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ADAPTIVE E-LEARNING DESIGN BY ARTIFICIAL NEURAL NETWORK TECHNIQUES: A CASE OF ETHIOPIAN HIGHER LEARNING INSTITUTION

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Examiner

DECLARATION

The thesis is my original work, has not been presented for a degree in any other university and that all sources of material used for the thesis have been duly acknowledged.

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Melkamu Beyene

June 2010

The thesis has been submitted for examination with our approval as university advisors.

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Workshet lamnew

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Abstract

An e-learning system is expected to recognize the different learner characteristics, the complex learning process that can be influenced by learner characteristics such as previous knowledge, learning styles, background, etc. The system is also expected to analyze students need to use learning material and an order of presentation that depends upon their own characteristics and needs. More adaptivity is expected from e-learning systems since students need to be considered independent.

The purpose of this study is to investigate and demonstrate the possibility of developing Adaptive e-learning model for Ethiopian higher learning institutions learners.

In this research, an experiment was made to build a learner model for an adaptive e-learning model. Firstly, Information independent of the course like learner goals and background and experiences as well as domain dependent data like prior knowledge about the course and learner expectations from the course were assessed. Secondly, an experimental learning styles predictive model is built through neural network data mining modeling technique.

From the analysis of the assessment in this study, Ethiopian higher learning institutions learners' students have varying learning goals, learner background and experiences, preferences, learning styles as well as prior knowledge about the course and their expectations from the course.

The learning style predictive model is experimented by neural network data mining technique from student learning style questionnaire that received from 1296 respondents. Fourteen variables were selected from the twenty variables for each model. From the total dataset, 80%, 10% and 10% of the data is used for training, validating and testing purpose respectively.

Neural network model is built which can correctly classify 93.07%, 92.30%, 96.15% and 94.61% of the validation set for visual-auditory, sequential-global, activist-reflective, sensitive-intuitive and learning styles respectively. Lastly, an adaptive e-learning model prototype was designed.

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

In today's rapidly changing electronic world, Knowledge is the key to maintaining the appropriate impetus and momentum in organizations and academic environment. Therefore, continuous, convenient and economical access to training and qualification assumes the highest priority for the ambitious individual or organization where this requirement could easily be met by electronic learning [1]. E-learning is one of the most recent technology-based innovations in education [2]. E-Learning can be a solution for national specific Problems. It can solve crowded classrooms. It can reduce high price of traditional educational books. It creates chance for handicapped & special needs students. It can reduce transportation problems and costs. It can enhance adult education and specialized training. It can be good Chance for talented students to participate in the International educational community [3].

Universities have also benefited from these new forms of transmission of knowledge by transforming the current teaching system from a package of information to be delivered, to a permanent open learning environment, which has given birth to the digital campus. Indeed, e-learning provides great flexibility by allowing learners to choose the specified place and time that they wish to devote to their training according to their professional and personal availability. This has made it possible for the staff to implement great projects at lower costs and thus bolster the company in a world of competitiveness in the context of globalization. E-learning has also given place to an even better third form of education which attempts to maximize the advantages of face-to-face discussion and online methods as two balanced and combined teaching modes, aiming at the development of the learner's knowledge [4].

However, for a learning system to be effective a learning environment should be capable of monitoring the activities of its users. Interpreting these on the basis of domain-specific models; inferring user requirements and preferences out of the interpreted activities, appropriately representing these in associated models; and, finally, acting upon the available knowledge on its users and the subject matter at hand, to dynamically facilitate the learning process [5].

To the contrary, traditional e-learning systems are focused on the content, and most of them fail in considering the end user. In fact, the idea of individualized learning, learning suited to the specific requirements and preferences of the individual cannot be achieved especially at a "massive" scale using traditional approaches. There are factors that further contribute in this direction: the diversity in the "target" population participating in learning activities and the diversity in the access media and modalities that one can effectively utilize today in order to access, manipulate, or collaborate on are some of them. Adaptive systems record user's goals, options and knowledge, and are capable of adapting to them. After identifying the user learning style, such a system provides content accordingly [7].

The term adaptive is often confused with adaptable [8]. Systems that adapt to the users automatically based on the system's assumptions about user needs are called adaptive where as systems that allow the users to change certain system parameters and adapt their behavior accordingly are called adaptable. An important characteristic of adaptive systems is that the systems adapt their behavior to each individual user on the basis of non-trivial inferences from information about that user. Compared to adaptability, adaptivity represents a more advanced step towards artificial intelligence [8].

In this context when adaptation is discussed, it is not about product differentiation by learning delivery location, as in hybrid e-learning content did not compare to fully online courses [*9]* nor is it about differentiation in time, as in synchronous and asynchronous learning rather one of three types of adjustment is usually involved [6]; Differentiation of content**:** Offering students the chance to start at different places in the curriculum and/or proceed at different paces. Differentiation of learning style approach: Emphasizing many modalities of learning style or learning preference, such as visual and auditory learners. Differentiation of product: Giving different assignments to different students, and turn in different work products.

Generally an e-learning system that recognizes the different learner characteristics, the complex learning process that can be influenced by characteristics such as previous knowledge, learning styles, background, etc; should be made in place[10]. This system is also expected to analyze students need to use learning material and an order of presentation that depends upon their own characteristics and needs. An e-learning system of such kind in which the Ethiopian students are searching for is termed as an adaptive e-learning.

1.2. STATEMENT OF THE PROBLEM

Developing adaptive e-learning, as mentioned, is an extremely difficult task, and researchers from around the world are investigating different ways to facilitate it. This subject is important enough that a series of workshops, called A3H (Authoring of Adaptive and Adaptable Hypermedia) and dealing with this specific topic, have been successfully held during the last few years: A3H at User Modeling 2007 (UM'07); A3H at Adaptive Hypermedia 2006 (AH'06), in Dublin; at the 12th International Conference on Artificial Intelligence in Education (AIED 2005), in Amsterdam; at Adaptive Hypermedia 2004 (AH'04), in Eindhoven; and at the IASTED International Conference on Web-Based Education (WBE 2004), in Innsbruck [11].

According to the preliminary study, there are many e-learning courses available online but Ethiopian learners in general and Ethiopian higher learning institution learners do not use most of them in particular. This is may be because of the traditional e-learning systems may not consider Ethiopian students varying goals, different backgrounds, and knowledge levels and learning styles among other factors. One of the hypothesis in this research for non-usability of e-learning courses is they lack adaptivity to Ethiopian students.

On the other hand, study conducted in Ethiopian government schools on the functionalities of plasma system investigated; students spend the majority of their instructional time adapting them to the "plasma" transmission; they are passive and dissatisfied with the mode of instruction. The major factors associated with their dissatisfaction are the high level of English language skills assumed by the system, the speed of the presentations that creates difficulties for conceptual understanding [12]. This proven the need of adaptivity in learning within Ethiopian learners; a new learning idea that can be developed based on the characteristics, knowledge levels, goals and learning styles of students.

Not all students learn in the same way. Many years ago, educational research has identified a number of factors that account for some of the differences in how students learn. One of these factors, learning styles, is broadly described as "cognitive, affective, and physiological traits that are relatively stable indicators of how learners perceive, interact with, and respond to the learning environment" [13]. The Cultural and economical differences also make differences in learning styles. For example, research showed that members of industrialized and non-industrial societies respond to visual illusions quite differently [14]. Other research shows socio-economic difference affecting students learning style. For instances, [15] who studied ethnic groups in elementary schools, found that the pattern of mental abilities (e.g., visual, spatial, abstract, and numerical) displayed by middle-class and lower class Chinese children differed from the pattern displayed by middle-class and lower class Jewish children. So the e-learning system developed somewhere cannot fit to Ethiopian student learning needs.

If the Ethiopian higher learning institutions learners, exhibit unique learning style characteristics, when they are forced to learn content outside a certain culture, then they use most of their time and effort trying to adjust to their new learning situations. These factors force the researcher to see all possibilities of designing an e-learning system that considers the culture, socio-economical situation and the cognitive, affective and physiological traits of Ethiopian learners.

Even though, the truth reveals cultural difference, the economic situation of the society has great impact on how people learn, and it is prerequisite for any e-learning system design, to the best of the researcher's knowledge, there is no research conducted on designing learning systems based on the above assumption for Ethiopian learners given the influence of cultural and economical difference in learning design. Therefore, to fill this gap in Ethiopian e-learning system, an experimental research is conducted to explore the possibilities of designing adaptive e-learning systems for Ethiopian higher learning institution learners.

Therefore, the research focused on answering the following questions.

- What are the different possibilities of designing adaptive e-learning system for Ethiopian higher learning institution students?
- How to model learner goals, motivational state, learner background and experiences, preferences, factual and historic data, previous knowledge and expectations
- Is that possible to build learning style predicting model by using neural network technique?

1.3. Objectives of the Study

1.3.1 General Objective

The general objective of the study is to investigate and demonstrate the possibility of developing an adaptive e-learning model for Ethiopian higher learning institution students

1.3.2 Specific Objectives

To achieve the above general objective the following specific objectives should be attained;

- Modeling learner needs, preferences, characteristics, backgrounds, knowledge levels
- Predicting learning styles by using neural network technique
- Reviewing literatures on learning design aspects and data mining modeling techniques for predicting learning styles
- Training the model with appropriate learning algorithm and representative data
- Evaluating the model with independent testing dataset
- Designing adaptive e-learning system prototype

1.4. Scope/Coverage of the Study

Even though the study is broad and sensitive that needs to cover the learning need of all Ethiopians, due to shortage of time, it is only confined in the case of higher learning institutions of Ethiopia. Where as effective adaptive e-learning model includes media model, domain model, adaptation model, learner model; due to shortage of time, the research focuses on adaptivity from learner modeling perspective. Again due the same problem to collect enough data, the learning style model in this research is based on the data taken from 1296 dataset though the researcher believe the network performs better with large dataset.

1.5. Research Methodology

1.5.1 Review of Related Literature

To learn what others have done in the area from various corners of the world and to understand where the gap lies to move one-step to the Ethiopian education system, literature revision was made. Exhaustive literature review was performed to investigate the underlying principles/theories and styles of learning because these theories of learning provide empirically-based accounts of the variables which influence the learning process, and provide explanations of the ways in which that influence occurs [16]. Learning style shows the way in which each person absorbs and retains information and/or skills. Another extensive literature revision was also made about machine learning techniques and their significance in the e-learning industry. Revision was also conducted on features and different aspects of adaptive e-learning.

1.5.2 Sampling Techniques

The research is aimed to develop an adaptive e-learning model for Ethiopian higher learning institution students. Purposive sampling technique is used to select both the domain area and the sample size. The domain area/course selected in this research is introduction to computer. The course is chosen by considering two facts: Firstly, the course/skill is integrated in the curricula of all undergraduate disciplines so more respondents are expected to be accessible to train the model. Secondly, this course has high role to create awareness and skill in e-learning systems.

Two purposive sampling techniques were used in the research to determine the sample population:

Convenience/accessibility sampling: Addis Ababa University is selected as a target population. The strategic location of the university from the place where this research is conducted in relation to the time given for the research is one basic reason to select the university as a target population. Moreover, some of the questions are vague despite many arrangements made after the pilot test. The reason behind is many of the respondents have no experience for e-learning systems. Therefore, at the time of data collection, clarification of some the question is necessary for respondents. To collect accurate data the researcher has to select a target population where questionnaire administration is easy. Since respondents in Addis Ababa University are students of the researcher and his colleagues, accurate data is expected from this university.

Judgmental sampling: the other factor to select Addis Ababa University as a target population is based on the preliminary study. ICT infrastructure to use e-learning is better in Addis Ababa University which is pre-requisite for e-learning systems. Besides, the objective of the study is designing e-learning systems for Ethiopian higher learning institution learners. Accurate and large volume of data is needed especially on learning style model building. More important is the quality of data collected its representativeness from the different cultures, socio economical background of Ethiopian. It should also represent different departments assuming students from different department may have different learning needs and learning styles. To achieve all this, the researcher was forced to select a university that has high number of students, various disciplines and representative student population from each corner of Ethiopia. After an effort to include the different departments, assuming that they have different learning needs; respondents are selected randomly from each department.

1.5.3 Sample Size

Two types of data were used for this research. Large volume of data is needed to build neural network model that predict learning styles of students. For this case questionnaire, for 1400 respondents were distributed among which1296 of the questions were returned back. The data is collected from Addis Ababa University regular and extension students who are taking introduction to computer/information communication technology course in the second semester of 2009/2010 academic year.

The other portion of data is used to asses learners goals, expectations, knowledge level and needs from the domain i.e. introduction to computer as well as needs independent of the domain. This data, which is used to asses the learning expectations, goals and objectives of students from the course was collected from some 105 selected students. At this point it was not tried to elicit the needs of each and every details of learners because this can be done at the implementation but basic learner information to build the model is collected and analyzed by using SPSS software package.

1.5.4 Data preprocessing

1.5.4.1 data collection

Learners have different needs. Incorporating these needs improves the learning system and helps create adaptive systems. Learners differ in the following ways: Level of Knowledge about the subject matter, learning goals from a certain subject matter, learning styles about the subject and cognitive traits of the individual. In this research, for an effective adaptive e-learning system design, the information about each student is collected through questionnaire distribution. The questionnaire is adopted from [17] developed to asses learning style of learners.

1.5.4.2 DATA PREPARATION

Data preparation is to define and process the mining data and make it fit specific data mining technique, in this case to the neural network. Data preparation is the first important step in the data mining and plays a decisive role in the entire machine learning process. The following data preparation tasks were undertaken; filling the vacancy value of the data, eliminating the noise data, correcting the inconsistencies in the data, converting the categorical variables into small range numeric values by giving zero weight for each 'no' responses and weight of one for 'yes' responses.

1.5.4.3 MODELING TECHNIQUES AND TOOLS

There is still an active debate within the research community regarding the best model. The data mining modeling technique selected in this research is multilayer perceptron artificial neural networks. This modeling technique is selected after various model assessment and performance metric [19, 20].

In order to gather experimental results the researcher have adapted Weka (version 3-6-2), a data mining tool from the University of Waikato in New Zealand [18]. The rationale for using the Weka data-mining tool from the other data mining tools is described as follows. Weka is an open source Java application. The Weka system contains some visualization, pre and post-processing tools as well as a suite of data mining algorithms for classification, clustering and associations. The Weka explorer window allows users to run sets of test with any of the classification algorithms. This system is extremely useful because of its wealth of functionality and the ability that it give the user to implement new functions or change existing code to better suit his or her purpose.

The WEKA, artificial neural network architecture, allows to specify number of hidden nodes and layers, momentum, learning rate, decay, and validation set size and threshold, maximum number of epochs, which are very important for the performance of the model.

1.6. Ethical Considerations

In the process of the study, the following ethical issues were considered. In order to obtain an informed consent from the respondents, the purpose of the study was explained clearly. Respondent i.e. students were asked to give their informed consent orally before filling out the questionnaire. Information obtained from the respondents was promised to be kept confidential. Necessary efforts were made so that the languages in the data collection tools would consider the culture, religion and the comprehending level of the respondents.

1.7. Significance of the Study

It is the researcher's strong believe the research can contribute a lot for the nation in general and for higher learning institutions in particular in the following ways:

- It can be a bench mark to design appropriate and adaptive e-learning model for all courses given in higher learning institutions of Ethiopia
- The result of the research is an adaptive e-learning model for introduction to computer/information communication technology course, it can reduce all traditional classroom costs
- In this research of modeling the characteristics of learners of can help Ethiopian higher learning institutions in many ways: learning content development, curriculum design, materials development, student orientation, and teacher training

1.8. Organization of the Thesis

This research is organized into six chapters. Chapter one consists of background, statement of the problem and its justification, objectives of the study, methodology followed in the course of the study and the scope/scope of the study. In chapter two, literature reviews on basic learning aspects such as learning theories and learning styles, e-learning design trends and needs for adaptivity in e-learning as well as adaptive e-learning system components, designing processes were performed. Chapter three presents data mining application in e-learning in general and for adaptive e-learning systems in particular. In addition, neural network features were presented in chapter three. In Chapter four, analysis results of some domain dependent and domain independent learner profiles are presented. Chapter five describes building neural network model for learning style prediction. From the thesis analysis and from the researcher understanding, conclusions and recommendations are given in chapter six.

CHAPTER TWO

LEARNING THEORIES, STYLES AND TECHNOLOGICAL TRENDS IN LEARNING

This literature review is divided into five main parts. Part one discusses the different learning theories on how people learn. Part two deals with learning styles, different models developed to identify learning styles and teaching strategies for the different style of learners strategies which describe the basic notions for the inception and need for the study of learning styles and strategies. Part three describes the function of ICT (information communication technology) in learning. Part four also discusses e-learning, its challenges and opportunities as well as the limitations that lead to the starting of adaptive learning. The last part deals with adaptive e-learning. The theoretical approaches of adaptive e-learning design, the process of adaptive e-learning design are discussed.

2.1. INTRODUCTION

Learning is the acquisition of new knowledge and skills. It spans a range of processes from practice and rote memorization to the invention of entirely novel abilities and scientific theories that extend past experience. Learning is not restricted to humans: machines and animals can learn, social organizations can learn, and a genetic population can learn through natural selection. In this broad sense, learning is adaptive change, whether in behavior or in belief [21]. A learning problem specifies; what is to be learned, a range of relevantly possible environments in which the learner must succeed, the kinds of inputs these environments provide to the learner, what it means to learn over a range of relevantly possible environments, and the sorts of learning strategies that will be entertained as solutions [21]. In learning, the following are activities to be jointly taken by those concerned [21];

1 **Need identification;** finding out learners' needs through asking question, observation, interview etc. to generate/stimulate interest and identify interests and basic knowledge already acquired by individual learners
2 **Standard setting;** setting targets and standards so as to enable learners to learn in accord with their aptitude and interests and to their highest potential
3 **Planning for learning;** planning of learning activities in accordance with learners' needs
4 **Learning;** is an interactive process of building knowledge from analytical thinking, planning and action
5 **Evaluation;** is an assessment of experiences in the organization of the learning process, focusing on benefits obtained by learners
6 **Conclusion of learning out comes;** application of assessment outcomes for further development, amendment deficiencies in learning and organization of teaching-learning activities

2.2. Learning Theories

Theories of learning provide empirically based accounts of the variables, which influence the learning process, and provide explanations of the ways in which that influence occur. It is interesting to think about your own particular way of learning and to recognize that not everyone learns the way you do [16]. There are many different theories of how people learn. What follows is a variety of them;

Sensory Stimulation Theory: traditional sensory stimulation theory has as its basic premise that effective learning occurs when the senses are stimulated [22]. Laird, [22] quotes research that found that the vast majority of knowledge held by adults (75%) is learned through seeing. Hearing is the next most effective (about 13%) and the other senses touch, smell and taste account for 12% of what we know. By stimulating the senses, especially the visual sense, learning can be enhanced. However, this theory says that if multi-senses are stimulated, greater learning takes place. Stimulation through the senses is achieved through a greater variety of colors, volume levels, strong statements, facts presented visually, use of a variety of techniques and media.

Reinforcement Theory: this theory was developed by the behaviorist school of psychology, notably by B.F. Skinner [22, 23]. Skinner believed that behavior is a function of its consequences. The learner will repeat the desired behavior if positive reinforcement (a pleasant consequence) follows the behavior. Positive reinforcement, or 'rewards' can include verbal reinforcement such as 'That's great' or 'You're certainly on the right track' through to more tangible rewards such as a certificate at the end of the course or promotion to a higher level in an organization. Negative reinforcement also strengthens a behavior and refers to a situation when a negative condition is stopped or avoided as a consequence of the behavior. Punishment, on the other hand, weakens a behavior because a negative condition is introduced or experienced as a consequence of the behavior and teaches the individual not to repeat the behavior which was negatively reinforced.

Cognitive-Gestalt Approaches: The emphasis here is on the importance of experience, meaning, problem solving and the development of insights [16]. Burns notes that this theory has developed the concept that individuals have different needs and concerns at different times, and that they have subjective interpretations in different contexts.

Holistic Learning Theory: the basic premise of this theory is that the ‘individual personality consists of many elements. Specifically, the intellect, emotions, the body impulse (or desire), intuition and imagination [22] that all require activation if learning is to be effective.

Facilitation Theory: Carl Rogers and others have developed the theory of facilitative learning. The basic premise of this theory is that learning will occur by the educator acting as a facilitator, that is by establishing an atmosphere in which learners feel comfortable to consider new ideas and are not threatened by external factors [22].

Experiential Learning Theory: Kolb proposed a four-stage learning process with a model that is often referred to in describing experiential learning [23]. The process can begin at any of the stages and is continuous, i.e. there is no limit to the number of cycles you can make in a learning situation. This theory asserts that without reflection we would simply continue to repeat our mistakes. [23] Research found that people learn in four ways: learning can be achieved through concrete experience, observation and reflection, abstract conceptualization and active experimentation.

Adult Learning: adult learners are different from traditional college students. Many adult learners have responsibilities (e.g. families and jobs) and situations (e.g. transportation, childcare, domestic violence and the need to earn an income) that can interfere with the learning process. Most adults enter educational programs voluntarily and manage their classes around work and family responsibilities. Additionally, most adult learners are highly motivated and task-oriented [24]. Adults have many challenges today, such as multiple careers, fewer stable social structures to rely on, living longer, and dealing with aging parents.

2.3. LEARNING STYLES

Generally, it is believed that learners with similar learning styles are characterized by similar learning needs, goals, capacity and preference. In this part of the literature, the researcher discusses the different learning styles developed by experts. This helps to select learning styles that suits Ethiopian learners and make benchmarks to discovering learning styles. Learning style is "the way in which each person absorbs and retains information and/or skills" [13]. It refers to the way in which each individual collects, organizes and transforms information.

Differences in learning styles, the idea that people learn in different ways, has been explored over the last few decades by educational researchers. Kolb, [23] one of the most influential of these, found that individuals begin with their preferred style in the experiential learning cycle. Learning styles, different to approaches to learning, is a term used to describe the attitudes and behaviors, which determine an individual's preferred way of learning. Most people are not even aware of their learning style preferences [25].

Learning styles are usually more intrinsic, part of the learners' inherent personal traits. This however does not mean that learning styles cannot be modified. Students can easily become bored and frustrated if the teaching method is only tapping into one types of learning style, as most classes have students with a range of learning style preferences.

Many years ago, educational research has identified a number of factors that account for some of the differences in how students learn. One of these factors, learning styles, is broadly described as "cognitive, affective, and physiological traits that are relatively stable indicators of how learners perceive, interact with, and respond to the learning environment" [14]. Research on cultural differences in learning styles indicates, for example, that members of industrialized societies and members of non-industrial societies respond to visual illusions quite differently [15]. [15] Who studied ethnic groups in elementary schools, found that the pattern of mental abilities (e.g., visual, spatial, abstract, and numerical) displayed by middle-class and lower class Chinese children differed from the pattern displayed by middle-class and lower class Jewish children. If, indeed, learners outside culture exhibit unique learning style characteristics, then students out of a certain culture may use most of their time and effort trying to adjust to their new learning situations. Therefore, identifying the learning style preferences of learners have wide-ranging implications in the areas of learning content development, curriculum design, materials development, student orientation, and teacher training. In the coming sections, the researcher revises some of the learning styles of learners given by different professionals.

Different models on learning styles have been developed by different group of individuals. To mention some of them; The model by [17] in North Carolina State University, on learning styles was originally developed in collaboration with an educational psychologist, Dr Linda Silverman. They developed both a model and an 'Index of Learning Styles'. It has become recently a very popular model to use to describe learning styles. The model divides learning styles based on how they perceive, acquire and process information as is explained below.

1. Perception: What type of information does the student preferentially perceive: sensory (external) sights, sounds, physical sensations, or intuitive (internal) possibilities, insights, hunches? So based on this dimension students are classified as sensory or intuitive learners.

Sensory learners: these students like facts, data and experimentation. They perceive concrete, practical, and are oriented towards facts and procedural information. When solving problems, sensory students are routinely very patient with details and usually dislike surprises. Because of these characteristics, they show a slower reaction to problems, but they typically present a better outcome.

Intuitive learners: intuitive learners prefer theories and principles. They rapidly become bored with details and mechanical problem solving. They generally solve problems quickly, not paying much attention to details. This makes them fast but prone to errors and, then, they often get lower qualifications than sensitive learners do.

2. Input: Through which sensory channel or external information most effectively perceived: visual-pictures, diagrams, graphs, demonstrations or verbal written or spoken sounds? Again based on this dimension students are classified as visual or verbal learners.

Visual learners: they remember, understand and assimilate information better if it is presented to them in a visual way. They tend to remember graphics, pictures, diagrams, time lines, blueprints, presentations and any other visual material.

Verbal learners: cognitive scientists have established that our brains generally convert written works into their spoken equivalents and process them in the same way that they process spoken words. Hence, verbal learners are not only those who prefer auditory material but also those who remember well what they hear and what they read.

3. Processing: How does the student prefer to process information: actively through engagement in physical activities or discussions, or reflectively through introspection? So based on this dimension students are classified as active or reflective learners.

Active learners: they feel more comfortable with active experimentation than with reflexive observation. An active person learns by trying things out and working with others. They like doing something in the external world with the received information. Active learners work well in groups and in situations that require their participation.

Reflective learners: reflective learners prefer introspective examination and manipulation of information. They learn by thinking things through and working alone or with another person.

4. Understanding: How does the student progress towards understanding: sequentially in continual steps, or globally in large jumps, holistically? Based on this dimension students are classified as sequential or global learners.

Sequential learners: sequential learners follow a line of reasoning when progressing towards the solution of a problem; they like things to be linear. They learn better if information is presented in a steady progression of complexity and difficulty (i.e. they learn in small incremental steps).

Global learners: global learners make intuitive leaps and may be unable to explain how they come up with solutions. They are holistic, system thinkers; they learn in large leaps. They need to understand the whole before understanding the parts that compose it; they need to get the 'big picture'. In conclusion, the model classified learners into Active or Reflective Learners, Sensing or Intuitive Learners, Visual or Verbal Learners and Sequential or Global Learners.

Another model by [27] adapted in 1984 divides the learner based on their learning styles and proposed teaching strategy for each group of learners in the following ways;

Concrete Experience (CE): A receptive, experience-based approach to learning that relies for a large part on judgments based on feelings. CE individuals tend to be empathetic and people oriented. They are not primarily interested in theory; instead, they like to treat each case as unique and learn best from specific examples. In their learning they are more oriented towards peers than to authority and they learn best from discussion and feedback with fellow CE learners.

Reflective Observation (RO): A tentative, impartial and reflective approach to learning. They rely on careful observation of others and/or like to develop observations about their own experience. They like lecture format learning so they can be impartial objective observers. For these learners Self-reflection exercises, journals, brainstorming are needed.

Abstract Conceptualization (AC): An analytical, conceptual approach to learning: logical thinking, rational evaluation. These learners are oriented to things rather than to people. They learn best from authority directed learning situations that emphasize theory. They do not benefit from unstructured discovery type learning approaches. They like Lectures and papers.

Active Experimentation (AE): An active, doing approach to learning that relies heavily on experimentation. These learners learn best when they can engage in projects, homework, small group discussion. They do not like lectures, and tend to be extroverts.

Others [28] formulated Instrument, considering the learning styles and a description of teaching strategies of each learning styles. The following table summarizes the [28] learning style and their proposed teaching strategy.

Learning Style	Teaching strategy
Visual-Language: This is the student who learns well from seeing words in books, on the chalkboard, charts or workbooks. He/she may write words down that are given orally in order to learn by seeing them on paper. He or she remembers and uses information better if it has been read.	This student will benefit from a variety of books, pamphlets and written materials on several levels of difficulty. Given some time alone with a book, he or she may learn more than in class. Make sure important information has been given on paper, or that he or she takes notes if you want this student to remember information.
Visual-Numerical: This student has to see numbers on the board, in a book, or on paper in order to work with them. He or she is more likely to remember and understand math facts if he or she has seen them. He or she does not seem to need as oral explanation.	This student will benefit from worksheets, workbooks, and texts. Give a variety of written materials and allow time to study it. In playing games and being involved in activities with numbers and number problems, make sure they are visible, printed numbers, not oral games and activities. Important data should be given on paper.
Auditory-Language: This student learns from hearing words spoken. You may hear him or her vocalizing or see the lips or throat move as he or she reads, particularly when striving to understand new material. He or she will be more capable of understanding and remembering words or facts that have been learned by hearing.	This student will benefit from hearing audio tapes, rote oral practice, lecture or a class discussion. He or she may benefit from using a tape recorder to make tapes to listen to later, by teaching another student, or conversing with the teacher. Groups of two or more, games or interaction activities provide the sounds of words being spoken that are so important to this student.
Auditory-Numerical: This student learns from hearing numbers and oral explanations. He or	This student will benefit from math sound tapes or from working with other people, talking about a

she may remember phone and locker numbers with ease, and be successful with oral numbers, games and puzzles. He or she may do just about as well without a math book, for written materials are not as important. He or she can probably work problems in his or her head.	problem. Even reading written explanations aloud will help. Games or activities in which the number problems are spoken will help. This student will benefit from tutoring another or delivering an explanation to his or her study group or to the teacher. Make sure important facts are spoken.
Auditory-Visual-Kinesthetic: The student learns best by experience and self-involvement. He or she definitely needs a combination of stimuli. The manipulation of material along with the accompanying sights and sounds (words and numbers seen and spoken) will make a big difference to him or her.	This student must be given more than just a reading or math assignment. Involve him or her with at least one other student and give him/her an activity to relate to the assignment. Accompany an audiotape with pictures, objects and an activity such as drawing or writing or following directions with physical involvement.
Social-Individual: This student gets more work done alone. He or she thinks best, and remembers more when he or she has learned by alone. He or she cares more for his or her own opinions than for the ideas of others. You will not have much trouble keeping this student from over-socializing during class.	This student needs to be allowed to do important learning alone. If you feel, he or she needs socialization, save it for a non-learning situation. Let him or her go to the library or back in a corner of the room to be alone. Do not force group work on him or her when it will make the student irritable to be held back or distracted by others.
Social-Group: This student strives to study with at least one other student and he or she will not get as much done alone. He or she values others' ideas and preferences. Group interaction increases his or her learning and later	This student needs to do important learning with someone else. The stimulation of the group may be more important at certain times in the learning process than at others and you may be able to facilitate the timing for this student.

recognition of facts. Socializing is important to this student.	
Expressive Oral: This student prefers to tell what he or she knows. He or she talks fluently, comfortably, and clearly. The teacher may find that this learner knows more than written tests show. He or she is probably less shy than others are about giving reports or talking to the teacher or classmates. The muscular coordination involved in writing may be difficult for this learner. Organizing and putting thoughts on paper may be too slow and tedious a task for this student.	Allow this student to make oral reports instead of written ones. Whether in conference, small group or large, evaluate him or her more by what is said than by what is written. Reports can be on tape, to save class time. Demand a minimum of written work, but a good quality so he or she will not be ignorant of the basics of composition and legibility. Grammar can be corrected orally but is best done at another time.
Expressiveness-Written: This student can write fluent essays and good answers on tests to show what he or she knows. He or she feels less comfortable, perhaps even stupid when oral answers are required.	This student needs to be allowed to write reports, keep notebooks and journals for credit and take written tests for evaluation. Oral transactions should be under non-pressured conditions, perhaps even in a one-to-one conference.

TABLE 2-1 Learning Style and Teaching Strategy (WVABE Instructor Handbook, 2003-04)

2.4. BENEFIT OF ICT IN LEARNING

The term ICT (information communication technology) has becoming part of everyday language and is synonymous with television, the internet, e-mail, the mobile phone, CD-ROM, DVD, hand-held personal devices, and an ever-growing array of new inventions. ICT has changed the way people communicate, learn, and conduct business. ICT can help in meeting learning challenges in many ways [29]:

ICT enables information and knowledge to travel faster and further. New information and communication technologies overcome the barriers of distance and time, and significantly improve the accessibility of information and knowledge. As a result, the sharing of information and knowledge quickly and effectively becomes feasible and acts as a key element in achieving development goals and mitigating the impact of unforeseen events such as natural disasters or outbreaks of disease. The Internet is fast becoming the communication tool that is unrivalled for its power, speed and ability to reach a vast number of users worldwide. Video conferences that allow people to see each other and to exchange information and ideas in real time can also reach large numbers.

ICT supports information and knowledge sharing on a large scale. Knowledge sharing and learning are increasingly recognized as being powerful contributors to the classic training model, which has been and continues to be widely used to transmit knowledge and information to trainees does not usually promote knowledge sharing and learning in the manner now considered more effective in contributing to the growth of individuals and communities. The development and increasing availability of new and affordable information communication technology, such as email, e-discussion tools, instant messaging, IP phone and VC, offers promise for widening the scope and scale of knowledge sharing and learning for development.

ICT makes available just-in-time information and knowledge for learning. In the workplace and in everyday living people seek specific knowledge and skill when and where they need it. ICT makes available and accessible just-in-time information and knowledge and provides opportunities for continuing and life-long learning. Those who own or have access to computers and the Internet can open up a wealth of information and learning resources either by on-line searching or by using CD-ROMs or DVDs for self-paced learning.

ICT has brought about revolutionary advances in distance learning. Distance learning, where learning takes place away from the place of instruction, has a long history and correspondence courses can be dated back to the mid 19th century. One of the major strengths of ICT is its ability to reach out to and include learners and clients who are separated by geography or are prevented from participating in learning activities by infrastructure, time or financial constraints. Due to its great accessibility and flexibility, distance-learning using modern ICT has invigorated both adult education and training, and organizational training and learning.

ICT can significantly reduce learning costs. Due to advances in ICT, the personal computer continues to become more and more accessible and affordable. The internet and cellular phone is becoming commonplace for millions of people including those in developing countries. The cost of videoconferencing connection is also lowered if internet Protocol (IP) is used. By using ICT, training and learning can reach a large number of people at a low marginal cost. The savings on travel and the economies of scale gained reduce learning costs and bring about cost effectiveness.

However, ICT in Ethiopia at present is at the very early stage of development. Nearly the entire rural population lacks telecommunications infrastructure. The vast majority of the population is dependent only on the conventional and traditional information delivery system, the radio or newspapers. Not only is ICT least developed in Ethiopia; it is also highly skewed towards major cities and towns, particularly Addis Ababa. In part, this is due to limitations in both physical and ICT infrastructure, and partly due to the limited number of computers. Consequently, while the Internet and other forms of information and communications technology are readily available in Addis Ababa, limited access to ICT by the rural population continues to be a major impediment to the use of ICT nation-wide. These constraints present the government with challenges, but also opportunities, for an accelerated development of ICT in Ethiopia.

2.5. E-LEARNING

There are still discussions about the definition of the term e-learning. According to [30], e-learning is defined as follows:

"E-learning is mostly associated with activities involving computers and interactive networks simultaneously. The computer does not need to be the central element of the activity or provide learning content. However, the computer and the network must hold a significant involvement in the learning activity."

A number of other terms are also used to describe this mode of teaching and learning. They include online learning, virtual learning, distributed learning, network and web-based learning. Fundamentally, they all refer to educational processes that utilize information and communications technology to mediate asynchronous as well as synchronous learning and teaching activities. The term e-learning also comprises a lot more than online learning, virtual learning, distributed learning, networked or web-based learning. As the letter "e" in e-learning stands for the word "electronic", e-learning would incorporate all educational activities that are carried out by individuals or groups working online or offline, and synchronously or asynchronously via networked or standalone computers and other electronic devices [31].

2.5.1 Trends in E-learning

The growing interest in e-learning seems to be coming from several directions. These include organizations that have traditionally offered distance education programs either in a single, dual or mixed mode setting. They see the incorporation of online learning in their repertoire as a logical extension of their distance education activities. The corporate sector, on the other hand, is interested in e-learning as a way of rationalizing the costs of their in-house staff training activities. E-learning is of interest to residential campus-based educational organizations as well [32] see e-learning as a way of improving access to their programs and also as a way of tapping into growing niche markets. The growth of e-learning is directly related to the increasing access to information and communications technology, as well it's decreasing cost. The capacity of information and communications technology to support multimedia resource-based learning and teaching is also relevant to the growing interest in e-learning [33].

2.5.2 OPPORTUNITIES OF E-LEARNING

For the e-learning industry to be popular, the following are some of the opportunities:

The flexibility that e-learning technology affords; Flexible access which refers to access and use of information and resources at a time, place and pace that is suitable and convenient to individual learners rather than the teacher and/or the educational organization. The concept of distance education was founded on the principles of flexible access [34]. It aimed to allow distance learners, who were generally adult learners in full or part-time employment to be able to study at a time, place, and pace that suited their convenience [35].

Electronic access to hypermedia and multimedia based resources; With the growing of Information and communications technology, the capture and storage of information of various types including print, audio, and video is possible. Networked information and communications technologies enable access to this content in a manner that is not possible within the spatial and temporal constraints of conventional educational settings such as the classroom or the print mode [35]. In the context of this distributed setting, users have access to a wide variety of educational resources in a format that is amenable to individual approaches to learning and accessible at a time, place and pace that is convenient to them. Typically, these educational resources could include hyper-linked material, incorporating text, pictures, graphics, animation, multimedia elements such as videos and simulations and also links to electronic databases, search engines, and online libraries.

2.5.3 CHALLENGES OF E-LEARNING

Despite this level of interest in e-learning, it is not without constraints and limitations. The fundamental obstacle to the growth of e-learning is lack of access to the necessary technology infrastructure, for without it there can be no e-learning. Poor or insufficient technology infrastructure is just as bad, as it can lead to unsavory experiences that can cause more damage than good to teachers, students and the learning experience. While the costs of the hardware and software are falling, often there are other costs that have often not been factored into the deployment of e-learning ventures. The most important of these include the costs of infrastructure support and its maintenance, and appropriate training of staff to enable them to make the most of the technology [36].

As e-learning matures as an industry and a research stream, the focus is shifting from developing infrastructures and delivering information online to improving learning and performance [37]. Examples of e-learning on the Internet today are, too often, little more than lecture notes and some associated links posted in HTML format. However, the true power of e-learning comes from the exploitation of the wide range of capabilities that technologies afford. One of the most obvious is to provide assessments and instructional content that adapt to learners' needs or desires. There are many e-learning systems, but they provide only the same materials to all students regardless of individual ability. The material is still oriented for on-campus homogeneous, well prepared and motivated students. However, the students are heterogeneous having very different goals, backgrounds, and knowledge levels and learning capabilities. The traditional e-learning systems have got problems to achieve its learning goals.

2.6. Adaptive E-learning

An adaptive e-learning system according to [38] is described as follows:

"An adaptive e-learning system is an interactive system that personalizes and adapts e-learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise."

The challenge of improving learning and performance largely depends on correctly identifying characteristics of a particular learner. Examples of relevant characteristics include incoming knowledge and skills, cognitive abilities, personality traits, learning styles, interests, and so on [3]. For instruction to be maximally effective, it should capitalize on these learner characteristics when delivering content. Instruction can be further improved by including embedded assessments, delivered to the student during the course of learning. In short, enhancing learning and performance is a function of adapting instruction and content to suit the learner [3]. The effectiveness of e-learning may be gauged by the degree to which a learner actually acquires the relevant knowledge or skill presented online. This acquisition is generally regarded as a constructive activity where the construction can assume many forms; thus e-learning environments should be flexible enough to accommodate various constructive activities [3]. This is because individuals differ in how they learn as well as what they learn, and different outcomes of learning (e.g., conceptual understanding) reflect differences in general learning processes (e.g., inductive reasoning skill), specific learning processes (e.g., attention allocation), and incoming knowledge and skill.

The goal of adaptive e-learning is aligned with exemplary instruction: delivering the right content, to the right person, at the proper time, in the most appropriate way any time, any place, any path, any pace [28].

Particular information about the user is needed to change the behavior of the system in order to satisfy the needs of that user. In adaptive systems, this information is stored in a profile or in a model of the user. Hence, a detailed user profile or a user model is needed to enable adaptivity of the system [39].

2.6.1 Instructional Adaptation Approaches

In the context of e-learning, the adaptation of instruction is affected. Instruction is the form how learner are educated. There exist several possibilities how the instruction is adapted. The four main theoretical approaches are: the macro-adaptive approach, the aptitude-treatment interaction approach, the micro-adaptive approach and the constructivist collaborative approach. These approaches describe the different possibilities of adaptive instruction.

1. **Macro-adaptive Approach**

Early attempts to personalize instruction to learners took place on the so-called macro-level. The students were grouped or classified by grades. This grouping resulted in a homogeneous evaluation of the learners and had minimal effects on the adaptation because the groups received different instructions very seldom. To better accommodate different student abilities, the macro-adaptive approach was invented in the early twentieth century, where the adaptation of instruction is concerned on a macro-level as well. Within the macro-adaptive approach, alternative instructions are computed, based on a few main components such as learning objectives, levels of detail and delivery system. The selection of the appropriate instruction is mostly based on the student's instructional goals, general abilities and achievement levels in the curriculum structure [40].

According to [41], the selection of instructions (i.e., activities) depends on learning objectives such as compensate students' weaknesses or developing new skills and student aptitudes. These aptitudes are categorized into three types, namely intellectual abilities and prior achievement, cognitive, learning styles, academic motivation, and personality.

2. Aptitude-treatment Interaction Approach

The aptitude-treatment interaction (ATI) approach adapts instructional strategies to students' aptitudes. This strategy recommends different types of instructions for students with different characteristics. [42], Lists the most important characteristics as intellectual abilities, cognitive styles, learning styles, prior knowledge, anxiety, achievement motivation, and self-efficiency. ATI further offers the user full or partial control over the learning process. The user is able to control the style of the instruction or the way through the course. Three levels of control are defined, complete independence, partial control within a given task scenario and fixed tasks with control of pace. Studies have shown that the learner's aptitudes influence the learning result when offering different levels of control of the instruction to the learner. For example, students with low prior domain knowledge get better results if this control is limited [41].

3. Micro-adaptive Approach

Learning needs during instruction are used by the micro-adaptive approach to adapt the instruction. Theses needs are examined and an appropriate prescription is generated. Compared to the pretask measurements of the macro-adaptive and the ATI approach, the micro-adaptive approach is rather based on on-task measurements. The student behavior and performance are observed by measuring e.g., response errors, response latencies and emotional states.

The first model for the micro adaptive approach is the idea of programmed instructions and was originally applied by Pressey in the year 1926. Through the usage of technology, a number of different micro-adaptive instructional models have been developed. These models differ from the programmed instruction idea by applying a specific model or learning theory. [40], lists following models; the mathematical model, the trajectory model, the Bayesian probability model and the structural and algorithmic approach.

According to [42], in case of the micro-adaptive approach adaptive e-learning is separated in two main processes, the diagnostic process and the prescriptive process. The first step (the diagnostic process) is used to characterize the learner by identifying the aptitudes or the prior knowledge and to formulate the task. Secondly, the interaction between the learner and the task is optimized by adapting the learning content to the students' aptitudes and actual performance.

4. Constructivist-collaborative Approach

The constructivist pedagogical approach focuses on how an e-learning system can be integrated into the learning process. The learner takes an active role in the process of learning, where the knowledge is constructed by experiences in the specific knowledge domain according to the constructivist learning theory.

Another major part of this approach is the employment of collaborative technologies, where the pedagogical approach of collaborative learning activities is integrated.

Five characteristics of effective collaborative learning are identified by [43], namely participation, social behavior, performance analysis, group processing and conversation skills and primitive interaction. To enable a learning success through collaborative technologies, these five characteristic should be available to the learner.

2.6.2 ADAPTIVE LEARNING DESIGN PHASES

Adaptive learning design comprises the following processes. These include: learning styles definition, Tests, learning designs and adaptive rules.

2.6.2.1 LEARNING STYLE DEFINITION

Learning styles, which establish indicators on how learners perceive and process Information, might be helpful to design learning materials suitable to the way each Learner learns. The Kolb's Experiential Learning Theory [27] is a well-known example of a learning style approach. It proposes four dimensions to characterize the way the student perceives information (theorist and activist dimensions) and the way s/he process it (reflectors and pragmatist dimensions).

2.6.2.2 TEST DEFINITION

In the definition of tests, authors will describe assessments to measure the knowledge and learning style of the students. There are four types of tests: learning style, initial knowledge, current knowledge, and final knowledge. The students' results on these tests will set values that could be stored in the student model, or be used to define adaptive rules and connect them with the learning style of the activities.

2.6.2.3 LEARNING DESIGN

This phase describes the pedagogical approach of the adaptive learning design defining its learning objectives, prerequisites, roles, outcomes (learning and support activities), environments (learning objects and services), and the method of instruction. Effective instructional strategies might involve learning styles [44]. Consequently, they are included in the definition of activities and integrated in the learning design definition.

2.6.2.4 ADAPTIVE RULE DEFINITION

In this phase, it is intended to make use of the authors' pedagogical approach and expertise on the knowledge field, and give them freedom to decide what characteristics and variables should be considered to perform adaptively. Therefore, authors will be provided with a formalism to define adaptive rules, which adjust the learning design to the students' characteristics and to the nature of the knowledge [45].

2.6.3 LEARNER MODELING

A learner model represents the system's beliefs about its main target user, the learner, and provides the necessary information for tailoring the instruction to the needs of the learner. This necessary information is represented by the content of a learner model. An extensive learner model must contain information about the learner's domain knowledge, the learner's progress, preferences, goals, interests and other information about the learner, which is important for the used systems [46].

2.6.3.1 TYPES OF INFORMATION IN LEARNER MODEL

In [47], it is stated that learner models can be classified according to the nature and form of information contained in the models. Considering the subject domain, the information stored in a learner model can be divided into two major groups: domain specific information and domain independent information.

Domain Specific Information

Domain specific information represents a reflection of the learner's state and the level of knowledge and skills in a particular subject. In [47], the domain specific information is named as knowledge model. This knowledge model can be based on different types of models or a combination of these types. The possible types of knowledge models are described in the following [47, 48].

Scalar Model: within a scalar model, one identifier describes the level of the learner's knowledge on the entire domain. The scalar model is the simplest form of a knowledge model and provides no information about knowledge in a sub-domain

Overlay Model: The entire domain information consists of a set of knowledge elements or curriculum elements and represents the expert's knowledge in this domain. The overlay model describes the learner knowledge as a subset of the complete domain model. Lack of knowledge by the learner is derived by comparing it to the expert's knowledge. To each knowledge element in the learner's overlay model, a certain measure is assigned representing the estimated knowledge of the learner on that element. The measure can be a scalar (for example an integer, a probability measure or a flag) or a vector estimate.

Error Model: A disadvantage of overlay models is the incapability of storing errors or mistakes made by the learner. For this reason, the bug model or error model has been developed. With an error model, it is possible to define and reflect erroneous behaviors of learners and the reasons for these errors. Error models can be categorized into perturbation models and differential models. Perturbations or misconceptions for each knowledge element are stored in a perturbation model. It is assumed that one or more perturbations exist for each knowledge element of the domain model. Thus, a learner's perturbation model represents a subset of all possible perturbations, which are the cause for incorrect learner behavior regarding particular knowledge elements.

Genetic Model: The described models, overlay and error model, represent the state of the learner's knowledge. Nevertheless, these models do not express the structure of the domain knowledge. Therefore, genetic models are used to describe the development of the learner's knowledge. This process can evolve from simple to complex or from special to general. For example, the learner starts with a very special knowledge and proceeds toward a broad and general knowledge. It is possible to describe a genetic model by a genetic graph, where the nodes and the relationships between the nodes represent knowledge elements and their interactions.

Other Domain Specific Information: Besides the already described domain specific information stored by different types of models, additional domain specific information can be stored in the learner model. According to [48] this information includes prior knowledge about the domain of the learner, records or learning activities (taken lectures, number of asks for help, time to solve problems), and Records of assessments and evaluations

Domain Independent Information

In addition to the learner's current knowledge level, domain independent information is needed to enable adaptivity. Domain independent information about a learner may include learning goals, cognitive aptitudes, motivational state, background and experiences, preferences as well as factual and historic data [47, 48].

Goals: To establish the correct teaching strategy, it is important to know the learner's goals. These goals answer the questions why the learner uses the e-learning system and what the learner wants to achieve. The goals can be divided into two different types. The learning goal that is relatively stable for a course unit and the problem-solving goal, which may change from one problem to another even within one teaching unit.

Cognitive Aptitudes: Cognitive aptitudes are intellectual abilities for differing kinds of cognitive performance. For example, musical aptitude, math aptitude and reading aptitude are all different kinds of cognitive aptitudes.

Motivational States: To measure the drive in instruction the motivational state of the learner is used. The motivation is measured using a number of long-term and short-term parameters. Such parameters are for example effort, attention, interest, distraction, persistence, etc. These parameters are connected to other factors such as knowledge level, readiness, complexity of the topic and learning outcome.

Background and Experience: To derive parameters of the learner model, information about background and experiences is used. Background information includes skills that may affect the learning achievement. Such information is for example, profession, work experience or perspectives. Experience represents knowledge about the learning environment. Learners, which are new to a particular learning environment or even new to e-learning may need different system support regardless if they are novices or experts in the subject domain. This information might be used to select the appropriate adaptive navigation method.

Preferences: The learners may have different preferences related to some aspects of the learning environment. These preferences are considered as not inducible by the system. Thus, the learner has to inform the system directly or indirectly about his or her preferences. It is important for an adaptive e-learning system to present and organize the learning material based on the learner's preferences. Learner preferences can also be used to form groups of learners. This technique is called group modeling. Two parts of the preferences are the learning style and the multiple intelligence, whereby learning style and multiple intelligence are mutually related to each other.

Factual and Historic Data: Demographic data such as name, age, parents, ID etc. is often stored in learner models. This information, combined with other factual data such as for example interests, is necessary to initialize an individual learner model [48].

2.6.3.2 Initialization of Learner Models

The initialization of a learner model represents the process of gathering information about the learner and transferring this information into the model [46]. This section describes methods, how information about the learner is retrieved.

According to [46], a learner model can be initialized in three ways, through explicit questions, initial testing or by stereotyping.

Explicit Questions: The initial learner models are often constructed by directly questioning the learner. This method is a very effective way to obtain general information about a learner. The problem is to find the appropriate amount of questions and to get the optimum amount of information out of these questions on the other side; too many initial questions could irritate the learner and increase the declination to the system. The worst case would be, if the learner leaves the system and never returns on the other side, too less or not well-selected questions do not allow the system to extract enough information to initialize the learner model.

Initial Tests: By asking the learner to take a test, the initial parameters in the learner model can be obtained by analyzing the test results. In order to control the length of the test, the concept of neighborhood of knowledge states may be applied. For example, if curriculum elements A and B are in the same neighborhood, mastery of A implies mastery of B. This leads to a reduction of the test length but presupposes a well constructed test. Initial tests are often used to get information about the domain knowledge of the learner.

Stereotyping: the learner modeling system may use stereotype methods in order to group similar learners to categories. Although stereotyping is very powerful in providing considerable information based on only a few observations, it does not provide an accurate learner model. The required information to be able to apply stereotyping can be retrieved by using explicit questionnaires. Another method is to assign a new and unknown learner to a default stereotype and refine the applied stereotype by observing the learner. This can also help to reduce the initial questions [48].

2.6.3.3 UPDATING LEARNER MODELS

Updating a learner model means to bring the contained data and information about a learner up-to-date. For the process of updating a learner model, information sources and update methods are needed. The used information to update a learner model can be retrieved from different information sources. At first, the information currently stored in the learner model must be considered. This information can be used as a base to infer new information or perform changes on the inferred information. Further, information currently stored in other system components can be of use.. The main source of information can be gained through monitoring the learner's interaction with the system.

According to [49], there are several ways to obtain information from the mentioned information sources: implicit, explicit, structural, and historical acquisition.

Implicit acquisition of information is based on observing actions of the learner during the learning process. Direct dialogues between system and learner are called explicit acquisition (e.g. questionnaire). Structural acquisition is performed by analyzing interrelations between curriculum elements. For example, if curriculum element A is a prerequisite of element B, an expertise in B implies the mastery of A. Assumptions based on the learner's experience are performed during a historical acquisition of information.

Information to update the learner model has to be derived by analyzing learner responses. These three methods are analytical processes and are called cognitive diagnosis. Cognitive diagnoses is defined as the process of inferring a person's cognitive state based on the performance of this person. Another method to update a learner model is to determine old data and do not using this old data anymore [46].

Analysis of Learner Responses: The analysis of learner responses is also called performance measuring [47]. Questions of an exam during instruction can be divided into simple questions and complex questions. Simple questions are only related to one specific curriculum element while complex questions require the knowledge of more than one single curriculum element. Accordingly, the learner responses to these two types of question must be handled differently. For example, a correct answer to a simple question increases the relevance of the related curriculum element, while a wrong answer decreases the relevance of the underlying curriculum element. Analyzing the response to a complex question needs more effort. Correct answers may lead to an increase of all related curriculum elements but an incorrect answer needs to be investigated more thoroughly. The question has to be split based on the structure of the domain model and the resulting parts have to be considered.

Analysis of the Process of Problem Solution: Analysis of the problem solving process requires a technology, where all possible correct rules, which can be used by the learner during the solution process, are available. By combining these rules with a collection of misconceptions responsible for error that may occur the system is able to calculate and detect all correct solution steps and misconceptions made by the learner in every step of the problem solving process [47].

Analysis of Learner Actions: Actions of the learner can be analyzed by considering them as results of the acquisition of a set of curriculum elements or misconceptions. This is possible if the subject domain is known. For this, a simply tracing of the learner actions is needed. This method is called issue tracing [47].

Discounting Old Data: Considering only topical data reduces the value of old data in the learner model. This gives importance to data, which is derived from recent actions. The process of discounting old data is based on the assumption that the time elapsed since this old data was stored, decreases the importance and the influence of the old data to the current state of the learner [47].

CHAPTER THREE

DATA MINING TECHNIQUES TO E-LEARNING PROBLEMS

3.1 INTRODUCTION

The Internet and the advance of telecommunication technologies allow us to share and manipulate information in nearly real time. Distance education arose from traditional education in order to cover the necessities of remote students and/or help the teaching-learning process, reinforcing or replacing traditional education. E-learning is a new context for education where large amounts of information describing the continuum of the teaching-learning interactions are endlessly generated and ubiquitously available just a click away [50].

As [50] cited in [51], it could equally be seen as an exponentially growing nightmare, in which unstructured information chokes the educational system without providing any articulate knowledge to its actors especially learners. Data mining in e-learning was born to tackle problems like this. At its most detailed, it can be understood not just as a collection of data analysis methods, but also as a data analysis process that encompasses anything from data understanding, pre-processing and modeling to process evaluation and implementation.

3.2 THE CLASSIFICATION PROBLEM IN E-LEARNING

In classification problems, one can usually aim to model the existing relationships between a set of multivariate data items and a certain set of outcomes for each of them in the form of class membership labels [50]. There are plenty of classification methods in a Data Mining process that would fit in e-learning application. In the following section, the researcher revised few techniques that have been applied to e-learning from [50].

Fuzzy logic methods

[50], mentioning literatures like [51], Fuzzy logic-based methods have only recently taken their first steps in the e-learning field . Fuzzy theory was used to measure and transform the interaction between the student and the intelligent tutoring into linguistic terms. Then, Artificial Neural Networks were trained to realize fuzzy relations operated with the max-min composition. These fuzzy relations represent the estimation made by human tutors of the degree of association between an observed response and a student characteristic.

ARTIFICIAL NEURAL NETWORKS (ANNS)

According to [52], artificial neural network has been used in both user model and domain model in order to select a set of suitable learning object for a student. Artificial neural network models have particular property such as ability to adapt, to learn, or to cluster data. For classification problem, the network needs a training corpus of objects with known category membership.

In the e-learning area, ANN has been widely used in classification of students based on their preferences or learning styles. In that case, ANN has been used to build the learner model, which consists of personal static data, system usage data and preferences. However ANN rarely been employed in educational system in the classification and modeling of the domain knowledge and learning materials [52].

Graphs and Trees

As [50] cited in [53], graph and/or tree theory was applied to e-learning. An e-learning model for the personalization of courses based both on the student's needs and on capabilities and on the teacher's profile was described.

In conclusion, from the different literatures summarized in [50] data mining have been used in different e-learning subjects. The following are a list them:

- Data mining applications dealing with the assessment of students' learning performance
- Data mining applications that provide course adaptation and learning recommendations based on the students' learning behavior.
- Data mining approaches dealing with the evaluation of learning material and educational web based courses.
- Data mining applications that involve feedback to both teachers and students of e-learning courses, based on the students' learning behavior.
- Data mining developments for the detection of a typical students' learning behavior

3.3 More on Artificial Neural Networks

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons by [54].

The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras. Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, relatively few researchers made important advances. The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. Nevertheless, the technology available at that time did not allow them to do too much.

3.3.1 WHY USE NEURAL NETWORKS?

Either humans or other computer techniques can use neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, to extract patterns and detect trends that are too complex to be noticed. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. Other advantages include [20]:

- A neural network acts as an associative memory. It stores information by associating it with other information in the memory. For example, a thesaurus is an associative memory.
- It can generalize; that is, it can detect similarities between new patterns and previously stored patterns. A neural network can learn the characteristics of a general category of objects on a series of specific examples from that category.
- It is robust; the performance of a neural network does not degrade appreciably if some of its neurons or interconnections are lost. (distributed memory)

- Neural networks may be able to recall information based on incomplete or noisy or partially incorrect inputs.
- A neural network can be self-organizing. Some neural networks can be made to generalize from data patterns used in training without being provided with specific instructions on exactly what to learn.
- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience
- Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
- It can be used when development time is short and training time for the neural network is reasonable.
- Neural network Performs well where Standard technology is inadequate, Qualitative or complex quantitative reasoning is required and Data is intrinsically noisy and error-prone

Generally, artificial neural networks have been applied to almost every application area where a dataset is available and a good solution is sought. Artificial neural networks can cope with noisy data, missing data, imprecise or corrupted data, and still produce a good solution [20]. Among supervised learning artificial neural networks multilayer perceptron (MLP) with backpropagation algorithm (further used as ANN) achieved popularity in numerous research areas. One of the reasons for this was that it is a pioneer artificial neural network which showed promise to solve ill-defined, complicated, complex problems which are hard to describe in mathematical formula or expression [20]. The choice of ANN architecture depends on a number of factors such as the nature of the problem, data characteristics and complexity, the number of sample data, etc. Three types of neural network architectures are [55]:

1. The Feed-Forward Neural Network (FFNN) or multi-layer perceptron. There is at least one hidden layer. All neurons have a single sigmoid output. In classification applications its outputs may be interpreted as class confidences or posterior probabilities, provided the network is well trained.
2. The Radial Basis Neural Network (RBNN) has a first hidden layer of neurons of which the outputs are radial basis functions of the inputs. This can be an exponential function (e.g. the Gaussian function) of the distance between the input and a 'position' of the neuron in the feature space. The neurons in the next layer may weight all the contributions of the radial basis functions.
3. The Self Organizing Map (SOM) consists also of a set of neurons 'positioned' in feature space. During training they are now connected in a low dimensional grid (1, 2 or possibly 3-dimensional). During testing the 'winner takes all' strategy is used, i.e. the output of the network is determined by the neuron closest to the input.

3.3.2 NEURAL NETWORK STRUCTURE

Neural networks consist of a number of processing units, called neurons, analogous in some respects to the neurons found in the human brain. All of the processing of a neural network is carried out by this set of neurons (or units). Each neuron is a separate computation device, doing its own relatively simple job. A unit's job is simply to receive input from other units and, as a function of the inputs it receives, to compute an output value, which it sends to other units. The system is inherently parallel in that many units can carry out their computations at the same time.

The units in a neural network are arranged in layers, usually classified as input, output, and hidden. Input unit receive inputs from sources external to the system under study.

The output units send signals out of the system. The hidden units are whose only inputs and outputs are within the system. They are not visible outside the system.

A network has one input and one-output layers but may have any number of hidden layers or none at all. Multi-layer networks maybe formed by simply cascading a group of single layers: the output to one layer provides the input to the subsequent layer. A layer consists of a set of weights and the subsequent units that sum the signals they carry [56].

The number of processing units in a layer will depend on the problem, which has to be solved. The choice of the number of input- and output units for a specific problem is quite straightforward. The choice of the number of units in the hidden layer(s) is, however, more difficult. There are only rules of thumb to help a researcher with this choice. For most applications, only one hidden layer is needed. If there is no good reason to have more than one hidden layer, then you should stick to one. The training time of a network increases rapidly with the number of layers [57].

Some recommendations from previous research works, for example, [58] heuristically suggested that the number of hidden nodes should be set as one-half of the total input and output nodes. The other suggestions by [20] involved on how to choose network parameters in a situation where the training set is clustered in groups with similar features. The number of these groups can be used to choose the number of hidden layers, the minimum number of hidden nodes should be $h \geq (p-1) / (n+2)$, where p is the number of the training examples and n is the number of the inputs of the networks. In a situation where the training data are sparse and do not contain any common features, the number of connections might need to be close to the number of training examples in order for the network to reach a convergence. The greater the number of hidden nodes in a network, the more characteristics of the training data it will capture, but more will be time-consuming the learning procedure [63].

3.3.3 State of activation

The level of activation of the units taken collectively represents the state of the system. It is convenient to look on the processing carried out by the system as the evolution of the system state. Activation of any particular unit induces or hinders the activation of units to which it is connected according to whether the interconnection is excitatory or inhibitory.

According to [60], the notion of activation may be viewed in two different ways. First, the activation value of a unit indicates its degree of confidence that its associated feature is present or absent, as opposed to merely providing a yes/no answer regarding the presence or absence of a feature. Alternatively, the activation value of a unit might suggest the quantity of a feature that is present. The activation value is passed through a function to produce an output value.

3.3.3.1 The Output function

Units interact by transmitting signals to other units. The strength of their signals, and therefore the degree to which they affect other units, is determined by their degree of activation. The output value can be seen as passing through a set of unidirectional connections to other units in the system. Associated with each unit, there is an output function f, which maps the current state of activation to an output signal. Sometimes, the output level is exactly equal to the activation level of the unit. In other cases, the output function is some sort of threshold function so that a unit has no effect on another unit unless its activation exceeds a certain value. Alternatively, the output function might be a stochastic function in which the output of the unit depends in a probabilistic fashion on its activation values.

3.3.4 NEURAL NETWORK TOPOLOGY

One important aspect used in classification of neural networks is their topology. The arrangement of neural processing units and their interconnection can have a profound impact on the processing capabilities of the networks [61]. Units are connected to one another. It is this pattern of connectivity that constitutes what the system knows and that determines how it will respond to any arbitrary input. The total pattern of connectivity can be specified by defining the weights for each of the connections in the system. The weight or strength wji of a connection determines the amount of effect that unit i has on unit j.

Depending on the pattern of connectivity, two types of networks can be distinguished: feedforward networks and recurrent networks. Feedforward networks are used in situations when we can bring all of the information to bear on a problem at once, and we can present it to the neural network [61]. In this type of network, the data flows through the network in one direction, and the answer is based solely on the current set of inputs. Feedforward networks have no feedback connections, that is, they have no connections through weights extending from the outputs of a layer to the inputs of the same or previous layers. Feedforward networks have no memory; their output is solely determined by the current inputs and the values of the weights. Recurrent networks do contain feedback connections. In some configurations, according to Wasserman cited in [60], recurrent networks recirculate previous outputs back to inputs; hence, their output is determined both by their current input and their previous outputs.

3.3.5 Training Neural Networks

In order to be immediately useful, a neural network must be trained before actually being used. A network is trained so that application of a set of inputs produces the desired (or at least consistent) set of outputs. Each such input (or output) set is referred to as a vector. Training is accomplished by sequentially applying input vectors, while adjusting network weights according to a predetermined procedure. Training algorithms can be categorized as supervised and unsupervised training.

Supervised training requires the pairing of each input vector with a target vector representing the desired output; together these are called a training pair. Usually a network is trained over a number of such training pairs. An input vector is applied; the output of the network is calculated and compared to the corresponding target vector, and the difference (error) is fed back through the network and weights are changed according to an algorithm that tends to minimize the error. The vectors of the training set are applied sequentially, and errors are calculated and weights adjusted for each vector, until the error for the entire training set is at an acceptably low level.

In unsupervised training or clustering, the training set consists solely of input vectors. The training algorithm modifies network weights to produce output vectors that are consistent; that is, both the application of one of the training vectors or the application of a vector that is sufficiently similar to it will produce the same pattern of outputs. The training process, therefore, extracts the statistical properties of the training set and groups similar vectors into classes.

3.3.5.1 Back propagation Learning Algorithm

Back-propagation, the most successful of the current neural network algorithms, provides a systematic means for (supervised) training of multi-layer feedforward networks. A back-propagation network starts out with a random set of weights. The network adjusts its weights each time it sees an input-output pair. Each pair requires two stages: a forward pass and a backward pass. Backpropagation (short for back-error propagation) is the most widely used supervised learning algorithm in neural computing [57]. It is very easy to implement. A backpropagation network includes one or more hidden layers. This type of network is considered feedforward because there are no interconnections between the output of a processing element and the input of a node in the same layer or in a preceding layer. Externally provided correct patterns are compared with the neural network's output during (supervised) training, and feedback is used to adjust the weights until the network has categorized all the training patterns as correctly as possible (the error tolerance is set in advance). Starting with the output layer, errors between the actual and desired outputs are used to correct the weights for the connections to the previous layer. For any output neuron j, the error (delta) = $(Z_j \_ Y_j)(df/dx)$, where Z and Y are the desired and actual outputs, respectively. Using the sigmoid function, $f=[1 + \exp(\_x)]^{-1}$, where x is proportional to the sum of the weighted inputs to the neuron, is an effective way to compute the output of a neuron in practice. With this function, the derivative of the sigmoid function $df/dx = f(1 \_ f)$ and the error is a simple function of the desired and actual outputs. The factor $f(1 \_ f)$ is the logistic function, which serves to keep the error correction well bounded. The weights of each input to the jth neuron are then changed in proportion to this calculated error .A more complicated expression can be derived to work backward in a similar way from the output neurons through the hidden layers to calculate the corrections to the associated weights of the inner neurons. This complicated method is an iterative approach to solving a nonlinear optimization problem that is very similar in meaning to the one characterizing multiple-linear regression. The learning algorithm includes the following procedures:

- Initialize weights with random values and set other parameters.
- Read in the input vector and the desired output.
- Compute the actual output via the calculations, working forward through the layers.
- Compute the error.
- Change the weights by working backward from the output layer through the hidden layers.

This procedure is repeated for the entire set of input vectors until the desired output and the actual output agree within some predetermined tolerance. Given the calculation requirements for one iteration, a large network can take a very long time to train; therefore, in one variation, a set of cases are run forward and an aggregated error is fed backward to speed up learning. Sometimes, depending on the initial random weights and network parameters, the network does not converge to a satisfactory performance level. When this is the case, new random weights must be generated, and the network parameters, or even its structure, may have to be modified before another attempt is made.

3.3.5.2 Training considerations in Neural Network

Training issues starts from selecting the right dataset to actual building models. If a neural network is going to be effective the training dataset must be complete enough to satisfy the following goals [63]: Firstly, every group must be represented: The training dataset consists of several subgroups, each having its own central tendency toward a particular pattern. All of these patterns must be represented.

Secondly, within each class, statistical variation must be adequately represented. The range of data presented to the neural network must represent the entire range of data with noise included.

When a subclass lies near a decision boundary, it is important to use a large dataset in order to avoid learning patterns of noise, which are in common among a large fraction of the representatives of that subclass. In general, proper selection of the training dataset leads to the success of the neural network classification or prediction. Larger networks require large training datasets. However, unless we use some over fitting protecting mechanism like validation over fitting is more likely when the model is large. Generally when designing a neural network and selecting the training dataset for a given problem, the designer has to explore answers for the following questions [64, 65]:

- Are there any transformations required for the training dataset?
- Are there enough sample representations in all sub-classes?
- How many neural network architecture layers are needed?
- How many hidden neurons?
- What type of transfer functions?
- How long is training required for the network?

CHAPTER FOUR

LEARNER MODELING

4.1 INTRODUCTION

Most techniques in adaptive e-learning model design starts with learner modeling. In the same way, this adaptive e-learning model design starts with modeling of learner characteristics and needs. In this research, the learner modeling experiment is conducted on the domain course introduction to computer. Therefore, the following experiment in designing learner model includes information related to this course.

Learner model represents the system's beliefs about its main target user, the learner and provides the necessary information for tailoring the instruction to the needs of the learner. The prerequisite for any adaptive learning modeling is an extensive learner model, which contains information about the learner's domain knowledge, preferences, goals, interests and other domain independent information about the learner, which are important for building the system.

Learner modeling is important for adaptive e-learning systems design in the following ways: it is useful in assisting a learner during learning of a given topic. It helps to offer information adjusted to the learner. It is basic to adapt the interface to the learner. It helps a learner to find information, give the user feedback about his knowledge, support collaborative work and give assistance in the use of the system. As stated in the literature [47], the learner profiles required in this research are categorized into domain dependent and domain independent information.

1. Information Related to the Course (Domain Specific Information)

These profiles include a reflection of the learner's state and the level of knowledge and skills for the course. In this research, two-information specific to the course are prior knowledge about the course and learner expectations from the course. Understanding this information from the course is basic for any e-learning system design. For instance, it is unthinkable to provide content for learners without understanding their previous knowledge about the content and their expectations. These profiles are collected by an explicit questionnaire. However, additional domain dependent information is initialized after implementation. Such information include records of learning activities (taken lectures, number of asks for help, time to solve problems) and records of assessments and evaluations.

2. Domain Independent Information

In addition to the above domain specific information, domain independent information modeling is required to achieve adaptivity. Domain independent information about a learner may include learning goals, cognitive aptitudes, motivational state, background and experiences, preferences as well as factual and historic data [48].

In this research however, among domain independent information required to build the model, more focus is given to assess learning goals, learner background and experiences, preferences as well as learning styles. The reason behind focusing on these characteristics is that they are basic and pre-requisite profiles to design the adaptive e-learning model. For instance, without understanding students experience about the learning environment or without isolating learners, which are new to a particular learning environment or even, new to e-learning, providing different system support is not possible regardless of they are novices or experts in the subject domain. On the other case, to establish the correct teaching strategy and provide content, it is important to know the learner's goals. In the same way, to model adaptive e-learning systems, one has to consider the different approaches or ways of learning since every learner has different preferences in how, when, where and how often to learn knowledge which is called learning styles. Nevertheless, learning style prediction modeling, one of the wide domain independent learner profiles is not discussed in this chapter. Learning style predictive modeling will be conducted in chapter five by using neural network technique. On the other hand, even though the researcher believes cognitive aptitudes and motivational state modeling is important, they are not easily identified by simple questionnaire. They are related with the psychological traits of humankind and are even non-identifiable by the learner themselves but mostly known while learning is on progress.

In this research, explicit questions and initial pre-testing do the initialization of a learner model, the process of gathering information about the learner, and transferring this information into the model. The initial learner models are constructed by directly questioning the learner. This method is found to be a very effective way to obtain general information about a learner. The researcher adopts the appropriate amount of questions from [17] learning style classification model, so that it was not challenging to get the optimum amount of information out of these questions. Some of the information is generated by asking the learner to take a test; the initial parameters in the learner model are obtained by analyzing the test results.

It is also clear that effective instructional strategies in addition to the above learner modeling i.e. learning styles prediction modeling, learning goal identification, learning objective design and knowledge level of learners involve selecting the appropriate content [44]. For any content model design, the view of content specialist must be included. The content model houses domain-related bits of knowledge and skill, as well as their associated structure or interdependencies. This may be thought of as a knowledge map of what is to be instructed and assessed, and it is intended to capture and prescribe important aspects of course content, including instructions for authors on how to design content for the model. The requirements for any domain model fall into two categories [37]: requirements of the delivery system and requirements of the learning content that is to be delivered. On the delivery side of the equation, we need a system that is content independent, robust, flexible, and scalable. On the content side of the equation, the content must be composed in such a way that the delivery system can adapt it to the needs of the particular learner.

In this research, however more emphasis is given to make the system more adaptive that can best be achieved by modeling what learners need from the course. The actual content of the course is not discussed. The main objective of this chapter is letting the e-learning system interface, the content and the learning environment adaptive enough to learners. To achieve this objective, the most widely accepted option is to gather both the domain specific and domain independent needs of learners before starting design. In this study, students' needs are collected through questionnaire. The basic reason for the assessment is that stakeholders (learners) should participate in learning system design to represent both their domain related and domain independent needs.

4.2 DATA PRESENTATION AND ANALYSIS

The questions were distributed to 105 purposely-selected respondents. Awareness is created about the purpose of the questionnaire. Respondents were selected from five sections based on their willingness to answer the questions. From the distributed questionnaire, 100(95.25%) of the questionnaire returned filled but the remaining 5(4.76%) of the questionnaires were not able to be return back. The data obtained from the respondents cannot include the whole learning history of learners. It is practically impossible to include that but incorporating their comments and preferences in the adaptive e-learning system design has no choice to satisfy their needs. With this assumption in mind, the returned numbers of questions are sufficient for the feedback. The questions were simple and close ended. Some of the questions are vague for non-technical students who have no experience for e-learning environments but detail explanation was given about all of the questions and to all respondents to clarify the idea of these questions. In fact, some modification is made to the questions after the pilot test. The questions are shown are shown in appendix-II. The analysis result is described in the following sections.

Table 4-1 Respondents Willingness to Access Introductory Learning Material

Response	Frequency	Percent	Valid Percent
no	16	16.0	16.0
yes	84	84.0	84.0
Total	100	100.0	100.0

Table 4.1 shows respondents willingness to access introductory learning material from basic computer skill course. As It is shown the majority of students i.e. 84 (84.0%) of them need introductory learning material where as the remaining few 16(16.0%) did not prefer to learn introductory parts from the course.

TABLE 4-2 Respondents to Access Intermediate Learning Material

Response	Frequency	Percent	Valid Percent
no	33	33.0	33.0
yes	67	67.0	67.0
Total	100	100.0	100.0

Table 4.2 is the summary of respondents needs to learn intermediate learning material from the course. As can be seen from the figure, the majority 67(67.0%) of the respondents need to learn intermediate learning materials where as the rest 33(33.0%) of the respondents did not need learning intermediate lessons.

TABLE 4-3 Access to Advanced Learning Material

Response	Frequency	Percent	Valid Percent
No	27	27.0	27.0
Yes	73	73.0	73.0
Total	100	100.0	100.0

Table 4.3 shows the proportion of learners willing to learn advanced concepts from the course. The majority, 73(73.0%) of the respondents need advanced learning concepts while few of them i.e. 27(27.0%) do not want learn advanced concepts.

TABLE 4- 4 Respondents to Access Practical Learning Material

Response	Frequency	Percent	Valid Percent
no	16	16.0	16.0
yes	84	84.0	84.0
Total	100	100.0	100.0

Table 4.4 is the response of respondents to their preference whether to learn practical lessons or not. The result of the survey showed 84.0% of the respondents preferred to learn practical lessons while very few 16.0% of learners did no accept learning practical lessons from the course.

TABLE 4- 5 Respondents to Access Theoretical Learning Material

Response	Frequency	Percent	Valid Percent
no	30	30.0	30.0
yes	70	70.0	70.0
Total	100	100.0	100.0

Table 4.5 shows the proportion of respondents who need to learn theoretical lesson. From the table one can deduce that 30% of the respondents were not willing to take theoretical part but the majority of the students I.e. 70% of them preferred to learn the theoretical lesson from the course.

TABLE 4-6 Respondents to Access to Technical Learning Material

Response	Frequency	Percent	Valid Percent
no	18	18.0	18.0
yes	82	82.0	82.0
Total	100	100.0	100.0

Table 4.6 is a summary of survey made to assess students in learning technical lesson. From the table, 18% of the respondents have no interest to learn the technical part while 82% are in need of the technical part.

TABLE 4- 7 Respondents to Access Overview Learning Material

Response	Frequency	Percent	Valid Percent
no	45	45.0	45.0
yes	55	55.0	55.0
Total	100	100.0	100.0

Table 4.7 shows the proportion of respondents ready to use overview materials. Unlike the other cases, nearly equal proportions of learners respond in favor and against. From 100 respondents, 55(55%) of them need to learn overview lessons from introduction to computer course where as 45% do not need the overview part from the course.

TABLE 4-8 Respondents to Access detailed learning material

Response	Frequency	Percent	Valid Percent
no	29	29.0	29.0
yes	71	71.0	71.0
Total	100	100.0	100.0

From table 4.8 one can deduce that still the majority (71%) of the respondents prefer detailed material while the remaining 29% of the respondents do not.

TABLE 4-9 Respondents View about Material Suggestion When Published

Response	Frequency	Percent	Valid Percent
no	30	30.0	30.0
yes	70	70.0	70.0
Total	100	100.0	100.0

Once the system is built, based on the learning materials requirement and the available material, there is still the possibility to provide new materials when published per the interest of learners. Table 4.9 shows the proportion of students who are interested in new materials to be suggested when they are published. So from the survey it is found that 70(70.0%) of the students need new materials to be suggested when published where as the remaining 30(30.0%) of respondents do not need new learning materials to be suggested for the introduction to computer course under study.

TABLE 4-10 Respondents Response on the Presentation of Material that Match Objectives

Response	Frequency	Percent	Valid Percent
no	40	40.0	40.0
yes	60	60.0	60.0
Total	100	100.0	100.0

Any course is designed to achieve a certain course objectives. However, the course objectives and students goals may not fit. In cases like this, the adaptive e-learning principle pushes the course objectives to suit to the student need. The above table summarizes the number of students who are willing to take materials that course objectives. From the total of 100 respondents who correctly fill the questionnaire, 60(60.0%) of them replied that they need a way of presentation that matches course objectives While nearly an equal proportions of learner 40 in number in surprising way do not want presentations that match the objectives.

TABLE 4-11 Suggestion of Which Part to Study Next

Response	Frequency	Percent	Valid Percent
no	26	26.0	26.0
yes	74	74.0	74.0
Total	100	100.0	100.0

The adaptive e-learning model has several options up to suggesting of the order of study. As an adaptive system, the system cannot simply suggest the content to be studied next; it must first check the learners' willingness to suggest or no to suggest the next part to be studied. Therefore, the above table is a survey result of some 100 respondents for the question "do you want the system to suggest which part to study next?" as can be easily deduced from the table, 74(74.0%) of the respondents respond yes we need the system to suggest the order of presentation of materials where as the remaining 26.0% respond against the statement by saying no.

TABLE 4-12 Use of Self-Test to Make Decision at Various Points

	Frequency	Percent	Valid Percent
no	24	24.0	24.0
yes	76	76.0	76.0
Total	100	100.0	100.0

As per the characteristics of adaptive systems, the system alone cannot pass decisions without the involvement of learners. For such systems to be effective, they have to be greatly depending on the goals, characteristics and knowledge level of user. To discover these characteristics the system is designed to use students self tests. To make it more effective, the respondents were asked whether the system should Use the result of their self-test to make decision at various points. In a similar case, 76% of the respondents agreed the self-test result to be used for decision at various stages while 24% the respondents did not prefer the pre test to determine decisions at various points.

TABLE 4-13 Students Goal

Response	Frequency	Percent	Valid Percent
Passing exam	17	17.0	17.0
Problem solving	83	83.0	83.0
Total	100	100.0	100.0

It is common that different learners may want achieve different goals from the same course. For instance: some learners may need to have a problem solving skill at the end of the lesson while others learn for only the mere fact of passing exams. The respondents' response in this research also reflects the same thing. As is shown in the above table, respondents were asked what they intended to achieve after learning introduction to computer. It is found that 83% of the respondents primarily aim is to solve problems by using the knowledge generated from the course but few of them i.e. 17%, need the knowledge for only academic achievement which is for only passing exams.

TABLE 4-14 Learners Previous Experience

Response	Frequency	Percent	Valid Percent
No background know-how	67	67.0	67.0
Basic skills	27	27.0	27.0
Sufficient skill	6	6.0	6.0
Total	100	100.0	100.0

One of the pre-requisite for designing learner model is understanding their previous knowledge about the course and their experience to use such e-learning systems because this understanding can help what to include and to help learners while learning. Table 4.15 also supports this assumption. From the total respondents 67%, 27% and 6% of them do not have background knowledge, Basic introductory skills and sufficient skill respectively.

4.3 CONCLUSION

Generally, the above need assessment is found to be a good feedback for the researcher to design adaptive e-learning system. The survey result presented above, is a good manifestation and clear evidence for the presence of varying needs, goals, preferences and knowledge levels of learners for the course introduction to computer. Therefore, the need of adapting the learning environment to these variations is required. However, the survey result does not show why those variations of needs among learners happened. The reason behind these variations is beyond the objective of the researcher in particular and adaptive e-learning systems in general. The basic assumption of adaptive e-learning systems and this research as well is learners have varying needs, goals, preferences and knowledge levels etc so that we have to adjust the learning environment to those variations. As it was indicated by different research works, to keep students actively involved in learning, understanding learning style preferences and adjusting teaching materials to meet the needs of a variety of learning styles, needs, goals, preferences and knowledge levels of learners is the first step [46]. The result of the above need assessment about the course is found to be an important benchmark to model content for introduction to computer course. For example, for the need on the type of learning materials learners are searching, some of the respondents need introductory, others need intermediate and the remaining advanced, still others detailed, where as others theoretical part too, and the rest search for practical learning materials though the degree of the need for each type of learners varies. Therefore, at the implementation, all type of learning materials should be presented and learners select one among the others from the list. On the other hand, when assessing students learning goal, some of them need the e-learning course to pass exams where as others need for general problem solving. Therefore, this information from the need assessment helps any content designer to include materials that can help to answer course exams as well as for problem solving purpose. On a similar case, their view about material suggestion when published is so significance. Learners still have two opposing ideas. Majority of them need the materials be suggested when published where as the others did not. At the implementation, it is clear that before suggesting new published materials to learners we have to ask the willingness of learners. The same information is generated from questions like presentation of material that match learning objectives, suggestion of which part to study next and use of self-test to make decision at various points. Through these ways, the content model, the adaptive e-learning architecture for the course and the prototype for the adaptive e-learning system are shown in figure 4.1, 4.2 and 4.3 respectively.

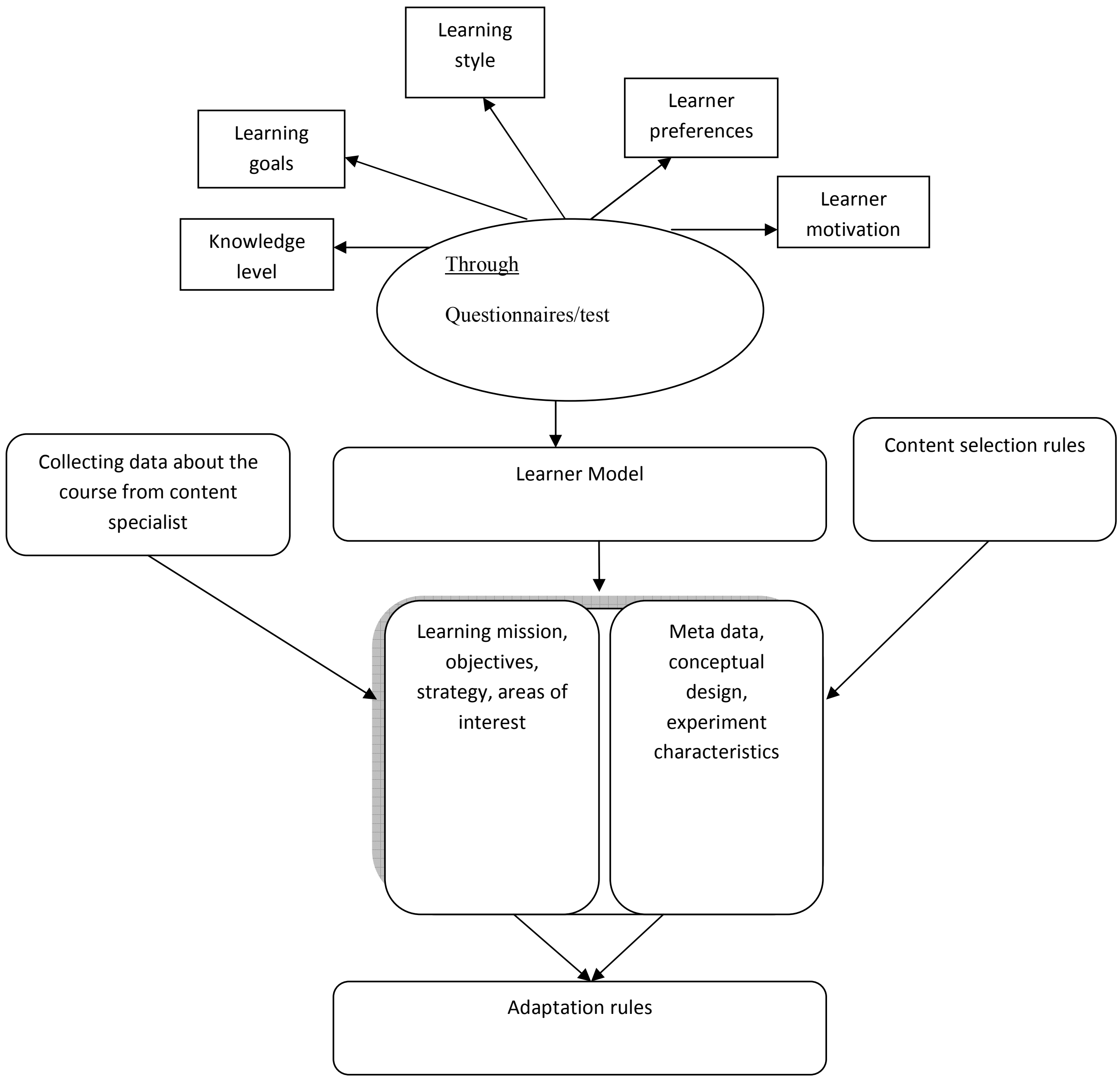

FIGURE 4-1 Content Model

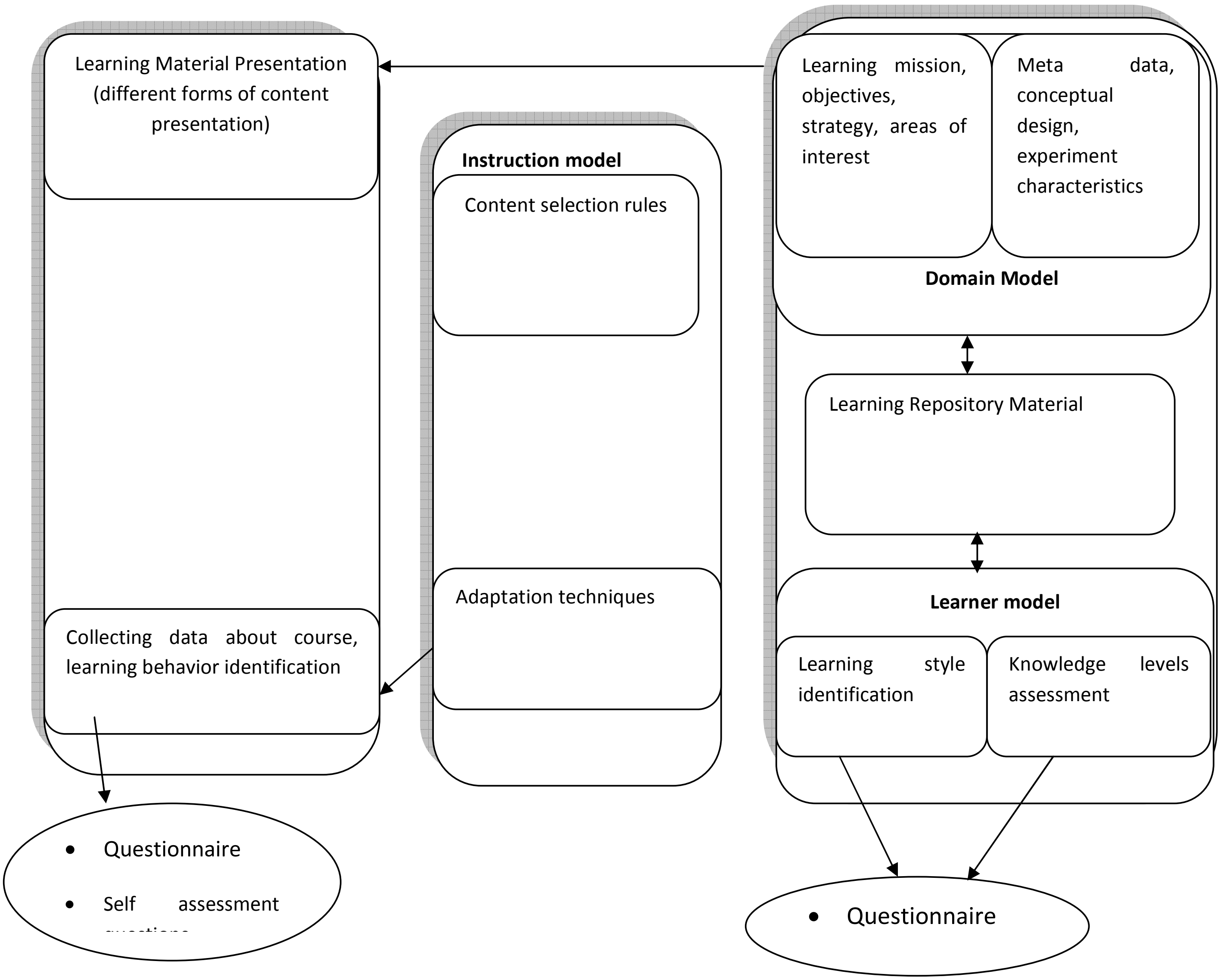

FIGURE 4-2 Adaptive E-Learning System Architecture

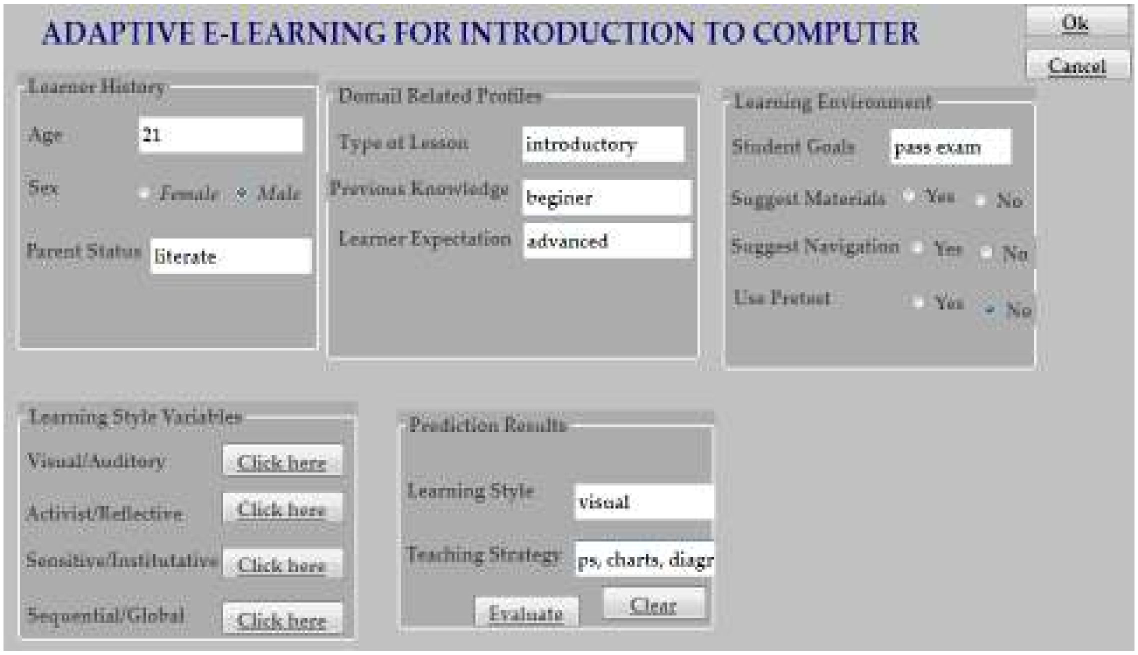

FIGURE 4-3 Prototype of the Adaptive E-Learning System

CHAPTER FIVE

EXPERIMENTATION

Every learner perceives and process information in very different ways. In this chapter, the researcher group common ways of how people learn which is represented in learning style theory. Learning style theory has been developed and applied in various curricula for all levels of education with the assumption that by recognizing and understanding the individuals to their own learning styles, the techniques can be used better and improve the speed and quality of learning [66].

In this chapter, an experiment is made to build a neural network model for learning style prediction. The main goal of this chapter is exploring the possibilities of designing learning style prediction model for Ethiopian higher learning institution learners by neural network techniques. In this chapter, the researcher describes the source of data as well as the techniques that have been used in preprocessing the data. The model training parameters and processes and learning algorithm are also presented. Test results are then presented and discussed.

5.1 ARTIFICIAL NEURAL NETWORK MODEL

Learning style prediction is conducted using artificial neural network. The intention of the researcher at this stage is designing learning style predictive model after exploring all the possibilities of neural networks in learning style prediction. After identifying their learning styles, the system can give the appropriate content and content links and the required teaching strategy for each learner. Two basic activities carried out in selecting multilayer perceptron neural networks for the learning style prediction problem.

1. **Model Assessment/Evaluation**: a long process of evaluating the key performance characteristics of the prediction models within the context of learning style data and with specific model performance requirements. Inline with this, artificial neural network have been applied to almost every application area where a dataset is available and a good solution is sought. Artificial neural networks can cope with noisy data, missing data, imprecise or corrupted data, and still produce a good solution [20]. Multilayer perceptron (MLP) with backpropagation algorithm achieved popularity in numerous research areas. One of the reasons for this was that it is a pioneer artificial neural network which showed promise to solve ill-defined, complicated, and complex problems which are hard to describe in mathematical formula or expression [20].
2. **Performance Metric:** In addition to multilayer perceptron neural network, the learning style data can fit to the other data mining techniques. The researcher employed a performance related measurement to experiment with the best modeling techniques. This measurement determines the highest performance modeling technique from the remaining after comparison. The multilayer perceptron is selected after the above two assessments are done. Table 5.1 shows the performance of some selected data mining techniques for learning style prediction.

Table 5-1 Performances Comparison Data Mining Techniques

Data mining technique	**Performance**
C4.5 Decision Tree	89.11
Multilayer Perceptron	93.23
RBF network	91.28

5.2 DATA PREPROCESSING

When prediction or classification of students into different learning styles is done by using neural networks model, the following are agreed upon steps. Identifying the input and output features, transforming the inputs and outputs, Setting up a network with an appropriate architecture, training the network on a representative set of training examples and using the test set to see how well it performs [70]. Luck enough, the WEKA, the tool used, performs most of these steps automatically. So more focus is given in this research on choosing the right training set (i.e. representative and adequate for each class). The task of representing the data in such a way to maximize the ability of the network to recognize patterns, interpreting the results from the network and finally understanding some specific details about how they work such as network architecture and parameters controlling training that can make better performing networks. Generally, the activities carried out in this chapter are organized in to four parts: data preprocessing, model building, model validation and Evaluation.

5.2.1 DATA COLLECTION

The data is collected from Addis Ababa University regular and extension students taking the course of introduction to computer/information communication technology in 2009/10 academic year of second semester. Data access was not challenging because as many more students are taking the course by the time but the challenging was data quality despite the strong effort made by the researcher to ensure data quality. The alternative solutions taken were to control the data collecting procedures while administering the questionnaire. At most, care was taken when administering the questionnaire. At each point of administering the questionnaire, that tiresome task of explaining the purpose of the questions were clearly explained for all of the respondents and enough time was given for them, as most of the respondents were students of the researcher and his colleagues.

To build learning style prediction model by neural network approaches, learner profile used is collected by questionnaire from students learning introduction to computer course. In this research, initial questionnaire adopted from [17] were distributed to students. These are scientifically designed by research for studying students learning styles by psychologists and pedagogical experts. Different researchers come into an agreement that, learning style can be influenced by demographic, socio-cultural and economic situation of learners [14, 15]. With the assumption that, the learning style questionnaire adopted from [17] may not be clear and understandable by the Ethiopian higher learning institution learners, a pilot test is conducted to check the validity of the adopted questions. The questionnaire was distributed to 50 purposely-selected students taking the course. These respondents were asked to give their informed consent and comments. The feedback is collected from those learners. After the pilot test, satisfactory feedbacks are collected. For instance, it was found that some of the questions were irrelevant to discover learning style patterns, some of them were vague to be understood by the respondent where as the remaining were non-applicable for our learners. Therefore, non-applicable and irrelevant questions are removed where as vague questions are modified in such away that learners can understand with the principle stated in model [17]. After manual rearrangement of questions, the number of questions is reduced from ten to seven for defining each learning style. Lastly the questions have the structure as seen in appendix-I.

5.2.2 DATASET

The training set must consist of records whose prediction or classification values are already known. Choosing a good training set is critical for all data mining modeling. For neural network, modeling a poor training set dooms the network, regardless of any other work that goes into creating it. In fact, artificial neural networks need to be trained with large set of data [20]. The central point here is to see all possibilities of using artificial neural network for adaptive e-learning system design. The number of variables/attributes is large which implies the need of large dataset for training the network. Therefore, it is not believed that the dataset is large to train the network. However, it is good enough to achieve the objective of the research as stated above. A sample of 1296 dataset is used. The dataset is the response of students on the questionnaire prepared for assessing the learning style of students. From the total dataset 80%, 10% and 10% of the data is used for training, validating and testing purpose respectively. The questions from the questionnaire are treated as variables. These variables determine the value of the target class. The model is trained to classify students into their preferred learning style. After the model is trained in this way, the prediction model predicts students learning styles by questionnaire before the actual content delivery in the learning process. There are four models to be built in this experimentation. The learning style data used in this research is divided into four aspects based on the way learners perceives, process and understand information in the learning. Table 5.2 shows the proportion of training dataset used for each model in this research. The remaining dataset is used for testing and validating the neural network.

TABLE 5-2 Proportion of Training Dataset for Learning Style Prediction

Dimensions	Learning Styles	Size of Dataset
Perception	Sensory	671
	Intuitive	365
Processing	Activist	576
	Reflective	460
Input	Auditory	382
	Visual	653
Understanding	Sequential	624
	Global	411

5.2.3 DATA PREPARATION

Data is the raw material and input for data mining. Data comes in many forms, from many systems, and in many different types. The collected data from the respondents through questionnaire has some dirty features, incomplete fields, incomprehensible and incompatible values. The data collected from students' learning style assessment questionnaire need to be arranged and prepared to fit the neural network model. Generally, mapping of each field to an appropriate range is made using a limited range of inputs; to help networks had better recognize patterns.

In this research, each question in the questionnaire is the variables/attributes. These are categorical variables, which has a binary response yes or no. The variables/attributes are reduced from twenty to fourteen after the pilot test described above. The name of the variables is also coded as shown in the following tables since they had long names while used in the questions. All variables used are categorical variables. The lists of these variables and their descriptions are shown in tables 5.2, 5.3, 5.4.and 5.4.

5.2.3.1MANUAL VARIABLE DESCRIPTION AND DEFINING TARGET CLASSES

Visual-Auditory Learning Styles

For the learning style prediction experiment into visual or auditory, the variables used are shown in table 5.3. The variables shown in table 5.3 are the predictive variables/questions. The target values/classes are either visual or auditory. It is easy to note that a visual learner has a very low probability of being auditory if it happens; it is with exceptional situations such as multi style learners. This exceptional situation is excluded from the respondents' dataset. The weighted sum of the fourteen variables presented in the table was used to classify respondents into visual or auditory. From the list of variables in table 5.3, deriving the target class is based on [17]. When the sum value of the first seven questions/variables is greater than the sum value of the second seven variables the learner is grouped as visual learners where as if the sum value of the second seven variables is greater than the first seven, the student is classified as auditory learner. The summary of variables used in model building is shown in table 5.3.

Table 5-3 Variable Description for Visual/Auditory Learning Style

Variable code	Variable description	Value
Visualize-picture	In listening, visualize pictures, numbers, or words	Yes/No
Learn-video-TV	Learning with TV or video rather than other media	Yes/No
Use-of-color-coding	Use of color coding to help learn or work.	Yes/No
Look-at-people	Need to look people to understand what they say	Yes/No
Understand-lectures-better	understand lectures better when professors write on	Yes/No
Usage-Chart-diagram-map	Charts, diagrams, and maps help understand something	Yes/No
Remember-peoples'-faces	Remembering peoples' faces but not their names	Yes/No
Oral-directions	Need of oral directions for a task	Yes/No
Background-sound	Background sound helps to think.	Yes/No
Listen-to-music	Like to listen to music when study or work	Yes/No
Remember-peoples'-names	Remember peoples' names but not their faces.	Yes/No
Remember-jokes-hear	Easily remember jokes that are heard	Yes/No
identify-by-voices	Can identify people by their voices	Yes/No
TV-sound-than-watch	From TV, listen to sound more than watching the screen	Yes/No

Activist-Reflective Learning Styles Variable Description

The researcher follows the same method of data preparation procedure and defining target class procedure for activist or reflective learning styles as is done for visual or auditory except the different variables used. The predicting variables are listed in table 5.4 where as the target class is either activist or reflective. As shown in table 5.4, deriving the class is based on [17]. when the sum value of the first seven variables is greater than the sum value of the second seven variables, learner is be grouped as activist learners where as if the sum value of the second seven variables is greater than the first seven attributes the student is classified as reflective learner. The summary of variables and descriptions of them is shown in table 5.3.

Table 5-4 Variable Description for Activist/Reflective Classification

Variable code	Variable description	Value
Meet-new-people	Meet new people by jumping into the conversation	Yes/No
classroom-than-private tutor	Learning better in classroom than with a private tutor	Yes/No
Approach strangers	It is easy to approach strangers	Yes/No
Interacting-people-energy	Interacting with lots of people gives energy	Yes/No
Experience-things-first	Experience things first and then try to understand	Yes/No
Homework-in-groups	The idea of doing homework in groups, appeals	Yes/No
Understand-think-through	Understand something better after thinking it through	Yes/No
Sit-back-and-listen	On difficult material, more likely to sit back and listen	Yes/No
Study-alone	prefer to study alone	Yes/No
First-think-how-to do	would rather first think about how going to do it	Yes/No
Remember-thought	easily remember something have thought a lot about	Yes/No
No-homework in groups	The idea of doing homework in groups, does not appeal	Yes/No
Fully-understand-problem	more likely to try to fully understand the problem first	Yes/No
realistic	would rather be considered realistic	Yes/No

Intuitive-Sensitive Learning Styles Variable Description

The researcher follows the same method of data preparation procedure for intuitive or sensitive as is did for visual and auditory or activist and reflective learning styles and the variables used are presented in table 5.5. When classifying students into the two learning styles; the calculation is based on [17] i.e. when the sum value of the first seven variables is greater than the sum value of the second seven variables the learner is grouped as sensitive learners and the reverse is true for intitutive learner .

Table 5-5 Variable Description for Intuitive/Sensitive Classification

Variable code	Variable description	Value
facts-real-life-situations	prefer course that deals with facts and real life situations	Yes/No
Easier-learn-facts	Easier to learn facts	Yes/No
like-new-way of doing	teaches new facts or tells how to do something	Yes/No
Careful-details-my work	More likely to be Careful about the details of the work	Yes/No
Writers-clearly-what-mean	In reading for enjoyment, writers say what they mean	Yes/No
Prefer-one way of doing	to perform a task, Master one way of doing	Yes/No
Courses-Concrete-material	Prefer courses that emphasize Concrete material	Yes/No
Course-ideas-theories	Teach a course that deals with ideas and theories	Yes/No
Easier-learn-concepts	it easier to learn concepts	Yes/No
Gives-new ideas	prefer something that gives me new ideas to think about	Yes/No
Creative-do-work	considered Creative about how to do work	Yes/No
Creative-interesting	prefer writers say things in creative, interesting ways	Yes/No
New-ways-doing-task	to perform a task, come up with new ways of doing	Yes/No
Abstract-material	Prefer courses that emphasize abstract material	Yes/No

Sequential-Global Learning Style Variable Description

The usual procedure of data preparation is used for sequential and global data classification as is did for the rest learning style. Deriving the target classes is also done in the same way based on the principle listed in [17].

Table 5-6 Variable Description for Sequential/Global Classification

Variable Code	Variable Description	Value
One-step-at-a-time	When solving math problem, do one step at a time	Yes/No
clear-sequential-Materials	instructors layout the material in clear sequential steps	Yes/No
Focus-details-miss-big-picture	When considering a body of information, more likely focus on details and miss the big picture	Yes/No
Beginning-paper-progress forward	When writing a paper, more likely to work on the beginning of the paper and progress forward	Yes/No
Outlines-are-helpful	Lecture outlines are somewhat helpful	Yes/No
think-step-process	In solving problems, think of steps in solution process	Yes/No
From-whole-to-parts	understand the whole thing, see how the parts fit	Yes/No
See-solutions-figure-steps	In problems often see solutions then figure out steps	Yes/No
Instructor-overall-picture	instructor relate overall picture with other subjects	Yes/No
Big-picture-then-details	understand the big picture before getting details	Yes/No
different-parts-then-order	Work on different parts of the paper and then order	Yes/No
new-subject-connections-related subjects	make connections between that subject and related subjects	Yes/No
Outlines-Very-helpful	Lecture outlines are very helpful	Yes/No
consequences-solution	think possible consequences in a wide range of areas	Yes/No

5.2.3.2 VARIABLE SELECTION BY USING WEKA DATA MINING TOOL

The learning style model [17] used in this research assumes the above listed variables in each table are important for learning style classification. However, the significance of each variables/attributes for the target class is described in this section. The researcher uses the Weka attributes selection facility, which is single-attribute evaluators are used with the ranker, information gain search method to generate a ranked list as described in [61]. Despite the tool can rank and discard non-relevant attributes, the aim of this section is to identify which attributes are more important for Ethiopian higher learning institution learning style discovery. The tables from 5.7 to 5.10 show the order of variables in the classification process. The weights are calculated by the information gain value i.e. the value of the variable in splitting into the two classes. For more clarifications of variables a reader can relate variable names with the questions in appendix-I.

TABLE 5-7 Importance of variables for Sensitive-intuitive learning style

Variables	Weights
Prefer Courses That Talks With Abstract Material	0.2444
Come up With New Ways of Doing	0.1366
Careful About Details	0.116
Writers Say Things in Creative and Interesting Way	0.1155
Mastering one Way of Doing	0.0921
Easily Learn Concept	0.0877
New Ideas to Think About	0.0648
When Reading for Enjoyment Need the Writers Intension	0.0625
Emphasis Concrete Material	0.0593

Read that Tells How to Do Something	0.0496
Considered Creative	0.0493
Teach Ideas and Theories	0.0473
Easily Learn Facts	0.0447
Teach Facts and Realistic Situation	0.0445

TABLE 5-8 Importance of variables for visual-auditory learning style

Variables	Weights
Remembering of People Name	0.1298
Learn From TV or Video	0.1099
Prefer Sound than Watch	0.0804
Listening Music on Study	0.0803
Remember Peoples Face	0.0782
Need Oral Direction	0.0746
Use of Background Sound	0.0619
Usage of Charts, Maps And Diagrams	0.0565
Visualize Picture in Head	0.0489
Use of Color Coding	0.0483
Better Understand Written Lectures	0.048
Identify People by Sound	0.0261
Look At People to Understand	0.0247
Remember Jocks Heard	0.0224

TABLE 5-9 Importance of variables for Sequential-global learning style

Variables	Weight
Different-Parts-Then-Order	0.1206
Clear-Sequential-Materials	0.1092
Big-Picture-then-Details	0.0843
From-Whole-to-Parts	0.0692
Solve-Problem-Group-Think-Step-Process	0.0664
Think-Consequences-Applications-Solution	0.065
See-Solutions-Figure-Steps	0.0602
One-Step-Time	0.0597
Instructor-Overall-Picture	0.0547
Outlines-Are-Helpful	0.0539
Focus-Details-Miss-Big-Picture	0.0525
Beginning-Paper-Progress Forward	0.0321
Outlines-Very-Helpful	0.0316
New-Subject-Connections-Related Subjects	0.0244

TABLE 5-10 Importance of variables for activist-reflective learning style

Variables	Weights
Think Realistic	0.2144
Understand the Problem First	0.1901
No Group Work	0.1407
Interacting With Lots of People	0.0834
Experience Things First	0.0767
Doing Home Work in Group	0.0749
Easily Remember That I Thought	0.0744
First Think How to Do	0.0735
Prefer to Study Alone	0.066
Easily Approach Strangers	0.0519
Meet New Peoples	0.0519
Learn Better in Class Room	0.05
Understand Something Better by Thinking	0.0455
Prefer to Sit Back And Listen	0.0302

5.2.3.1 OUTLIERS, HANDLING MISSING VALUES AND NORMALIZATION

To make the data ready to be used for the neural network each response of 'yes' were labeled as 1 and each 'no' were labeled as 0. Technically, a weight of one is given for each yes and zero weight for each no. symbolically yes=1 and no=0. The fourteen questions (predictive variables) for each learning style models were inputs. The target variables or classes were calculated based on [17] learning style model. The sum weight of the variables determines the category (the target variable) or the actual class of learners. Generally, the dataset is arranged in a way that needs to cover the full range of values for all features that the network might encounter including the output

However, there are some outliers; typical infrequent observations that do not appear to follow the statistical characteristics of the rest of the data. Neural networks are noise tolerant. Nevertheless, there is a limit to this tolerance. If there are occasional outliers far outside the range of normal values for a variable, they may bias the training. The dataset collected by randomly distributing questionnaires has some unusual patterns, missing and non-normalized values. Few respondents answered the questions carelessly. For example, some of them give the same answer for the whole questions while others completed answering the questions within a minimum amount of time that implies their less-attention for the questions. Respondents like these patterns are discarded and excluded from the training dataset.

For several reasons, such as question vagueness, non-relevance, and shortage of time to fill the questionnaire some of the variables were suffering from missing values. The first and main measure taken to handle this problem was to consult the [17] learning style prediction rule. Based on the rule, since the sum weight of the variables has significance for prediction, the value of one of the variables may not have significant influence to determine the target class. For example, if the sum of the first seven listed variables is greater or less than the second seven variables, the value of the class can be predicted what ever missing values we have in the variables. However, if these two groups are equal then the class cannot be predicted. In this case, the case is excluded from the entire dataset. Apart from this, since all variable are converted to have continuous values there are suggested ways for handling such missing values. In this study, it is suggested that missing values be replaced with the mean value for that field. However, Instead of taking the mean value of the entire row, records were grouped based on similarity criteria by grouping attributes, which predict the same learning style for each learning styles. Then the average of each group was considered in substituting the missing values. It is important that the target values (desired response) be chosen within the range of the activation function [67]. In order to simplify this procedure, usually all the input and output variables of multilayer perceptron are scaled to the range of reasonable values. This procedure is called the normalization. The value of the input data for the neural network is between 0 and 1. The value 0 indicates no weight where as 1 shows a weight of one. The target values should be within the range of the linear values, but not at the asymptotic values [68]. The values of the predictor variables are either yes or no represented by 1 and 0 respectively. The target is also a binary value class for the whole models. At the time of data entry, checking mechanisms are made for the values are within this range. An arrangement is made to make the values within this range.

5.3 NEURAL NETWORK MODEL BUILDING

The combination of topology, learning rule, and learning algorithm define a neural network model. There are wide selections of neural network models. For data mining, perhaps the back-propagation network is the most popular [61]. It is very easy to implement. A backpropagation network includes one or more hidden layers. Thus, feed forward backpropagation neural network is used in this study to build learning style predictive model. Since trial and error is a necessary part of neural net applications, it is important to have an understanding of the standard method used to train a multilayered network: backpropagation. It is no exaggeration to say that the speed of the backpropagation algorithm made neural nets a practical tool in the manner that the simplex method made linear optimization a practical tool [62]. The revival of strong interest in neural nets in the mid 80s was in large measure due to the efficiency of the backpropagation algorithm. Backpropagation (short for back-error propagation) is the most widely used supervised learning algorithm in neural computing this type of network is considered feed forward because there are no interconnections between the output of a processing element and the input of a node in the same layer or in a preceding layer. Externally provided correct patterns are compared with the neural network's output during (supervised) training, and feedback is used to adjust the weights until the network has categorized all the training patterns as correctly as possible (the error tolerance is set in advance). Training a neural network is a challenge requiring setting of numerous parameters. Taking into account the time available to undertake the study and a bewildering set of parameters to adjust, five networks were designed and tested for each models.

5.3.1 NETWORK DESIGN

Building a neural network is a challenge requiring setting of numerous parameters. The first challenge is determining the number of hidden layers. In this regard, it has been reported by a research [69] that a single hidden layer usually be sufficient for most problems, especially for classification tasks. Based on these empirical evidences and considering the complexity level of the data, three layers of network is used. One input, one hidden and one output layers.

The second challenge in building neural networks is deciding how many neurons to use for the hidden layer(s). The problem is if we select too few neurons, the model may not be adequate to model student learning style where as too many neurons may over-fit to the training dataset and result in poor generalization to new data. However, it is vitally important to determine the optimum number of hidden layer neurons. Although most of empirical approaches to the determination of the number of hidden layers neurons proposed in the literature [71, 70] was a function of the numbers of input and/or output nodes, none of these suggestions has been universally accepted or used. In the literatures [71, 70], it is suggested that the minimum number of hidden neurons to be half of the sum of the input and output

Neurons. Thus, in this study, the researcher begins with eight hidden neurons, a small number of hidden neurons in each of the network design, and adds neurons during the training process if the network is not learning. The estimation of hidden neurons is based on the combination of input and output values. This is because there are fourteen and two input and output variables respectively while using cross validation(ten-fold-cross validation) to avoid the over fitting problem.

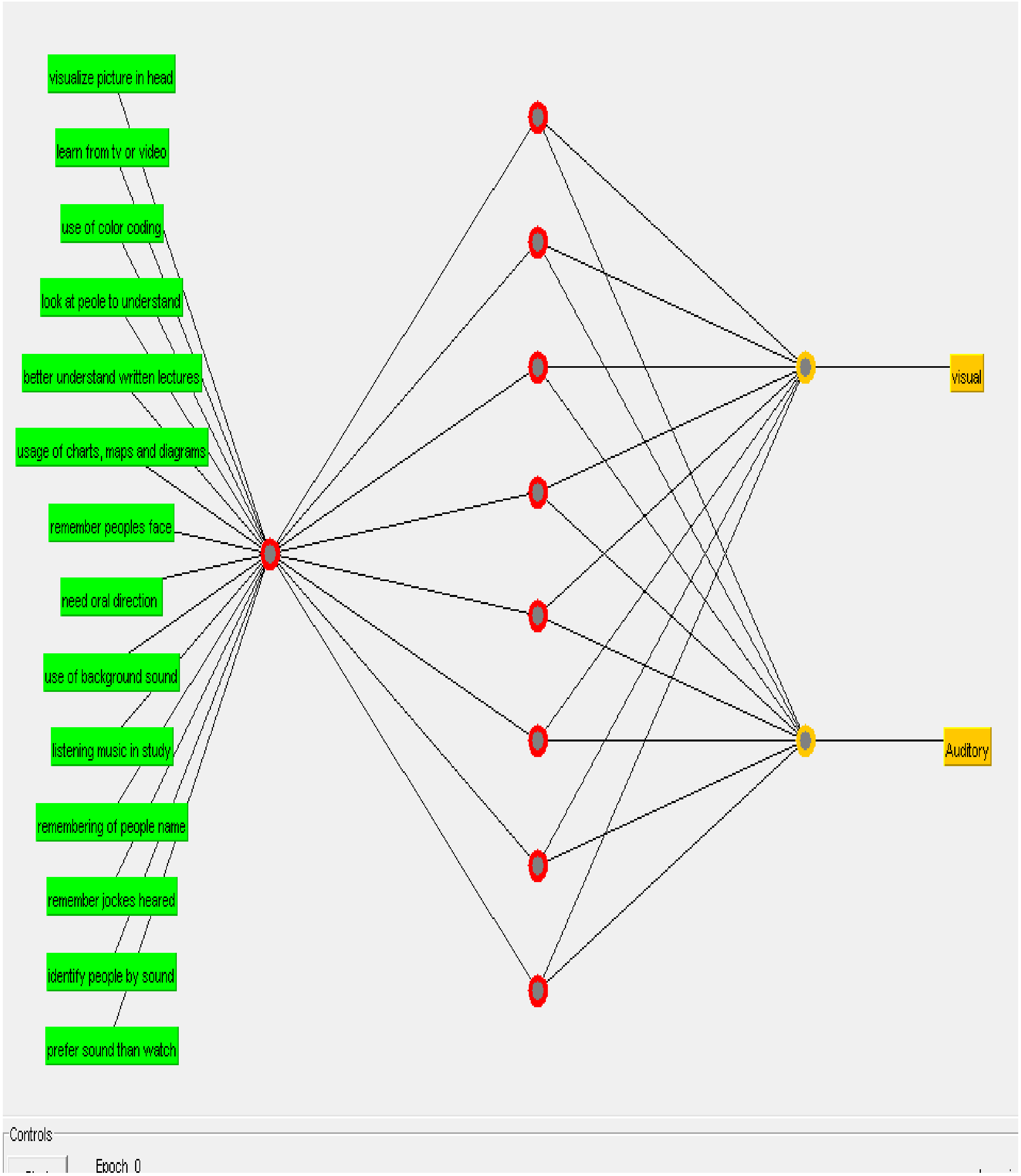

Figure 5-1 Neural Network Architecture

5.3.2 ACTIVATION FUNCTIONS IN THE NETWORK

The choice of activation functions may strongly influence the complexity and performance of neural networks. The most commonly used nonlinear functional forms of activation functions satisfying the approximation conditions of artificial neural networks are the sigmoid (logistic) and tangent hyperbolic functions [72].

Hidden Layer Activation Functions: According to [72] activation functions for the hidden units need to introduce nonlinearity into the network. Without nonlinearity, hidden units cannot make networks more powerful than just plain perceptron, which do not have any hidden units, just input and output units. The other reason is that a linear function of linear functions is again a linear function. Nevertheless, the capability to represent nonlinear functions makes neural networks so powerful [72]. Therefore, in this experimental research, sigmoid activation is used.

Output Layer Activation Functions: Different types of activation functions are available for the output layer. These are logistic (sigmoid) activation function, linear activation function and Softmax activation function. Softmax produces more accurate probability estimates than the other types of activation functions, but it is slower to compute these functions can also be used only for classification analyses [72]. In [72], different output activation functions are recommended based on the value of the target variable. For instance; for binary (0/1) targets, the logistic function is an excellent choice. Thus, in this research of predicting learning style of learners, the value of the target variable at one particular classification process is either visual or auditory, sensitive or intuitive, activist or reflective as well as sequential or global represented by binary values 1 and 0 for each model. As it is explained above for classification problems whose target values are binary, the sigmoid (logistic) activation function performs better than the others do. Consequently, the sigmoid(logistic) activation function is used in this research for both hidden and output layer activation.

5.3.3 TRAINING THE NETWORK

After the data preparation is completed and the neural network model and architecture have been selected, the next step is to train the neural network. Training a neural network is a challenge requiring setting of numerous parameters. Taking into account the time available to undertake the study and a bewildering set of parameters to adjust, five networks are designed and tested for the four learning style-predicting models.

Training a neural network is the process of setting the best weights on the edges connecting all the units in the network. The goal is to use the training set to calculate weights where the output of the network is as close to the desired output as possible for as many of the examples in the training set as possible. Although back propagation is no longer the preferred method for adjusting the weights, it provides insight into how training works and it was the original method for training feed-forward networks [61]. The back propagation algorithm measures the overall error of the network by comparing the values produced on each training example to the actual value. There are two important parameters when training with back propagation algorithm. The first is momentum, which refers to the tendency of the weights inside each unit to change the “direction” they are heading. That is, each weight remembers if it has been getting bigger or smaller, and momentum tries to keep it going in the same direction. A network with high momentum responds slowly to new training examples that want to reverse the weights. If momentum is low, then the weights are allowed to oscillate more freely. By starting from the highest value, the momentum value in the network design is set by trial and error.

Another important consideration while designing the network is setting the learning rate parameter. The data used for experimentation in this study are unevenly distributed; there are many more visual (653) than auditory (382), sensitive (671) than intuitive (565) and sequential (624) than global (411) learners as shown in table 5.2. A technique, which works well for many unevenly distributed datasets, is to set the learning rate to a very low value [76]. The network will then train very slowly, because the steps towards the answer are very small, and the advantage here will be that it does not move too quickly in the direction of the majority solution. In order to be able to find the patterns for the minority data, low learning rates are used in this study. The learning rate varies in the range of 0.2 to 0.4. An overview of the network designs is given in table 5.6.

Table 5-11 Summaries of the Trained Neural Networks

Design	**Learning Rate**	**Minimum No of Hidden Layers**
A	0.2	8
B	0.25	8
C	0.3	8
D	0.35	8
E	0.4	8

5.3.4 Data Organization for Model Building

When training a network, over-fitting is most likely to occur. Over-fitting occurs when the parameters of a model are tuned so tightly that the model fits the training data well but has poor accuracy on separate data not used for training [75]. The data mining modeling technique, Multilayer perceptron used in this research is subject to over-fitting as are most other types of models. However, the researcher uses evaluating the model as the parameters are being tuned and stopping the tuning when over-fitting is detected which is known as early stopping. An experiment is done to check the over-fitting problems in this research. For example the following results are obtained when the whole training dataset is used with no validation data. as shown in the table the network performs better for the training dataset but less for the testing set.

TABLE 5-12 the Effect of Over-fitting on Network Performance

Learning style types	**Network performance**
Visual-Auditory	98.55%
Sensitive-Intuitive	99.32%
Activist-Reflective	98.35 %
Sequential-Global	97.68 %

To cope with such problems, the available data is split into three parts. First, the working dataset, with 1296 cases, is divided into two sets: The first, 90% (1134), is for a training set used for determining the values of the weights, and a testing set used for deciding when to stop training. The second dataset, the remaining 10% (162), is for validation set. While 90% (1020) of the first dataset is used for training purpose, the remaining 10% (114) is used for testing. In all cases, sampling is made on random basis, and care has been taken in that data is available for all possible outcomes (or classes) so the model can learn about all cases.

5.3.5 EVALUATING THE LEARNING STYLE PREDICTION MODEL

There are several metrics commonly used in evaluating the learning style predicting system. In this case, we use precision and recall along with the time needed to build a neural network to evaluate the different network architectures. Precision is the percentage of correctly recommended items out of the total number of recommended items. Accuracy is the number of correctly classified items divided by the number of classified items. The combination of the precision and accuracy is represented by confusion matrix. In the confusion matrix, the columns represent the systems prediction and the rows represent the actual user rating. The confusion matrix keeps track of how many test items were correctly and incorrectly classified for a given target user. A confusion matrix is calculated for each of the target users over the testing dataset is then used to calculate the precision and accuracy values for that target user.

Precision=number of true positives/number of true positives + number of false positives

Accuracy=number of true positives + number of true negatives/number of test instances in the dataset

Generally, for each of the five network designs and the four learning style models, the network is trained over 7000 runs. Numerous models for each of the four designs were developed by adjusting the network parameters like the testing tolerance from 0.4 down to 0.1, and number of hidden neurons interactively for better network performance. After the completion of the training process, for each of the 20 (5x4) partitions, the networks from the runs with the minimum number of errors on the testing set were selected. The final choice from the 20 networks is based on the performance of these networks on the validation dataset.

The percentages of learning styles correctly classified by the different networks for the validation set by taking the highest values are given in table 5.9.

TABLE 5-13 Percentages of Correctly Classified Learning Styles

Learning style types	Network design				
	A	B	C	D	E
Visual-Auditory	93.07	90.76	91.11	92.30	90.00
Sensitive-Intuitive	94.61	92.34	90.10	87.89	93.23
Activist-Reflective	96.15	94.12	92.56	90.2	89.90
Sequential-Global	92.30	86.15	87.69	88.46	85.38

Table 5.9 shows the performance of the four models for the five-network design. The highest performance results for the four learning style-predicting models for the validation dataset are resulted with the network parameters; 0.3, 0.3,500 learning rate, momentum value and training time after a long iterative experimentation by exchanging the above determinant network parameters. The confusion matrix for the highest performance classifications for each of the learning style models is presented as follows. The predicting performances are shown in table 5.14, 5.15, 5.16 and 5.17.

TABLE 5-14 Confusion Matrixes for Sensitive-Intuitive Model

Actual	Predicted	
	Sensitive	Intuitive
Sensitive	81	2
Intuitive	5	42

TABLE 5-15 Confusion Matrixes for Activist-Reflective Model

Actual	Predicted	
	Reflective	Activist
Reflective	68	2
Activist	3	57

TABLE 5-16 Confusion Matrixes for Sequential-Global model

Actual	Predicted	
	Sequential	Global
Sequential	72	4
Global	6	48

TABLE 5-17 Confusion Matrixes for visual-Auditory model

Actual	Predicted	
	Visual	Auditory
Visual	79	5
Auditory	4	42

Generally, the predicting performance of the models is promising even though; there is still shortage of training data. In this chapter, a neural network model is trained and evaluated for predicting learning styles as shown in the above experiment.

5.4 LEARNING STYLES FINDINGS WITH TEACHING STRATEGY

In [17], the teaching strategy of each learning styles are presented. In this phase the learning styles and the Ethiopian higher learning institutions teaching strategy is summarized. There is no research conducted on Ethiopian students learning styles and teaching strategies for those learners. Thus, the researcher is forced to conduct a preliminary study especially on the teaching strategies of Ethiopian universities and colleges.

Visual learners remember best by what they see; pictures, diagrams, flow charts, time lines, films, and demonstrations. Auditory learners get more out of words: written and spoken explanations. Everyone learns more when information is presented both visually and verbally. From the preliminary study, most college or university classes give very little visual information to their students i.e. students mainly listen to lectures and read material written on chalkboards and in textbooks and handouts. Unfortunately, most people are visual learners. In this research, from the total training dataset, 36.50% of the respondents were auditory learners where as the remaining 63.50% were visual. This non-proportional distribution among respondents was one challenge in training the model with proportional data from each class.

On the other hand, the teaching strategy for the Activist/Reflective groups of learners is also suggested in [17]. Active learners tend to retain and understand information best by doing something active with it, discussing or applying it or explaining it to others but reflective learners prefer to think about it quietly first. “Let’s try it out and see how it works” is an active learner’s phrase; “Let’s think it through first” is the reflective learner’s response. Active learners tend to like group work more than reflective learners, who prefer working alone. Sitting through lectures without getting to do anything physical but take notes is hard for both learning types, but particularly hard for active learners. Everybody is active sometimes and reflective sometimes. If the student is an active learner in a system that allows little or no time for discussion or problem-solving activities, the student should try to compensate for these lacks when study. The learner is advised to study in a group in which the members take turns explaining different topics to each other. If the learners are a reflective learner in the system that allows little or not class time for thinking about new information, the student should try to compensate for this lack when study. The student is advised not to simply read or memorize the material; stop periodically to review what you have read and to think of possible questions or applications. Again from the preliminary study, most university/college classes in Ethiopia neither allow discussion or problem-solving activities nor allow class time for thinking about new information which is against the interest of the two groups of learners. The proportion of dataset used in the training for reflective learner is 54.90% while for activist is 45.09%, which is nearly proportional.

In the same manner, Sensing learners tend to like learning facts; intuitive learners often prefer discovering possibilities and relationships. Sensors often like solving problems by well-established methods and dislike complications and surprises; intuitors like innovation and dislike repetition. Sensors are more likely than intuitors to resent being tested on material that has not been explicitly covered in class. Sensors tend to be patient with details and good at memorizing facts and doing hands-on (laboratory) work; intuitors may be better at grasping new concepts and are often more comfortable than sensors with abstractions and mathematical formulations. Sensors tend to be more practical and careful than intuitors; intuitors tend to work faster and to be more innovative than sensors. Sensors don't like courses that have no apparent connection to the real world; intuitors don't like "plug-and-chug" courses that involve a lot of memorization and routine calculations. Based on the preliminary study, universities and colleges do not provide learning information appropriate for sensory learners who learns better by working and practical lessons. Besides, since majority of learners are sensitive learners their teaching strategy is against the majority. 64.94% and 35.05% of learners were sensitive and Intuitive respectively.

Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly "getting it." Sequential learners tend to follow logical stepwise paths in finding solutions; global learners may be able to solve complex problems quickly or put things together in novel ways once they have grasped the big picture, but they may have difficulty explaining how they did it. Many people who read this description may conclude incorrectly that they are global, since everyone has experienced bewilderment followed by a sudden flash of understanding. What makes you global or not is what happens before the light bulb goes on. Sequential learners may not fully understand the material but they can nevertheless do something with it (like solve the homework problems or pass the test) since the pieces they have absorbed are logically connected. Strongly global learners who lack good sequential thinking abilities, on the other hand, may have serious difficulties until they have the big picture. 39.71% of learners were sequential learners where as the remaining 60.29% are global learners..

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The purpose of this study was to investigate and demonstrate the possibility of developing adaptive e-learning model for Ethiopian higher learning institution learners. Given the circumstances and the limitations, the result obtained can be said is promising.

From the analysis of the assessment in this study, Ethiopian higher learning institution learners have varying learning goals, learner background and experiences, preferences, learning styles as well as prior knowledge about the course and their expectations from the course.

In this research of building an adaptive e-learning model for the course introduction to computer, two tasks were made. Firstly, information independent of the course (i.e. learner goals and background and experiences) as well as domain dependent profile (i.e. prior knowledge and expectations) were assessed through questionnaire and stored in the learner model. Secondly, an experimental research of learning styles predicting model through neural network modeling technique was conducted.

By conducting pilot test, the variables were reduced from twenty to fourteen for each classification models. The significant fourteen variables were used as input for the network and the output is with a binary value visual or auditory, sensitive or intuitive and sequential or global for each built model. The target class is manually calculated at the time of data entry based on the model [17] developed to study learning styles of learners.

Multilayer perceptron neural network with backpropagation learning algorithm is selected based on its suitability for the learning style data and its high achievement on the performance measurement. The model building for learning style prediction was undergone after various experiments made iteratively by making adjustments on the modeling parameters to come up with meaningful results. Lastly when evaluating the multilayer perceptron neural network, the model selected as a working model among the models generated, for the four dimensions of learning style was on average able to correctly classify 94.02% of the total validation dataset for the models.

The research shows that most college or university classes in Ethiopia do not give the necessary learning information for their learners. For instance, they give very little visual information to their students i.e. students mainly listen to lectures and read material written on chalkboards and in textbooks and handouts unfortunately most people are visual learners.

Prototype of the adaptive e-learning system was also developed. The prototype, for the adaptive e-learning system is developed under the assumption that work has been done in designing the required database.

To conclude, results from the study have shown the different possibilities of designing adaptive e-learning systems for Ethiopian higher learning institution learner. Moreover, learning style predictive model is designed by neural network data mining technique.

6.2 RECOMMENDATIONS

E-learning helps higher learning institutions and the e-learning sector by solving crowded classrooms, reducing high price of traditional educational books, reduce transportation problems and costs, allowing learners to choose the specified place and time. It is the researcher's believe that, this academic research can initiate Ethiopian academic institutions to design e-learning systems for the different courses.

Designing adaptive e-learning systems seems of no value in countries like Ethiopia where even traditional e-learning systems are not common. However, results from the study shows e-learning system can be usable if and only if it is adaptive enough to learners. To be adaptive is the first requirement and is an integral part of e-learning designs. Therefore, the researcher recommends e-learning system must be designed based on adaptivity principle.

For designing any adaptive e-learning model, one has to consider and analyze in detail about the domain, learner, navigation strategies, adaptation techniques, instructional models and others. However, because of the shortage of time, the adaptive e-learning model in this research is made based on learner model. The researcher recommends a larger experimental adaptive e-learning model be made based on the above all models. Another research is also necessary that shows the impacts of each model for effective e-learning system design.

Even though the neural network data mining modeling technique can cope with noisy and incomplete data, it's predicting capacity increases with increasing training dataset. It is recommended that a researcher who need to model adaptive e-learning systems with neural network modeling technique need to train the model with large volume of data as possible to increase model performance.

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APPENDIX- STUDENTS LEARNING STYLE ASSESSMENT

ADDIS ABABA UNIVERSITY

GRADUATE SCHOOL OF INFORMATION SCIENCE

Dear respondents,

I am going to ask you very personal questions that some people find difficult to answer. Your answers are completely confidential. Your name will not be written on this form unless willing, and will never be used in connection with any of the information you tell me. Your honest answers to these questions will help us to design better adaptive e-learning model for different courses. Please note that you and many learners can benefit from your genuine response. I would greatly appreciate your help in responding to this questionnaire.

The Learning Survey is designed to assess your general approach to learning basic computer skills. It does not predict your behavior in every instance, but it is a clear indication of your overall style preferences.

Appendix –I- learning style

Item	Option	
	yes	no
1. When I listen, I visualize pictures, numbers, or words in my head.		
2. I prefer to learn with TV or video rather than other media.		
3. I use color-coding to help me as I learn or work.		
4. I have to look at people to understand what they say		
5. I understand lectures better when professors write on the board.		
6. Charts, diagrams, and maps help me understand what someone says		
7. I remember peoples' faces but not their names.		
8. I need oral directions for a task		
9. Background sound helps me think.		
10. I like to listen to music when I study or work.		
11. I remember peoples' names but not their faces.		
12. I easily remember jokes that I hear.		
13. I can identify people by their voices (e.g., on the phone).		
14. When I turn on the TV, I listen to the sound more than I watch the screen.		
15. I meet new people easily by jumping into the conversation.		
16. I learn better in the classroom than with a private tutor.		
17. It is easy for me to approach strangers.		
18. Interacting with lots of people gives me energy.		
19. I experience things first and then try to understand them.		
20. The idea of doing homework in groups, appeals to me.		
21. Understand something better after I think it through		

22. In a study group working on difficult material, I am more likely to Sit back and listen.		
23. I prefer to study alone		
24. I would rather first think about how I'm going to do it		
25. I more easily remember something I have thought a lot about.		
26. The idea of doing homework in groups, does not appeal to me.		
27. When I start a homework problem, I am more likely to try to fully understand the problem first.		
28. I would rather be considered realistic.		
29. if I were a teacher, I would rather teach a course that deals with facts and real life situations.		
30. I find it easier to learn facts.		
31. In reading nonfiction, I prefer something that teaches me new facts or tells me how to do something.		
32. I am more likely to be considered Careful about the details of my work.		
33. When I am reading for enjoyment, I like writers to clearly say what they mean.		
34. When I have to perform a task, I prefer to Master one way of doing it.		
35. I prefer courses that emphasize Concrete material (facts, data).		
36. If I were a teacher, I would rather teach a course that deals with ideas and theories.		
37. I find it easier to learn concepts.		
38. In reading nonfiction, I prefer something that gives me new ideas to think about.		
39. I am more likely to be considered Creative about how to do my work		
40. When I am reading for enjoyment, I like writers to Say things in creative, interesting ways.		
41. When I have to perform a task, I prefer to come up with new ways of doing it.		
42. I prefer courses that emphasize abstract material (concepts, theories).		
43. When I solve math problems I usually work my way to the solutions one step at a time.		

44. It is more important to me that an instructor lay out the material in clear sequential steps.		
45. When considering a body of information, I am more likely to focus on details and miss the big picture.		
46. When writing a paper, I am more likely to work on (think about or write) the beginning of the paper and progress forward.		
47. When I am learning a new subject, I prefer to Stay focused on that subject, learning as much about it as I can.		
48. Some teachers start their lectures with an outline of what they will cover. Such outlines are somewhat helpful to me.		
49. When solving problems in a group, I would be more likely to think of the steps in the solution process		
50. Once I understand the whole thing, I see how the parts fit.		
51. When I solve math problems I often just see the solutions but then have to struggle to figure out the steps to get to them.		
52. It is more important to me that an instructor give me an overall picture and relate the material to other subjects.		
53. When considering a body of information, I am more likely to try to understand the big picture before getting into the details.		
54. When writing a paper, I am more likely to Work on (think about nor write) different parts of the paper and then order them.		
55. When I am learning a new subject, I prefer to try to make connections between that subject and related subjects		
56. Some teachers start their lectures with an outline of what they will cover. Such outlines are Very helpful to me.		
57. When solving problems in a group, I would be more likely to think of possible consequences or applications of the solution in a wide range of areas.		

APPENDIX-II

Questions to assess the learning preference, goals and objectives of basic computer skills

Item	Yes	No
Access introductory learning material		
Access intermediate learning material		
Access advanced learning material		
Access practical learning material		
Access theoretical learning material		
Access technical learning material		
Search for detailed learning material		
Search for overview material		
New materials are suggested when they are published		
only materials are presented that much your objectives		
Suggestions of which part to study next		
System uses your self-test to make decisions at various points		
13. Learning goals: A. For passing exams B. For problem solving		
14. Previous learners' knowledge A. No background skill B. Basic skills C. Sufficient skill		