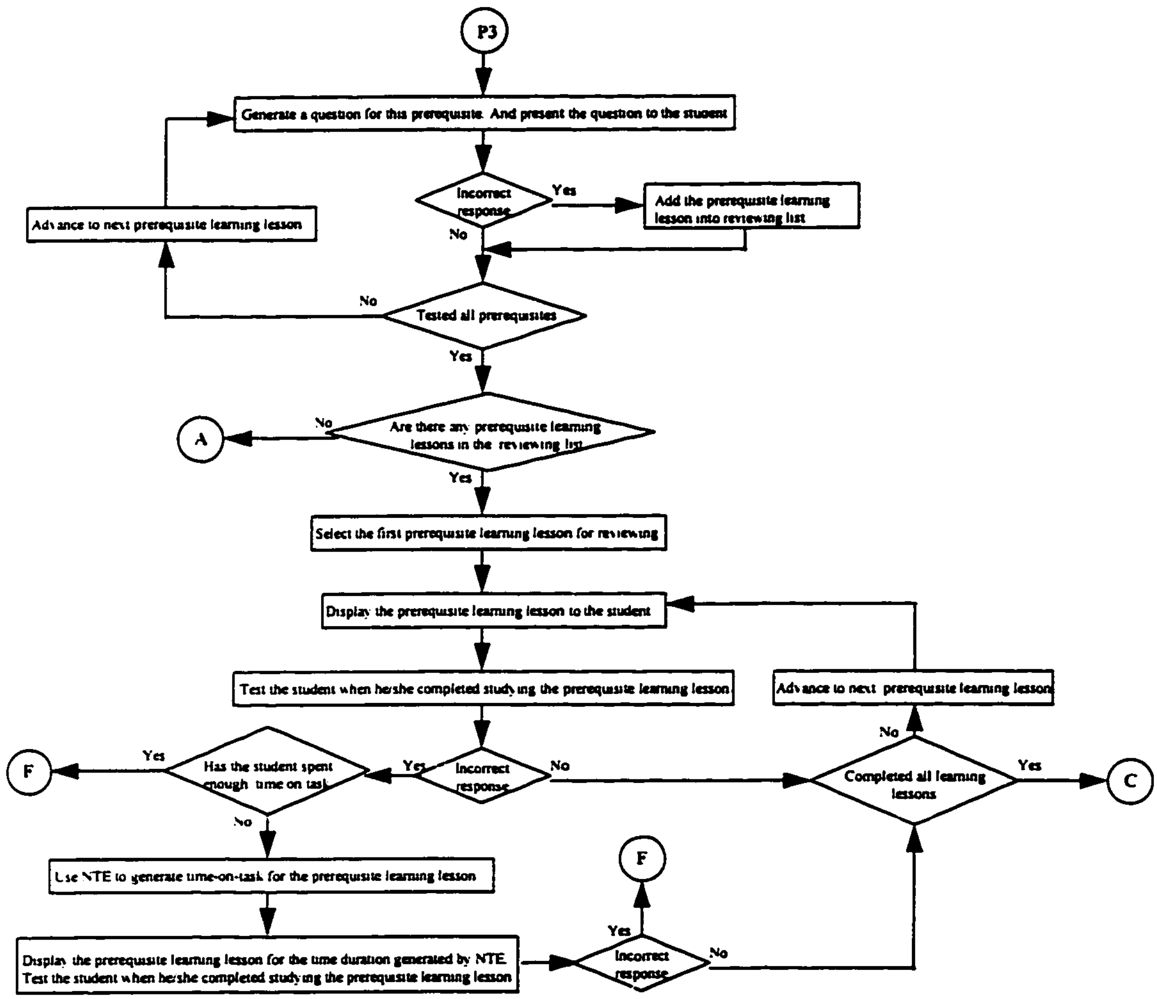
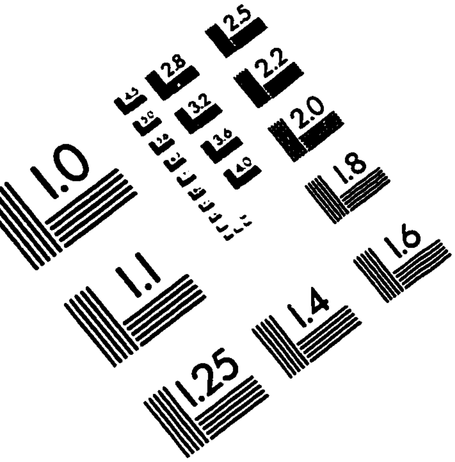
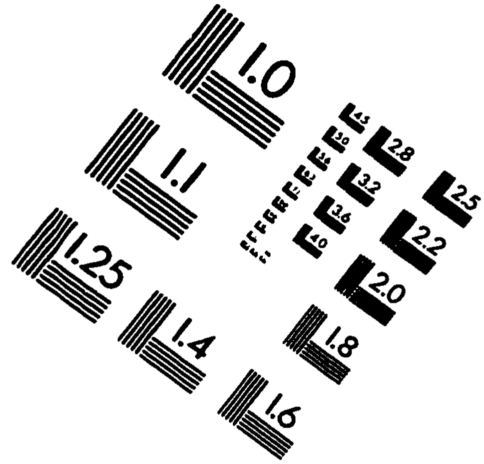
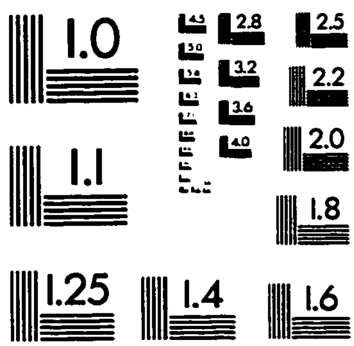
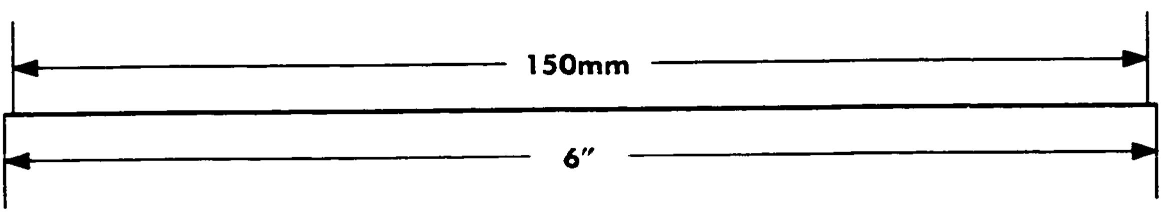


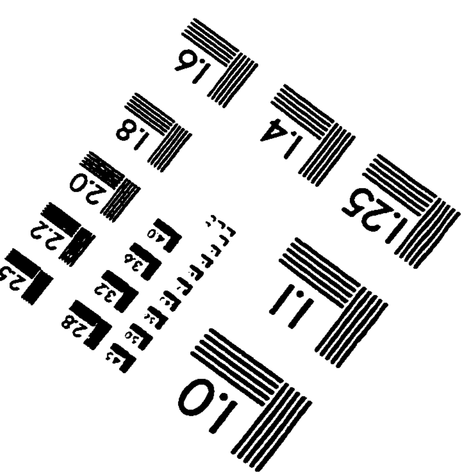
IMAGE EVALUATION TEST TARGET (QA-3)

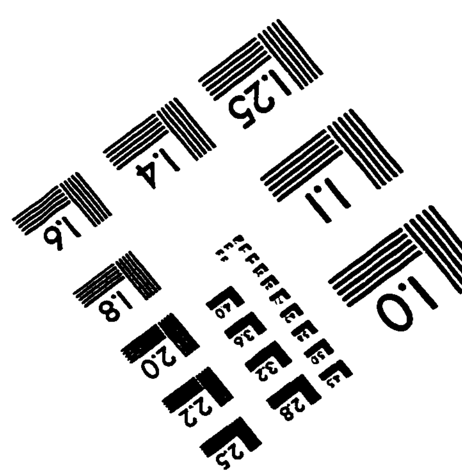












APPLIED IMAGE . Inc
1653 East Main Street
Rochester, NY 14609 USA
Phone: 716/482-0300
Fax: 716/288-5989