# Adaptive Virtual Learning Environment For Different Learning Styles

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For the Degree of Doctor in Information Technology

(DIT)

By

Renato R. Maaliw III

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## ENDORSEMENT FOR DISSERTATION FINAL ORAL DEFENSE

The Dean
School of Graduate Studies

Dear Madam:

This is to certify that **Mr. Renato R. Maaliw III**, a candidate for the degree Doctor in Information Technology (DIT) has been under my supervision, with his dissertation entitled: "**Adaptive Virtual Learning Environment for Different Learning Styles**".

This certifies further that I have assessed the above dissertation and is found to be in conformity to the standards set by the School of Graduate Studies through the Title Defense Committee which evaluated the same both in form and substance, and is now ready for final evaluation / defense. Issued this July 2016 for record and reference purposes, at AMA University, Project 8, Quezon City.

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## DISSERTATION COURSE/PREREQUISITES VERIFICATION

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## DISSERTATION APPROVAL SHEET

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## DEDICATION

This piece of work is humbly dedicated to my father, Renato P. Maaliw.

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## ABSTRACT

Virtual Learning Environment (VLE) such as Moodle, Blackboard, and WebCT are commonly and successfully used in E-education. While they focus on supporting educators in creating and holding online courses, they typically do not consider the individual differences of learners. However, learners have different needs and characteristics such as prior knowledge, motivation, cognitive traits, and learning styles. Recently, increasing attention is paid to characteristics such as learning styles, their impact on learning, and how these individual characteristics can be supported by learning systems. These investigations are motivated by educational theories, which argue that providing courses and contents which fit the individual characteristics of students makes learning easier for them and thus their learning progress.

This research primarily focuses on providing adaptation to VLEs by inferring learning styles according to the Felder-Silverman Learning Style Model (FSLSM). An automated data-driven approach for identifying learning styles from behavior and actions of learners has been designed, implemented, and evaluated, demonstrating that the approach is suitable for identifying learning styles. Based from this approach, an Adaptive Virtual Learning Environment prototype for automatic classification of learning styles in VLEs had been implemented.

This approach was experimented on five hundred seven (507) students of Computer Programming 1 Course created using Moodle. Student's behaviors

have been extracted from log data and the learning style for each student was mapped according to FSLSM. Classification accuracy and kappa statistics have been observed to measure the performance of each classifier. The results show that the efficiency of classification by means of J48 decision tree technique had the highest average value of correctly classified instances at 87.42% accuracy and it could be used to infer the learning style of students in an Adaptive VLE.

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## Definition of Terms

**Conjunctive Rule** is a classifier that implements a single conjunctive rule learner that can predict for numerical and nominal class labels. A rule consists of antecedents "AND" together and the consequent (class value) for the classification or regression.

**Cross Industry Standard Process for Data Mining (CRISP-DM)** is a data mining process that describes commonly used approaches that data mining experts use to tackle problems.

**Educational Data Mining (EDM)** describes a research field concerned with the application of data mining, machine learning and statistics to information generated from educational settings.

**Felder-Silverman Learning Style Model (FSLSM)** is a learning style model based on the notion that students have preferences in terms of the way they receive and process information. The model presents different dimension that are indicative of learning preferences.

**Index of Learning Styles (ILS)** is an instrument used to assess preferences on four dimensions of a learning style model formulated by Richard M. Felder and Linda K. Silverman.

**Information Gain** in data mining is the amount of information that is gained by knowing the value of the attribute, which is entropy of the distribution before the split minus the entropy of the distribution after it.

**ISO/EIC 20510** is a product quality model composed of eight characteristics (which are further subdivided into sub characteristics) that relate to static properties of software and dynamic properties of the computer system. The model is applicable to both computer system and software products.

**J48 Decision Tree** is a tree classifier that is an extension of ID3. In the WEKA data mining tool, J48 is an open source Java implementation of the C4.5 algorithm.

**Knowledge Discovery of Databases (KDD)** is a process that aims at the discovery of useful information from a large collection of data. Its main function in data mining is applying various methods and algorithms in order to discover and extract patterns in stored data.

**Learning Styles (LS)** refers to the composite characteristics of cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment. A common concept is that individual differs in how they learn.

**Logistic Regression** is a classification analysis that has been used for modeling trend if the target variable is a binary variable that depends on multiple regressors. The regressors can be both continuous and categorical in value.

**Moodle** is a free and open-source software virtual learning environment used for blended learning, distance education, flipped classroom and other e-learning projects in schools, university, workplaces and other sectors.

**Naïve Bayes** in machine learning is a simple probabilistic classifiers based on applying Bayes theorem with strong (naïve) independence assumptions between the features. They are highly scalable, requiring a number of parameters linear in the number of variables (feature/predictors) in a learning problem.

**SPSS (Statistical Package for the Social Sciences)** is a software package used for logical batched and non-batched statistical analysis. It is a widely used program for statistical analysis that is used by market researchers, health researches, survey companies, government, education researchers, marketing organizations, data miners, and others.

**Subset Selection** in machine learning and statistics is the process of selecting a subset of relevant features (variables, predictors) for use in model construction for simplification of models, shortening training times, avoiding dimensionality and enhanced generalization by reducing over fitting.

**Virtual Learning Environment (VLE)** or also known as Learning Management System (LMS) is a software application for the administration, documentation, tracking, reporting and delivery of educational courses or training programs.

**WEKA (Waikato Environment for Knowledge Analysis)** is a popular suite of matching learning software written in Java developed at the University of Waikato in New Zealand. It contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces.

# Chapter 1

# THE PROBLEM AND ITS BACKGROUND

## Introduction

There are increasing research interests in utilizing data mining in the field of education. This new emerging discipline is known as Educational Data Mining (EDM). Its primary concern is developing methods for exploring the diverse and unique types of data that comes from the educational settings. At present, Virtual Learning Environments (VLEs) increasingly serve as an important infrastructure features of most universities that enable educators to provide students with different representations of knowledge and to enhance interaction between teachers and students, and even amongst students themselves.

VLEs usually provide online tools for assessment, communication, uploading of content and various features. Whilst traditional teaching methods, such as face-to-face lectures, tutorials, lab assignments, and mentoring remain dominant in the educational sector, universities are investing heavily in learning technologies, to facilitate improvements with respect to the quality of learning (Dumciene, 2010). But what is almost completely overlooked is a vast collection of data that resides inside these specific environments. All this data represents a potentially valuable source which is not adequately considered.

The data stored in these VLEs can be used to improve the learning and pedagogical process to make it more efficient for both teachers and learners. Specifically, it can be used in the classification of students' learning styles (LS). Notable educational experts and researchers consider learning style as an important factor that directly affects the learning process. Understanding how different people learn is the key to a successful teaching and learning process.

**Background of the study**

The study is based on widely accepted theory that each learner has an individual or specific learning style. A learner with a specific learning style can face difficulties while learning, when their learning style is not supported by the teaching environment thus the study focuses on the identification of students' learning styles. Learning styles are characteristics preferences for alternative ways of taking in and processing information and it is considered as one of the factors influencing learner's achievement. The use of VLEs in higher education and beyond has dramatically increased over the last years. These environments, due to their web-based nature, allow for the automatic collection of usage data which in turn offers educators new opportunities to understand and improve student learning.

In the case of Southern Luzon State University specically the College of Industrial Technology which is composed of almost three thousand students, VLE are combined with traditional classroom methods. While students attend face-to-face classroom practices, classes are supplemented with computer-mediated activities regarding content and delivery. While the usage of VLE is proven to be effective and efficient, it provides no level of personalization or adaptability to cater different types of students. The field of education is particularly concerned with developing methods for exploring the unique types of data that came from educational settings, and using those methods to better understand students and the settings in which they learn (Baker & Yacef, 2009). Traditionally, most of student modeling systems have been limited to maintain assumptions related with student's knowledge and not pay too much attention to student's preferences. Studies have shown that each individual has a learning style that helps them learn better. This is one of the reasons why some individuals find it easy to learn in a particularly environment; whereas others find it difficult in the same one.

It is an inevitable fact that some individuals learn differently from the others. Some tends to learn by doing; whereas others tend to learn concepts; some like written texts and or spoken explanations better, whereas others prefer learning by visual information such as pictures or diagrams. Knowing student's learning styles can help in many ways to enhance learning and teaching. Primarily, teachers can benefit by getting information about how their students are used to learn, which provides them with a deeper understanding and might help when explaining or preparing learning materials for them. Furthermore, making students aware of their learning styles and showing them their individual strengths and weaknesses can help students understand why learning is sometimes difficult for them and is the basis for developing their weaknesses.

In addition, students can be supported by matching the teaching style with their learning style. Providing students with learning material and activities that fit their preferred ways of learning can make learning easier for them. The study aims to utilize educational data mining in supporting teachers to identify their student's learning styles in Virtual Learning Environments and provide course design and content adaptation to match each of the students learning styles. Many learning style models exist in literature, such as the learning style model by Kolb, Honey and Mumford, Pask and Felder and Silverman. While there are still many open issues with respect to learning styles, all learning style models agree that learners have different ways in which they prefer to learn.

In this study, Felder-Silverman learning style model (FSLSM) was used for the reasons that it is often used in technology-enhanced learning and that is also designed for traditional learning (Liu 2005). Moreover, FSLSM describes the learning style of a learner in more detail, distinguishing between preferences on four dimensions as compared to other learning style models that classify learners in only a few groups.

**Statement of the Problem**

According to Felder (2010) multiple studies have shown the relationships between learners' learning styles and their direct impact on how students learn. Virtual Learning Environment provides a variety of features to support teachers in creating, administering, and managing courses but they typically do not consider individual differences of learners and treat all learners equally regardless of their personal needs and characteristics. From the theoretical point of view, conclusion can be drawn that incorporating identification of learning styles of learners in a learning environment provides a concrete knowledge in order to make learning easier for them and increase their learning efficiency. Most common Virtual Learning Environments such as Moodle (2007), WebCT (2007), or BlackBoard (2007) are commonly successfully used but their focus is on supporting teachers and support online teaching as easy as possible. However, although educational and psychological experts suggest incorporating individual differences of learners, VLEs provide only little or in most cases, none at all in classifying learners.

The aim of this study is to combine the advantages of VLEs with data mining techniques in order to identify learning styles of the learners. In order to realize the goals, investigations regarding three research questions were conducted.

1. How learning styles are classified using learner's behavior in a Virtual Learning Environment?
2. How Virtual Learning Environment adapt to the different learning styles of the learners?
3. How classifications of learning styles affect the course design and contents of a Virtual Learning Environment?

**Objectives of the Study**

The general objective of this study is to develop a framework to be used in classification of student's learning styles in a Virtual Learning Environment. Specifically, it aims to attain the following:

1. To determine and map relevant behaviors of learners as attributes that are used in classification of student's learning styles in Virtual Learning Environment.

2. To determine what classification method accurately measures the classification of learner's learning styles in a Virtual Learning Environment.
3. To extend the capability of Virtual Learning Environment to adapt its course design and contents based on the classification of student's learning styles.

**Scope and Limitations of the Study**

The study focused on the user log data of the Virtual Learning Environment (Moodle) utilized by Southern Luzon State University, College of Industrial Technology. Data mining technique was used to generate data models of learning styles identification. The datasets was obtained from the Virtual Learning Environment's database and SQL scripts were used to extract the needed records. The study was delimited to students who were enrolled in Computer Programming 1 Moodle course from 2012 to 2015. This particular course is selected for the reason that it provides large data sets composed of 52,815 rows of data.

The results of the data mining was compared to the actual results of the Index of Learning Questionnaire (ILS) that is based from Felder-Silverman learning style model without considering the degree of preference to evaluate the learning styles of the students. The data set includes selected log files from the Virtual Learning Environment and excludes students who did not finished or dropped out from the course. The gathered data was evaluated using a data mining tool such as WEKA that consists of data mining tools and statistical packages to infer student's learning styles based on their behavior in VLE. The evaluation of the software prototype quality will be measured by selected end-users from Southern Luzon State University using evaluation criteria provided in the ISO/IEC 20150 software quality assessment tool.

**Significance of the Study**

The result of this study is expected to be of great value to the following stakeholders:

***Higher Education Institution.*** The framework of the study can act as a catalyst for higher education institution to effectively use Virtual Learning Environment as a source of knowledge in order to streamline the teaching and learning process.

***Educators.*** The result of the study can provide educators in depth understanding of their students in order to help them learn better by matching teaching strategies to their learning style preferences, recommend to students learning materials and activities that can enhance their learning, and have an accurate representation of their student's diversity in terms of their needs.

***Students.*** The findings of this study can help the students in order to identify their strengths and to convey awareness of their weaknesses when it comes to their learning styles. By knowing their own learning styles students can maximize their learning potentials by taking advantages of their learning styles and learning inclinations.

***Researchers.*** The study could serve as an empirical reference guide for researchers that will undertake a parallel study on learning style classifications on Virtual Learning Environments.

***Course Developers.*** The result of the study can benefit course developers to be aware of the different needs of the students in terms of providing their preferred learning materials.

# Chapter 2

## REVIEW OF RELATED LITERATURE

This chapter contains a discussion of the relevant concepts on the underlying theories of learning styles, various learning style models, data mining algorithms, and educational data mining researches.

### Learning Styles

A learning style (LS) is a student's consistent way of responding to and using stimuli in the context of learning. Keefe (1979) defines learning styles as the composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment. Stewart and Felicetti (1992) define learning styles as those educational conditions under which a student is most likely to learn. They are not concerned with what learners learn, but rather how they prefer to learn. Learning styles are points along a scale that help discovers the different forms of mental representations. When individual tries to learn something new they prefer to learn it by listening to someone, talk to someone, or perhaps they prefer to read about a concept to learn it, or perhaps would like to see a demonstration.

Learning styles can be defined, classified, and identified in many different ways. It can also be describe as a set of factors, behaviors, and attitudes that enhance learning in any situation. How the students learn and how the teachers teach, and how the two interact with each other are influenced by different learning styles. Each person is born with innate tendencies towards a particular style, and these biological characteristics are influenced by external factors such as: cultures, personal experiences, and developments. Each learner has a different and consistent preferred ways of perception, organization and retention. These learning styles are the indicators of how learners perceive, interact with, and respond to the learning environments. Learners have different styles of learning, and they learn differently from one another. Proponents for the use of learning styles in education imposes that teachers should assess the learning styles of their students and adapt their classroom methods to best fit each learner’s learning needs. There are sufficient evidences for the diversity in individual’s thinking and ways of processing various types of information, and shown that students will learn best if taught in a method deemed appropriate for their learning style (Pashler et. al, 2008).

**Learning Style Models**

Much research has been done to assess how the human mind operates, how it really perceives and process information. As a result many learning style models (LSM) have been developed by which an individual’s style of learning can be assessed and be understood. Educators can start by assessing their own teaching style and compare it to an assessment of their students learning styles. Butler (1995) points out that a teacher can “bridge the gap” to the learner through attitude, action, and understanding the learner’s preferred ways to learn. She stresses that the quality of a student’s outcome in an instructional activity depended as much on learning style and that matching learning styles with different levels of thinking allowed students to learn most efficiently, effectively, easily and with the greatest enjoyment. Through the years several learning styles have been developed to identify student learning behaviors. Coffield (2004) classified learning style models into five (5) families which are based on some overarching ideas behind the models, attempting to reflect the views of the main theorists of learning styles. The first family relies on the idea that learning styles and preferences are largely constitutionally based, including the four modalities: visual, auditory, kinesthetic, and tactive. The second family deals with the idea that learning styles reflect innate-seated features of the cognitive structure, including patterns of abilities. A third category refers to learning styles as one component of a relatively stable personality type. In the fourth family, learning styles are seen as flexibility stable preferences. The last category moves on from learning styles to learning approaches, strategies, orientations and conceptions of learning. The succeeding section describes the most commonly used learning style models. Based on Coffield's review, the selection of these models have theoretical importance in the field, widespread use, and their influence on other learning style models.

**Myers-Briggs Type Indicator**

One of the most popular learning style models is the Myers-Briggs Type Indicator (MBTI) which is based on Bloom's Taxonomy. It is a psychometric measurement instrument based upon on Jungian theory that classifies individuals based upon their individual preferences. The four preferences are then combined into the personality type via a four-way interaction. It classifies each person into one of the sixteen (16) personality types by first identifying each individual's four preferences. There are 16 learning styles categorized in the Myers-Briggs Type Indicator, which are a combination of the following four preferences: (1) extraversion versus introversion, (2) sensing versus intuition, (3) thinking versus feeling, and (4) judging versus perceptive. These preferences are determined by a 126-item testing instrument, which takes less than an hour to complete. The *extrovert and introvert* dimension refers to the orientation of a person. The preferred focus of people with an extrovert attitude is on the surroundings such as other people and things, whereas an introvert's preferred focus is on his/her own thoughts and ideas. *Sensing and intuition* deal with the way people prefer to perceive data. While sensing people prefer to perceive data from their five senses, intuitive people use their intuition and prefer to perceive data from the unconscious. The judgment based on the perceived data can be distinguished between *thinking and feeling.* Thinking means that the judgment is based on logical connections such as "true" or "false" and "if-then" while feeling refers to "more-less" and "better-worse" evaluations. However, judgment and decisions are in both cases based on rational considerations. The last dichotomy describes whether a person is more extroverted in his/her stronger judgment function (thinking or feeling) or in the perceiving function (sensing or intuition). Judging people prefer step-by-step approaches and structure as well as coming to a quick closure. Perceiving people have a preference for keeping all options open and tend to be more flexible and spontaneous.

**Pask's Serialist/Holist/Versatilist Model**

During the development of the conversation theory (Pask, 1972), Pask studied patterns of conversations between individuals to identify various styles of learning and thinking. A critical method according to the conversation theory is the "teach back" approach, where students teach their peers. Different patterns for designing, planning, and organizing of thought as well as for selecting and representing information were investigated, resulting in the identification of three types of learners (Pask, 1976). Serialist students use a serial learning strategy. They tend to concentrate more narrowly on details and procedures before conceptualizing an overall picture. They typically work from the bottom up, learn step-by-step in a linear sequence and concentrate on well-defined and sequentially ordered chunks of information. According to Pask, serial learners tend to ignore relevant connections between topics, which can be seen as their learning deficits. In contrast, *holists* use a holistic learning strategy. They tend to concentrate on building broad descriptions and use a top-down approach. They focus on several aspects of the subject at the same time and use complex links to relate multileveled information. While they are good in building interconnections between theoretical, practical, and personal aspects of a topic, holistic learners do not focus on enough details, which can be seen as their learning deficit. *Versatile* leaners employ both, serial and holistic learning strategies. They engage in global and detailed approaches and succeed in achieving a full and deep understanding. Therefore, versatile learners are proficient at learning from most or all modes of instruction.

Pask developed some tests such as the Spry Ring History Test (Pask & Scott, 1973) and the Clobbits Test (Pask, 1975) as measure for serial, holistic and versatile thinking. Some years later, Entwistle (1981, 1998) and Ford (1985) developed self-report inventories for identifying a preference for serial, holistic, and versatile learning styles. The Study Preference Questionnaire developed by Ford (1985) provided students with pairs of two statements (one on the left side and one on the right side) and asked them to indicate their degree of agreement with either statements, or to indicate no preference, using a five (5) point scale. Entwistle's learning style model is based on Pask's work. With respect to his model, Entwistle designed inventories to tap into a number of dimensions of study attitudes and behaviors, including also the serial/holistic/versatile dimension (Entwistle, 1981, 1998).

**Entwistle's Deep, Surface and Strategic Learning Approach**

Entwistle and his colleagues deal with the involvement of student's intentions, goals and motivation in their learning approach. Entwistle argued that the students' orientations and conceptions of learning lead to and are affected by the student's typical approaches to learning. The model is based on research by Pask (1976), Marton (1976), and Biggs (1979) and distinguishes between three approaches for learning and studying. Learners applying a *deep learning approach* are extrinsically motivated and aim merely at meeting the requirements of the course. They treat the course content as unrelated bits of knowledge, try to identify those elements of a course that are likely to be assessed and focus on memorizing these details. They carry out procedures routinely and find difficulty in making sense of new ideas presented. They see little value or meaning in either courses or tasks set, study without reflecting on either purpose or strategy, and feel undue pressure and worry about their work. In the *strategic learning approach,* students combine the deep and surface approach in order to achieve the best possible outcome in terms of marks. Students who adopt the strategic approach put consistent effort into studying, manage time and effort effectively, and find the right conditions and materials for studying, and monitoring the effectiveness of ways of studying.

For measuring the adopted approach of learning and studying of students, several versions of questionnaires have evolved such as the Approaches to Studying Inventory (ASI) (Ramsden & Entwistle, 1981), the Course Perception Questionnaire (CPQ) (Entwistle & Tait, 1995), the Approaches and Study Skills Inventory for Students (ASSIST) (Entwistle & Tait, 1996), and the Approaches to Learning and Studying Inventory (ALSI) (Tyler & Entwistle, 2003). Since Entwistle's model is based on Pask's serial and holistic learning strategy, this concept is also included in the questionnaires.

**Grasha-Riechmann Learning Style Model**

The learning style model of Grasha-Riechman focuses on the students' social interaction with their teachers and fellow students in the classroom environment. Grasha and Riechmann identified three bipolar dimensions in order to understand the student's behavior with respect to their social interaction: the *participant/avoidant*, *collaborative/competitive*, and *dependent/independent* dimensions.

The *participant/avoidant* dimension indicated how much a student wishes to become involved in the classroom environment. Students who adopt a participant style desire to learn the course content and enjoy attending the class. They take responsibility for their own learning and enjoy participating in the learning activities. In contrast, students who adopt an avoidant style do not like to learn and do not enjoy attending the class. They also do not take responsibility for their learning and avoid taking part in the course activities.

The *collaborative/competitive* dimension measures the motivation behind a student's interactions with other. Collaborative learners are characterized as learners who are cooperative, enjoy working with others, and see the classroom as a place for learning and interacting with others. On the other hand, competitive learners see their fellow students as competitors. They have the motivation to do better than others, enjoy competing, and see the classroom as a win-lose situation.

The *dependent/independent* dimension measures attitudes toward teachers and how much the student's desire freedom and control in the learning environment. Dependent students see the teacher as the source of information and structure. They want to be told what to do by authorities and learn only what is required. Independent learners are characterized as confident and curious learners. They prefer to think for themselves and work on their own. For measuring the preferences of students with respect to the six learning styles, a 90-item self-report inventory called Student Learning Styles Scale (SLSS) (Grasha & Riechmann, 1975) was developed. The questionnaire is created in particular for college and high school students. It is divided in six subcategories, each for one learning style. Each subcategory consists of 15 questions wherein students are asked to rate their agreement or disagreement to these questions on a 5-point Likert Scale. Considering the issue that the styles may change from class to class for each student, two different forms are designed, one that assesses a general class, and the second that relates to a specific course.

**Dunn and Dunn Learning Style Model**

Originally proposed in 1974, the Dunn and Dunn learning style model (Dunn & Dunn, 1974) distinguishes between adults and children, and includes five variables where each variable consists of several factors. The *environmental* variable includes sound, temperature, light, and seating/furniture design. The *sociological* variable incorporates factors dealing with the preference for learning alone, in a pair, in a small group, as part of a team, with an authority, or in varied approaches. For children, additionally the motivation from parents/teachers is included as factor. The *emotional* variable consists of the factors motivation, conformity/responsibility, persistence, and need for structure. The *physical* variable is comprised of factors regarding perception/modality preferences (visual, auditory tactile/kinesthetic external, kinesthetic internal), food and drink intake, time of day and mobility. The *psychological* variable was added later to the model and includes factors referring to global/analytic preferences, right or left hemisphericity, and impulsive/reflective preferences.

For detecting the learning style preferences according to the model, different version of questionnaires were developed. The Learning Styles

Inventory (Dunn, Dunn & Price, 1996) was developed for children and exists in three versions. This inventory consists of 104 questions which employ a 3-choice or 5-choice Likert Scale. The Building Excellence Inventory (Rundle & Dunn, 2000) is the current version for adults. It includes 118 questions and employs a 5-point Likert scale. As a result, a high or low preference for each factor is identified.

**Gregorc's Mind Styles Model**

The mind style model by Gregorc (Gregorc, 1982) is based on two dimensions dealing with the preferences for *perception* and *ordering*. Regarding perception, people can prefer an abstract or concrete way of perception, or some combination of both. Abstract perception refers to the ability to process information through reason and intuition, often visible to our physical senses. In contrast, concrete perception emphasizes the physical senses and refers to the ability to process information through these senses. The ordering dimension deals with the way a learner is arranging, prioritizing, and using information in either a sequential or random order, or in a combination of both. While a sequential style pertains to use a linear, step-by-step organizational scheme, a random order style refers to the use of a network-like format which relates data to each other in a variety of ways. The perceptual and ordering preferences can be combined into four basic mediation channels which lead to four types of learners.

The *concrete sequential* learners prefer to use their five senses for processing information and are considered as orderly, logical, and sequential. These learners look for authority and guidance in a learning environment and prefer to extract information from hands-on experiences. The *concrete random* learners are characterized by the need to experiment with ideas and concepts and will employ trial-and-error in learning. They like to explore the learning environment, are considered as insightful, can easily move from facts to theory, and do not like authoritative interventions. The *abstract sequential* learners have their strengths in the area of decoding written, verbal, and image symbols. They prefer rational and sequential presentations and are good in synthesizing ideas and producing new concepts or outcomes to new conclusions. They will defer to authority and has a low tolerance for distractions. The *abstract random* learners are characterized by a keen awareness of human behavior and an ability to evaluate and interpret atmosphere and mood. They prefer an unstructured learning environment and collaborations with others; are good in seeing relationships, tend to be reflective and need time to process data before reacting to it.

The Gregorc Style Delineator (Gregorc, 1982; Gregorc, 1985) is a self-report instrument to detect learners' preferences for the two dimensions and therefore their preferred channels. The instrument presents the students with 40 words arranged in 10 columns of four items each. The learners are then asked to rank the four words relative to how they fit to themselves (1 for being least and 4 for being most like themselves). Scores for each of the four learner types can range from 10 to 40, calculated by summing up the ranks of the respective words for each channel.

**Kolb's Learning Style Model**

Experiential Learning Theory is the basis of the Kolb's Learning Style Model (1984) which models the learning process and incorporates the important role of experience in this process. This theory perceives that learning has a four-stage cycle. Concrete experience is the basis for observations and reflections. These observations are used to form abstract concepts and generalizations, which again act as basis for testing implementations of concepts in new situations. Testing implementations results in concrete experience, which closes the learning cycle. According to this theory, learners need four abilities for effective learning: a) Concrete Experience abilities, b) Reflective Observation abilities, c) Abstract Conceptualization abilities, and d) Active Experimentation abilities. On in-depth analysis, there are two polar opposite dimensions: *concrete/abstract* and *active/reflective*. Kolb (1982) described that "as a result of our hereditary equipment, our particular past life experience, and the demands of our present environment, most of us develop learning styles that emphasize some learning abilities over others". Based on this assumption, Kolb identified four statistically prevalent types of learning styles.

*Convergers'* dominant abilities are abstract conceptualization and active experimentation. Therefore, their strengths lie in the practical applications of ideas, The name "Convergers" is based on Hudson's theory of thinking styles (Hudson, 1966), where convergent thinkers are people who are good in gathering information and facts and putting them together to find a single correct answer to a specific problem. In contrast, *Divergers* excel in the opposite poles of the two dimensions, namely concrete experimentation and reflective observation. They are good in viewing concrete situations in much different perspective and in organizing relationships to a meaningful shape. According to Hudson, a dominant strength of Divergers is to generate ideas and therefore, Divergers tend to be more creative. *Assimilators* excel in abstract conceptualization and reflective observation. Their greatest strength lies in creating theoretical models. They are good in inductive reasoning and in assimilating disparate observation into an integrated explanation. *Accomodators* have the opposite strengths to Assimilators. Their dominant abilities are concrete experience and active experimentation. Their strength lies in doing things actively, carrying out plans and experiments, and becoming involved in new experiences. They are also characterized as risk-takers and as people who excel in situations that call for adaptation to specific immediate circumstances.

For identifying learning styles based on Kolb's learning style model, the Learning Style Inventory (LSI) was developed (Kolb, 1976) and revised several times. The current version of LSI (Kolb, 2005) uses a forced-choice ranking method to assess an individual's preferred modes of learning (Concrete Exprerience, Reflective Observations, Abstract Conceptualization, and Active Experimentation). Individuals are asked to complete 12 sentences about their preferred way of learning. Each sentence has four endings and the individuals are asked to rank the endings according to what best describes how they learn (4 = most like you; 1 = least like you). The results of the LSI indicated the individual's preferences for the four modes. Furthermore, their score for the active/reflective and concrete/abstract dimensions can be derived from the preferred modes, which again lead to the preferred type of learning style.

**Honey and Mumford’s Learning Style Model**

The learning style model by Honey and Mumford (1982) is based on Kolb’s Experiential Learning Theory and is developed further on the four types of Kolb’s learning style model. The active/reflective and concrete/abstract dimensions are strongly involved in the defined types as well. Furthermore, Honey and Mumford stated that “the similarities between Kolb’s model and ours are greater than the differences” (Honey & Mumford, 1992).

In Honey and Mumford’s learning style model the types are called: Activist (similar to Accomodator), Theorist (similar to Assimilator), Pragmatist (similar to Converger), and Reflector (similar to Diverger). *Activists* involve themselves fully in new experiences, are enthusiastic about anything new, and learn best by doing something actively. *Theorist* excels in adapting and integrating observations into theories. They need models, concepts, and facts in order to engage in the learning process. *Pragmatists* are interested in real world applications of the learned material. They like to try out and experiment on ideas, theories, and techniques to see if they work in practice. *Reflectors* are people who like to observe other people and their experiences from much different perspective and reflect about them thoroughly before coming to a conclusion. For Reflectors, learning occurs mainly by observing and analyzing the observed experiences.

The Learning Style Questionnaire (LSQ), a self-report inventory for identifying learning styles based on the Honey and Mumford learning style model, as well as its manual was initially developed in 1982, revised in 1992 and then replaced in 2000 (Honey & Mumford, 2000) and again revised in 2006 (Honey & Mumford, 2006). Currently, two versions of the LSQ exist, one with 80 items and one with 40 items.

**Herrmann "Whole Brain" Model**

The Herrmann "Whole Brain" model (Herrmann, 1989) is based on the split-brain study carried out by Roger Sperry (1964), separating the brain in the *left and right cerebral hemispheres.* In addition, the Herrmann "Whole Brain" model considers, following MacLean (1952), the hypothesized functions of the brain's limbic system. Accordingly, individuals are modeled with respect to how they process information using either a cerebral mode, by thinking about the problem, or a *limbic mode*, which is a more active approach based on experimentation.

The "Whole Brain" model distinguishes between four modes or quadrants. Learners who have a primary preference for quadrant A (*left hemisphere, cerebral*) prefer logical, analytical, mathematical, technical thinking and can be considered as quantitative, factual, and critical. Learners with a primary preference for quadrant B (*left hemisphere, limbic)* tend to be sequential and organized, like details, structure and plans and have structured organizational and controlled thinking styles. Learners with a primary preference for the quadrant C (*right hemisphere, limbic*) are characterized as emotional, interpersonal, sensory, kinesthetic, and musical. Learners who have a primary preference for quadrant D (*right hemisphere, cerebral)* tend to be visual, holistic, and innovative and prefer conceptual, synthesizing, and imaginative thinking.

For identifying the preferred quadrant, the Herrman Brain Dominance Instrument (HBDI) was developed (Herrmann, 1989). The HBDI is a self-report inventory, containing 120 questions. As a result of the HBDI, a brain dominance profile is calculated, which shows the primary, secondary and tertiary preferences.

In a recent review of the learning styles literature by Litzinger, Lee, Wise and Felder (2007), they identified 71 different learning style models with their corresponding instruments and reviewed 800 papers relevant to it. In a related document, Coffield (2007) report that there are varieties of papers and articles related to learning style models covering a wide range of topics including the effects of learning styles on academic performance and on retention as well as on the design of technology-based learning tools. Among the articles referring to learning styles are nearly fifty (50) that use the Index of Learning Styles (ILS) of Felder and Silverman.

**Felder-Silverman Learning Style Model**

One of the most widely used models of learning styles is the Index of Learning Styles (ILS) developed by Richard Felder and Linda Silverman. The learning style model unlike other model is based on tendencies, indicating that learners with a high preference for certain behavior can also act sometimes differently. Felder-Silverman Learning Style Model (FSLSM) is used very often in advanced learning technologies and technology-enhanced education. According to Carver (2000), the FSLSM model is most appropriate for multimedia courseware and online-learning. Kuljis and Liu (2005) confirmed this by conducting a comparison of learning models with respect to the application in E-learning and Web-based learning systems. The result of their research confirmed that the use of FSLSM is the most appropriate model for technology-enhanced education environments.

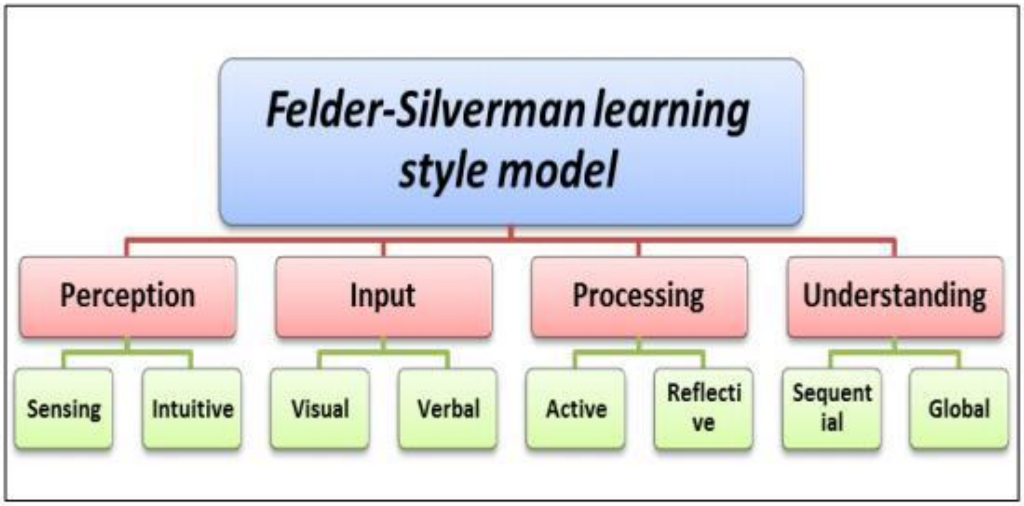



*Figure 2.1 Felder-Silverman Learning Style Model (Felder, 2005)*

There are four dimensions in FSLSM such as Perception, Input, Information Processing and Understanding. Each learner is characterized by a specific preference for each of these dimensions as shown in Figure 2.1.

These dimensions are based on major dimensions in the field of learning styles and can be viewed independently from each other. They show how learners prefer to process (active/reflective), perceive (sensing/intuitive), receive (verbal/visual), and understand (sequential/global) information. While these dimensions are not new in the field of learning styles, the way in which they describe a learning style of a student can be seen as new and innovative. While most learning style models, which include two or more dimensions, derived statistically prevalent learner types from these dimensions, such as the models by Myers-Briggs (Briggs & Myers, 1962), Gregorc (1982), Kolb (1984), and Honey and Mumford (1982), Felder and Silverman describe the learning styles by using scales from +11 to -11 for each dimension (including only odd values).

Therefore the learning style of each learner is characterized by four values between +11 and -11, one for each dimension. These scales facilitate describing the learning style preference in more detail, whereas building learner types does not allow distinguishing between the strength and preference. Additionally, the usage of scales allows expressing balanced preferences, indication that a learner does not have specific preference for one of the two poles of a dimension. Furthermore, Felder and Silverman consider the resulting preferences as tendencies, meaning that even a learner with a strong preference for a particular learning style can act sometimes differently.

The *active/reflective* dimension is analogous to the respective dimension in Kolb's model (1984). Active learners learn best by working actively with the learning material, by applying the material, and by trying things out. Furthermore, they tend to be more interested in communicating with others and preferred to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone or in a small group together with one good friend.

The *sensing/intuitive* dimension is taken from the Myers-Briggs Type Indicator (Briggs & Myers, 1962) and has also similarities to the sensing/intuitive dimension in Kolb's model (Kolb, 1984). Learners with a sensing learning style like to learn facts and concrete learning materials, using their sensory experiences of particular instances as a primary source. They like to solve problems with standard approaches and also tend to be more patient with details. Furthermore, sensing learners are considered as more realistic and sensible; they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings, with general principles rather than concrete instances being a preferred source of information. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners. Therefore, they score better in open-ended tests than in tests with a single answer to a problem. This dimension differs from the active/reflective dimension in an important way: the sensing/intuitive dimension deals with the preferred source of information whereas the active/reflective dimension covers the process of transforming the perceived information into knowledge.

The third, *visual/verbal* dimension deals with the preferred input mode. The dimension differentiates learners who remember best what they have seen (e.g., pictures, diagrams, flow charts and so on), from learners who get more out of textual or text-based representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, learners are distinguished between a *sequential and global* way of understanding. This dimension is based on the learning style model by Pask (1976), where sequential learners refer to serial learners and global learners refer to holistic learners. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. Then they are able to solve complex problems and put things together in novel ways; however, they have difficulties in explaining how they did it. Because the whole picture is important for global learners, they tend to be more interested in overviews and in broad knowledge, whereas sequential learners are more interested in details.

For identifying learning styles based on the FSLSM, Felder and Soloman developed the Index of Learning Styles (ILS), a 44-item questionnaire. As mentioned earlier, each learner has a personal preference for each dimension. These preferences are expressed with values between +11 to -11 per dimension, with steps +/-2. This range comes from the 11 questions that are posed for each dimension.

Several research studies have been conducted to test the validity and reliability of the Felder-Silverman Learning Style Model such as the research done by Felder and Gosky (2003) where 15,000 students of the Appalachian State University in North Carolina participated and completed the ILS questionnaire twice, once at the beginning of the fall semester and again at the end of the fall semester. The results on the research suggests that the ILS measurement is a reasonably valid and reliable measure of learning styles for students and they concluded that the results are consistent with published results for students from other universities as well. In a study by Litzinger (2007), they assessed the reliability, factor structure, and construct validity, and determine whether changing the dichotomous response scale of the ILS by reducing its numbers would improve its reliability and validity. Data collected in their study had internal consistencies across the four learning style scales of the ILS. Factor analysis and direct feedback from students whether they felt their scores accurately represented their learning style preferences provide evidences of the construct validity for the ILS.

Furthermore, Al-Azawei (2015), studied the psychometric analysis of the reliability and validity of the Index of Learning Styles by analyzing the soundness of the instrument in an Arabic sample. A total of 259 engineering students participated voluntarily in the study. The reliability was analyzed by applying internal construct reliability, inter-scale correlation, and total item correlation. The construct validity was also considered by running factor analysis. The overall results indicated that the ILS produces consistent results on learning style preferences of engineering students irrespective of their cross-cultural differences and suggested that it can be used to diagnose learning styles in order to improve academic achievements.

**Virtual Learning Environment**

The use of web-based education systems has grown exponentially in the last few years. It is encourage by the fact that neither students nor teachers are bound to a specific location and that resulted of computer-based education which is virtually independent of any specific hardware platforms. Specifically, collaborative communication tools are becoming widely used in educational contexts. This results to Virtual Learning Environment (VLE) to be currently installed by more and more universities, community colleges, schools, businesses, and even individual instructors in order to add web technology to their courses and to supplement traditional face-to-face courses. Such VLE systems are also known as a Learning Management System (LMS), Course Management System (CMS), Managed Learning Environment (MLE), Learning Support System (LSS) or Learning Platform (LP). These systems can offer a great variety of channels and workspaces to facilitate information sharing and communication between participants in a course that support educators to distribute information to students, produce content material, prepare assignments and test, engage in discussions, manage distance classes and enable collaborative learning with forums, chats, file storage areas, news services, and more features.

Using VLEs has been found to increase the level of communication and collaboration between users (Selinger, 1997). Student tends to have more of a chance of articulating their thoughts and understanding (Chou & Liu, 2005). This is a positive process as one can be developed further by interacting with another resulting in communicating effectively that aids in scaffolding learning, thus advancing the Zone of Proximal Development (ZPD) (Vygotsky, 1978). The use of VLE has been known also to refine student's learning styles, allowing them to use higher level of thinking skills and to develop time management skills (Gibbs, 1999). VLEs can be used for summative assessment, but due to potential exploitation and cheating, they are most frequent used for formative assessment (Becta, 2003). In particular, self-assessment, which may take the form of a multiple choice assessment, or quiz, which provides automatic marking and gives instant feedback to the student (Chohan & Nichols, 2004).

In terms of content delivery of a course it is often consists of notes, supporting links, images, and video clips. These elements are placed by the teacher into a shared area, accessible by all users registered to that space. Chohan and Nichols (2001) regard curriculum transparency as a positive aspect of VLEs; students are able to look ahead to forthcoming content and work ahead of the class at their own pace. However, studies by Sisk (2001) suggests that it is the opportunity to engage with content being looked at, at the time; having access to future content may have negative impact on student performance in the present. Management and tracking of student wise, security credentials are used, so that only registered students can access the environment. A teacher is able to generate statistics, based on which resources the user has accessed and when; a map can be built of an individual's learning pattern. Students can be connected into groups, mirroring the physical groupings that each student may or may not be accustomed to.

VLEs are hierarchically structured and allow content and instructions to be accessed by a student. Furthermore, they are taxonomically designed and content must be organized based on criteria set by the teacher. Whilst VLEs are sometimes used to support distance learning, such as that provided by Open Universities, they are more commonly being used to combine physical learning (face-to-face) and virtual learning (online) (Sisk, 2001); a technique called blended learning (Gillespie, 2007). The rate of technological development in VLE is so great that one must consider the future of the learning environments and the use of the data that comes hidden within its systems. The applied pedagogical strategies in VLEs focus mainly on how to teach learners from a general point of view, without considering the individual needs of learners. Researchers recommend software extensions of existing VLEs by incorporation of identification of individual needs specifically the detection and classification of learning styles.

**Advantages of Felder-Silverman Learning Style Model for use in Virtual Learning Environment**

Many different learning style models exist in literature but the benefits of FSLSM over other learning style models in the context of improving technology enhanced learning by incorporating learning styles in online learning has various argumentation. FSLSM combines several major learning style models. Each of the four dimensions of FSLSM (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) is quite strongly influenced by other learning style models such as the learning style model by Kolb (1984), Pask (1976) as well as the

Myers-Briggs Type Indicator (1962). Although the dimensions themselves are not new, the way in which they are combined and describe the learning styles of students can be seen as new. This enables a quite detailed description of the student's learning styles. In contrast, most other learning style models use few types to describe student's preferred learning styles.

Having a more detailed description of the student's learning styles allows providing more accurate classification. If only the preferred type is known, this information does not include how strong the student belongs to this type. If the student's preference is weak and quite close to another type, his/her needs might be different than for a student who has a strong preference for the same type. By using a scale between +11 and -11 for each dimension, the strength of the learning style preference is measured. The differentiation between strong and weak preferences is especially important when dealing with more than one dimension. In this case, the dimensions can have overlapping or even contrary implications for providing learning style detection. Therefore, differentiation is essential in order to be able to focus on providing courses that support the strong learning style preferences. While some learning style models consider learning styles as stable over time, subject and environment, others claim that they can change quite frequently. FSLSM considers learning styles as "flexibly stable", arguing that previous learning experiences and other environmental factors form the learning style of students (Felder & Spurlin, 2005). Accordingly, learning styles tend to be more or less stable but can change over time. Due to the more or less stable character of learning styles according to FSLSM, classification of student's learning style gives insight in order to provide teaching strategies and learning content that supports them in learning. On the other hand it can also give insights on student's weak abilities in order to enable them to learn also from material that does not match their preferred learning styles.

Furthermore, FSLSM is different from other learning style models in terms of considering learning styles as tendencies, meaning that students have a tendency for a specific learning style but might act in some situations differently. By incorporating the concept of tendencies, the description of learning styles considers also exceptions and extraordinary situations. Besides, FSLSM is often used in technology enhance learning and also in other systems. With this context, FSLSM is the most often used learning style model, where some system incorporate the whole model and some system include only some dimensions of FLSM. In addition, some researchers even argue that FSLSM is the most appropriate learning style model for technology enhanced learning (Carver, Howard & Lane, 1999; Kuljis & Liu, 2005).

**Implications of Learning Styles in Education**

Various attempts have been made to enhance student's academic achievements. It is the primary concern of many dedicated teachers that their students be as much successful as possible. In relation to this, many teachers are convinced that students need the positive attitude to succeed academically. Often, one's learning style is identified to determine the strengths for academic achievement. Dunn, Beaudry and Klavas (1987) assert that through voluminous studies, it has been indicated that both low and average learners earn higher scores on standardized achievement and attitude tests when they are taught within the realm of their learning styles.

Many educational theorists and researchers consider learning styles as an important factor in the learning process and agree that incorporating them in education has potential to make learning easier for students. Furthermore, Felder (2010), for example, argued that learners with a strong preference for a specific learning style might have difficulties in learning if their learning style is not supported by the teaching environment (Felder & Silverman, 1997). Thus, from theoretical point of view, it can be argued that incorporating learning styles of students makes learning easier for them and increases their learning efficiency. On the other hand, learners who are not supported by the learning environment may experience problems in the learning process. Learning styles can be considered in different ways in education. A first step is to make learners aware of their learning styles and show them their individual strengths and weaknesses. The knowledge about their learning styles helps students to understand why learning is sometimes difficult for them and is the basis for developing their weaknesses. Furthermore, students can be supported by matching the teaching styles with the learning styles of the students. Due to the nature of learning styles, providing students with learning material and activities that fit their preferred ways of learning seems to have high potential to make learning easier for them.

However, the matching approach aims at a short-term goal, conversely to make learning as easy as possible at the time students are learning. Looking at long-term goals, educational theorists such as Messick (1976), Kolb (1984) and Grasha (1984) suggested that learners should also train their not-preferred skills and preferences. Messick argued that when learners acquire more educational experience, they are required to adapt to a variety of instructional methods and styles. The ability to adapt to different instructional styles will prepare them with important life skills. Summarizing these aspects, conclusion can be drawn that the mismatching approach should be applied intentionally and depending on the adopted learning style model as well as on the learner's needs. In an environment, where students get their individual learning material and activities, the matching and the mismatching approaches can be applied in a controlled manner, depending on specific conditions such as the current learning goal, the experience of the learners in a particular subject, their motivation and so on.

Those students with multiple learning styles tend to gain more and obtain higher scores compared to those who rely solely on one style (Dunn, Beaudry & Klavas, 1989). Studies also reveal that matching teaching and learning styles can significantly enhance academic achievement at the primary and secondary school levels (Smith & Renzulli, 1990). According to Felder (1995), students learn more when information is obtainable in a variety of approaches than when only a single approach is applied. Much experiential research indicates that learning styles can increase academic performance in several aspects. In general, a rich data have been obtained through studies on learning styles whether on a traditional classroom or through a learning management systems. However, the data have rarely been exploited by administrators, educators and instructional designers to a great extend in order to understand more the learner's approach to learning. A less intensive approach for teachers is to support their learners by including learning material and activities in their courses that addresses different learning styles rather than teaching in a way that accommodate only one learning style. For example, if the learning material consists mainly of abstract material, teachers can include some concrete examples to support a sensing/concrete learning style or if the teacher is mainly lecturing in the course, he/she can include some group work activities in order to support active learners. By addressing different learning styles, some activities match with the students' strengths and some with their weaknesses.

**Knowledge Discovery of Databases**

The data mining of Knowledge Discovery of Databases (KDD) process aims at the discovery of useful information from large collections of data. The main functions of data mining are applying various methods and algorithms in order to discover and extract patterns of stored data. In knowledge discovery cycle, the training tuples will be cleansed, normalized and formatted in the preprocessing stage where the raw data will be analyzed by sets of classifiers using a data mining tool. According to Chapman (2000), the process model for data mining provides an overview of the life cycle of a data mining project. Data mining project consists of six phases as its cycle. The following outlines each phases of CRISP-DM methodology:

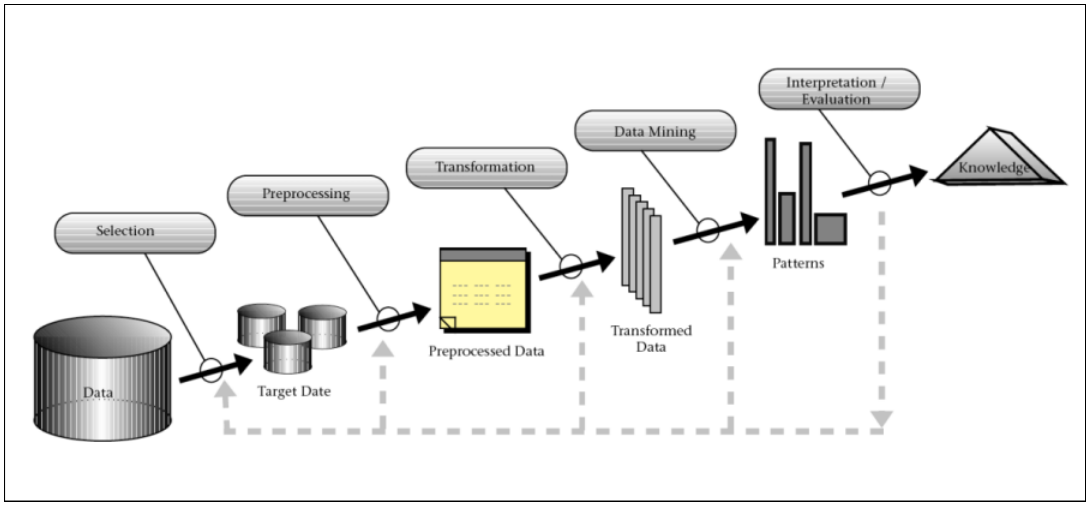



*Figure 2.2 Process of Knowledge Discovery of Databases*

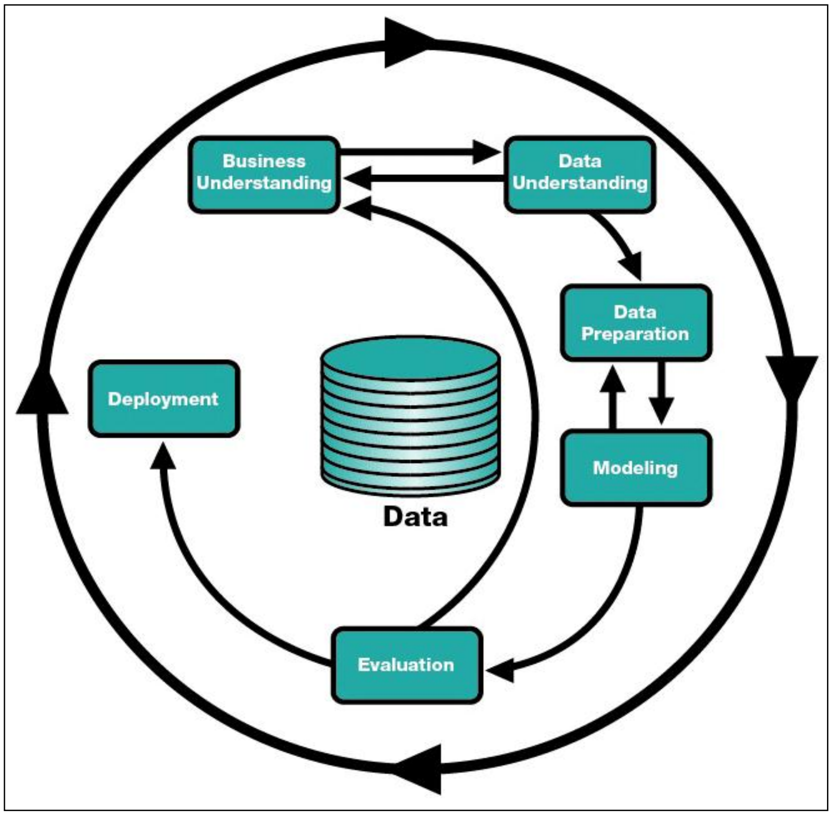



*Figure 2.3 Phases of the CRISP-DM Process*

**Business Understanding.** In this initial phase, the researcher focused on understanding the project objectives and requirements from different entities.

Understanding the specific goals and objectives of the intended outputs of the study are the key elements for the achievement of the objectives.

**Data Understanding.** In this phase, initial data collection and related activities are initiated in order to get familiarized with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses for hidden information will be done. Techniques and instruments such as observation and questionnaire are important sources of data and widely drawn on by the researcher to have a clear and better understanding of the collected data.

**Data Preparation.** The data preparation phase covers all activities to construct the final dataset that will be fed into the modeling tools from the initial raw data. The data set will be transformed into a format that is compatible for the data mining tool.

**Modeling.** The modeling phase covers selection of modeling techniques and its applications. The different classifiers will produce data model for classification. Classifiers are processed as the training set and each classifier produces a data model in which it will be used for classification.

**Evaluation.** At this stage, the model will be subjected to evaluation and testing using test sets of data. It is important to thoroughly evaluate the model and review the steps executed to construct the model to make certain that it properly achieve the objectives.

Most data mining researchers used the Cross-Industry Standard Process for Data Mining. This has been a standard methodology in data mining.

**Educational Data Mining in Educational Systems**

Educational data mining (EDM) integrates data mining and knowledge discovery methods into educational environments. EDM is “concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings which they learn in. Educational data mining is a process of converting raw data from educational systems to useful information that can be used to inform design decisions and answer research questions. In the educational field, data mining techniques can find useful patterns that can be used both by educators and learners. Not only may EDM assist educators to improve the instructional materials and to establish a decision process that will modify the learning environment or teaching approach, but it may also provide recommendations to learners to improve their learning and to create personalized learning environments.

Romero and Ventura (2007) introduced an educational data mining cycle model showing that the application of educational data mining is an iterative cycle of hypothesis formation, testing and refinement. The knowledge mined from educational data mining should be used to facilitate and enhance the whole learning process. From this cycle model, the application of educational data mining can be oriented to different actors each with their own views (Zorilla et al., 2005):

- Oriented toward learner: Purposes for EDM are to recommend to learners good learning experiences, effective learning sequences, useful resources, successful tasks carried out by other similar learners, and activities that would favor and improve their learning based on the tasks already done by other learners.

- Oriented toward educators: Purposes for EDM are to get more feedback for instructors, classify learners into groups based on their behaviors and needs, find effective learning patterns, find more effective activities, discover the most frequently made mistakes, organize the contents efficiently for instructors to adopt instructional plans, evaluate the learning process, and evaluate the structure of course contents.

Data mining techniques in educational systems are drawn from fields such as statistics, data modeling, information visualization, machine learning and psychometrics. Romero and Ventura (2008) reported the use of regression, clustering, classification, and association rule mining using models like decision trees, neural networks, and bayesian networks. Association rules were also used in educational data mining to extract associations between educational items. These rules present the results in an intuitive form to the teachers to improve teaching methods. Merceron et al. (2007) extracted association rules with data from Logic-ITA, a web-based environment, to get some results that were developed to enable student's performance improvement. Association rules require less extensive expertise in data mining than other methods.

Garcia et al. (2007) pointed out the drawbacks of association rule mining in learning management systems. They showed that the algorithms used too many parameters and too many rules were devised with lower interest and comprehensibility. Collaborative learning with online exchange of messages was also investigated by researchers. Anjewierden et al. (2008) investigated the application of data mining methods to provide learners with real-time adaptive feedback on the nature and patterns of their online communication during collaborative learning. They pointed out that the application of data mining methods to online chat is both feasible and can, over time; result in the improvement of learning environments. The data generated by e-learning system is very large in volume which makes it difficult to model user preferences and to filter the useful patterns.

Carmona et al. (2009) presented an adaptive user model in discovering student preferences. They used dynamic bayesian networks to represent student's learning style. Web mining techniques were also used by researchers to learn the performance of student. Nachimas et al. (2009) developed *learnogram*, a visualization technique to show the learning behavior. They showed results as a case study of a single student over time. Bharadwaj et al. (2010) used the decision tree method of classification for a sample of fifty (50) students to analyze their performance. Information like attendance, test results, assignment results, laboratory performance, and general proficiency were considered to construct the decision tree. The gain ratio was computed to compare the performance of the students.

Scheuer et al. (2011) extended the taxonomy of Baker and proposed six types of mining operations: supervised model induction, unsupervised model induction, parameter estimation, relationship mining, distillation of data for human judgment, and discovery with models. In supervised model induction, the prediction models are inferred based on the training instances for which the values of the target attribute are known.

Classification models predict categorical values and the regression models predict continuous values. The unsupervised model induction method infers prediction models when the values of the target attribute are unknown. Clustering is an example of this method. Barahate (2011) also proposed several more mining methods such as: outlier detection, text mining and social network analysis. Al Mazroui (2013) presented an excellent survey of data mining in e-learning where the author pointed out that data mining and learning analytics are two streams of research interest.

To summarize, data mining and its applications to the educational field has various applications and benefits. The use of data mining techniques in e-learning provides a favorable reassuring approach to explore educational data to resolve educational research issues. The applicability of data mining in e-learning is a continuous and repetitive process and it will not only help students but also instructors alike in providing a better access and ease with better student performance.

**Approaches in Detection of Learning Styles**

In a study by Kelly and Tangney (2006), they have created the EDUCE system that classifies students based on Gardner's theory of multiple intelligences (MI), using 4 types such as logical/mathematical, verbal/linguistics, visual/spatial and musical/rhythmic (Gardner, 1993). The student diagnosis is done both dynamically (by analyzing the student's interaction with MI differentiated material and using Naïve Bayes classification algorithm) and statically (by applying a Shearer's MI inventory) (Shearer, 1996)). The system presented in (Statchcopoulu, Grigoriadou, Samarakou & Mitropoulos, 2007) is based on Bigg's surface vs. deep student approach to learning and studying (Biggs, 1987). The student diagnosis is done by means of a neural network implementation for a fuzzy logic-based model. The system learns from a teacher's diagnostic knowledge, which can be available either in the form of rules or examples. The neuro-fuzzy approach successfully manages the inherent uncertainty of the diagnostic process, dealing with both structured and non-structured teacher's knowledge.

AHA, a system developed by Stash (2007) uses the notion of "instructional meta-strategies", which are applied in order to infer the learner's preferences during his/her interaction with the system. A meta-strategy can track student's learning preferences by observing their behavior in the system: repetitive patterns such as accessing particular types of information such as textual vs. visual form or navigation patterns such as breadth-first versus depth-first order of browsing through the course. These meta-strategies are defined by the authors, who can therefore choose the learning styles that are to be used. However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used,  so these strategies cannot completely replace psychological questionnaires.

The system presented by Amandi et al. (2007) is based on three dimensions of the FSLSM (active/reflective, sensing/intuitive and sequential/global). The behavior of students in an educational system (called SAVER) is observed and the recorded patterns of behavior are analyzed using Bayesian Networks. The system presented by Graf (2007) is base also on the FSLSM. The actions of the students interacting with Learning Management System are recorded then analyzed using a Bayesian Network Approach as well as a rule-based approach. Since the accuracy of the diagnosis was better in the latter case, the rule-based approach was implemented into a dedicated tool called DeLes, which can be used to identify the learning styles of students in a Learning Management System. Another system presented by Micarelli (2008) based on FSLSM learning style model uses fuzzy values to estimate the preference of the students towards one of the four categories without considering the pole for each dimensions (Sensing/Intuitive, Visual/Verbal, Active/Reflective, and Sequential/Global). The system provides a good classification accuracy of 71.21%

Sangsivit and Mugsing (2009) provide strategies in analyzing learning styles in accordance to online learners. The first phase of the research involves the collection of learning style questionnaire answered by each student based on the theory of Honey and Mumford that identifies four learning styles such as Activists, Theorist, Pragmatist and Reflector. The second phase of the research employs a Learning Management System in storing learning styles in online learning. The information gained in the second phase is obtained through the participation of the learners in each learning activity, frequency rate in joining learning activities, preference in choosing learning activities, and pos-test scores of the learners in the lesson. Results of the research found out that there is a low achievement in learners with learning style of Activist and Pragmatist style when text material is used while learners in the learning style of Reflector perform high learning achievement when video material is used. The research concluded the principles of learning styles proposed in Honey and Mumford is statistically significant with a value at 0.05.

Relevance Vector Machine (RVM) and Support Vector Machine (SVM) were the data mining techniques applied for the classification of learning styles based on learning objects (LO) by Shuib and Abdullah (2014). In the study, an RVM classifier based on a data mining approach to data was collected through questionnaire and was developed based on learning objects and learning styles. The questionnaire was constructed to provide a platform for the students to indicate their preference in the use of the learning objects. The RVM classifier was able to classify student's learning style based on the learning objects with an accuracy of 72.56%. The performance of the propose RVM classifier was found to perform better than the Support Vector Machine and Neural Network classifier.

Self-Organizing Map (SOM) was used by Alias, Ahmad and Hasan (2015) in order to cluster student's browsing behavior vs. their academic performance in a Moodle E-Learning Environment for one semester. The data sets contain the sum of the hits for each student based on the number of attributes and number of weeks. There are 126 attributes which contain 1394 datasets that was analyzed.

WEKA was used as a simulation tool that embedded data from Moodle and interpreted the result using SOM clustering. By using the attributes, visualization of the student's behavior was derived. It shows that, for the whole semester, students on a Cluster 2 actively browsed learning materials by 72% hit from 126 attribute followed by Cluster 1 (70%), Cluster 3 (64%) and lastly Cluster 0 (57%). The research also concluded that SOM is very helpful in visualizing the patterns that are hidden in the log data file and the mined knowledge is useful for prediction of future student's performance. Bousbia et al. (2013) deduced learning styles from navigational behavior and experimented with 45 graduate students at the Highter National School of Computer Science (ESI – Algiers). They worked on machines equipped with a trace collection tool with a web-based learning course. Based on their navigation traces, they have calculated five indicators to describe the learner's browsing behavior to identify two attributes of the learning process layer of FSLSM. Their values correspond to the two dimensions of the learning model, active/reflective and sequential/global and did not include the other two dimensions of the learning style model. Supervised classification methods to compare the psychological questionnaire ILS were used for the three classifiers (K-Nearest Neighbor, Decision Trees and Neural Network). Over 80% classification accuracy was observed on the two dimension of the learning model using J48 decision trees and the possibility of the application on a learning environment to deduce their learning styles using navigational information can be applied on a learning management system environment. The research suggested for future development to include the other dimensions.

On a recent study by Petchboonmee et al. (2015), learning style classification and the comparison of efficiency of David Kolb's experiential learning style model was used for the student in the Department of Computer Information System, Rajamangala University of Technology Lanna (Tak Campus) in Thailand. Data was collected by means of a rating-scale questionnaire, which was divided into two parts. The first part was about general information with several variables for data analysis such as gender, education level, and former education background, preferred learning styles, learning styles that the subjects were skilled at, and learning styles. The second part contained thirty-two (32) items of David Kolb's experiential learning style classification questionnaire. A total of 502 students answered both questionnaires for the 1st Semester of Academic Year 2013. Creation and test of the data classification model were conducted by WEKA program with the algorithms J48, NBTree and Naïve Bayes. The model was tested by means of 10 – fold cross-validation to find out the values of Correctly Classified Instances, Precision, Recall and F-measure. The results of the test were compared in terms of efficiency for each data classification technique and the overall results shows that J48 technique had the highest value of correctly classified instances at 85.65%.

**Architecture of an Adaptive Learning System with Learning Management System**

In this section the system architecture of the adaptive virtual learning environment is demonstrated and each components of the system is described. The infrastructure design of the system is composed of five (5) major central components as can be seen in Figure 2.4. The figure shows the main components and the subcomponents and a clear explanation of their features and interaction amongst them (Qazdar et. al, 2015).

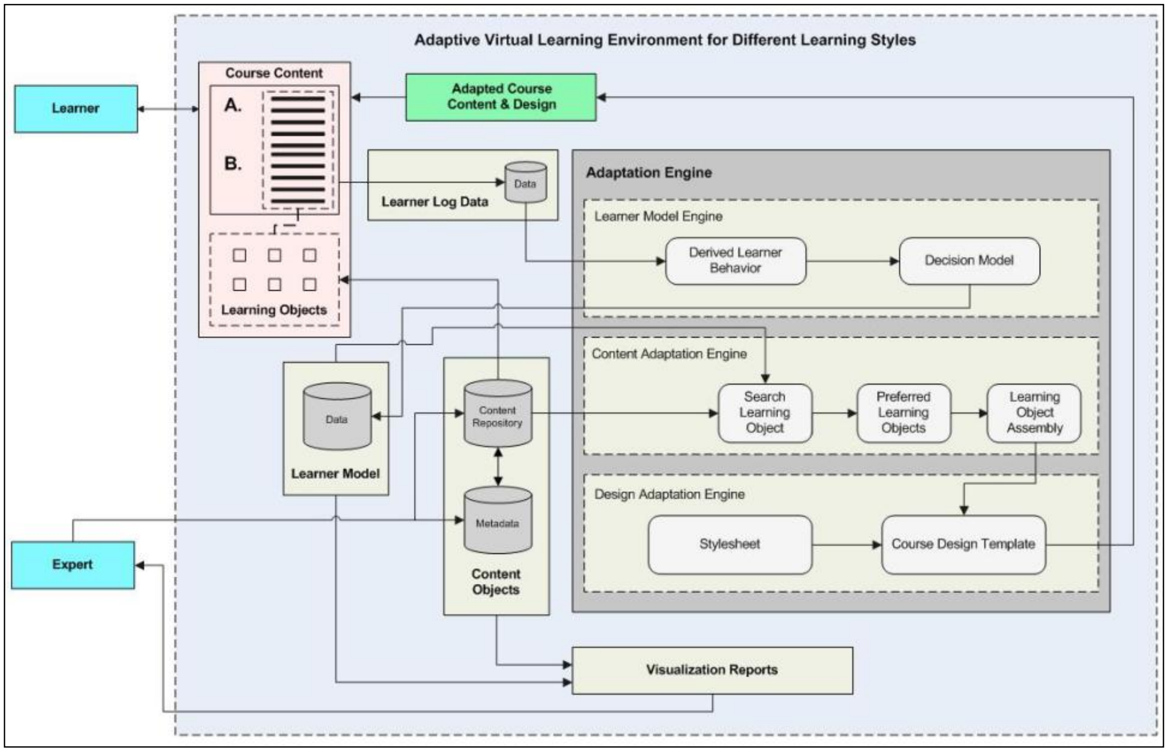



*Figure 2.4 System Architecture of an Adaptive Virtual Learning Environment (Qazdar, Cherkaoui, Er-Raha & Mammass, 2015)*

### A. The Learner Model

One of the most challenging and important questions in an adaptive virtual learning environment is how a particular system can provide a rich representation of the learner. This component provides reliable information and makes a representation of a particular learner. Information considered in this component includes their user identification, personal name and the preferred type of educational or course content. This component changes dynamically as each learner progress in their course.

**B. Content Objects/Learning Objects**

The content object module is the representation of concepts to learn, these are the available resources to the learners and how elements are structured. It is composed of two parts: content repository and metadata. The content repository contains resources that deal with domain concepts. These resources can be presented as a course overview, definition, tests, examples, simulation, forum, and varieties of learning objects. Each of these resources can be presented in various formats such as text, image, video and animation. The metadata part stores information that tags a resource that has been created as to what it truly represents such as an abstract learning material, concrete learning material, visual learning material, text-based learning material, self-assessment test, example and exercises.

**C. Learner Log Data**

The main role of the learner log data is to record all the interaction between the learner and the Virtual Learning Environment. These recorded interaction log data are crucial in classifying each learner on their preferred learning styles and all information recorded in this component will be directly fed to the learner model engine for processing.

**D. Learner Model Engine**

The primary role of this component is to process and derive relevant user behavior of the learner, to aggregate needed values to identify their preferred learning objects based from the learner log data. On this particular component, the result of their derived learning behavior works in conjunction with the decision model that are composed of rule sets to classify each learner to the four learning style dimension of the Felder-Silverman Learning Style Model. Finally, it permits to update the dynamic part of the learner model.

**E. Content Adaptation Engine**

This specific component produces individualized content based on the learner model of each learner. It allows providing similar content, additional content, and alternating or hiding contents. It allows searching learning objects from the content object's content repository based on their metadata then it filters out the preferred learning objects and matches it based from learning styles derived from learner model. Finally, the learning object assembly organizes and brings these learning objects that will be transferred later to the design adaptation engine.

**F. Design Adaptation Engine**

By combining the filtered learning object information with the style sheets for the presentation of the course design and content, the course design and content can be adapted to the specific needs of each learner. Each learning styles has its own course design template and the new adapted course design is then shown to the learner.

### G. Visualization Reports

The all-important interaction of users with the Virtual Learning Environment through its interface results in large amounts of data that can be visualized for the experts. The visualization reports generated from the system is a part of the system that can be used by the teachers or experts in order to have more in depth understanding of the learners by understanding their learning process.

### Synthesis

The review of literature establishes the foundation of the research by defining the concepts of learning styles, identification of learning style models with their underlying theories and presented studies on the relevance of learning styles in improving the learning process. In recent years, there has been a shift from a teacher-centered style of teaching, wherein the teacher was the only source of information by the students to a learner-centered approach that emphasizes each student’s interest. Each learner is particularly different for they have specific needs. Educators can bridge the gap of these needs by assessing the learning styles of their students in order to adapt their methods to best fit each learner’s learning needs. By adapting and matching their needs it allows them to learn most efficiently, effectively, easily and with most enjoyment. Voluminous studies from educational experts and researchers have considered learning styles as one of the most important aspects of the learning process and they have agreed that integrating them in educational settings has a potential to make learning easier for students.

Technological advancement has already reached the educational sphere and at heart of these phenomenal advancements are the utilizations of Virtual Learning Environments (VLEs) that hold tremendous amounts of data that can be leveraged to better understand learners' behavior by specifically identifying their behaviors and learning styles. Understanding how diverse people learn in terms of their learning style is the key to a successful teaching and learning process. Classification of learning styles gives insight to educators to provide teaching strategies and learning content that supports students in learning and it can also give insights on student's weak abilities from the learning material that does not match their preferred learning styles.

Virtual Learning Environment systems (Moodle, Blackboard, WebCT) provides a great variety of features for creating knowledge representation such as learning materials, quizzes, forums and so on. As such, they have become very successful in technology enhanced learning and are commonly used by educational institution, but their contents are static and provide no adaptation at all.

To address this issue, learning style identification must be incorporated to Virtual Learning Environments, including investigations about how to automatically classify or identify learning styles and how to provide course design and contents that fit the learning styles of the students. This study integrated the dimensions of the Felder-Silverman learning style model to automatically infer learning styles of students to all four dimensions of FSLSM using data mining techniques and developed a prototype of an Adaptive Virtual Learning Environment to cater student's different learning styles.

**Conceptual Framework**

Figure 2.5 illustrates the conceptual framework for the learning style classification and the adaptive virtual learning environment of this study. All participating students in the study answered the Index of Learning Style Questionnaires to define the class labels in terms of their learning styles. Every time a student uses a VLE, it records the student's logs and activities into its database. Primarily, a search query (SQL) was conducted to retrieve varieties of data from the VLE such as student's behavior patterns and navigation patterns. Behavior patterns and navigation patterns are based from the student's characteristics as described according to the Felder-Silverman Learning Style Model and these sets of patterns served as the student's attributes that will be used to construct the data sets. The data preprocessing phase was performed to remove all unwanted and irregular data from the VLE database. Attribute values was extracted through calculation of variable data such as number of interaction of students to a particular learning object, number of posts a student made to a forum, the number of exercise submitted attempts just to name a few.

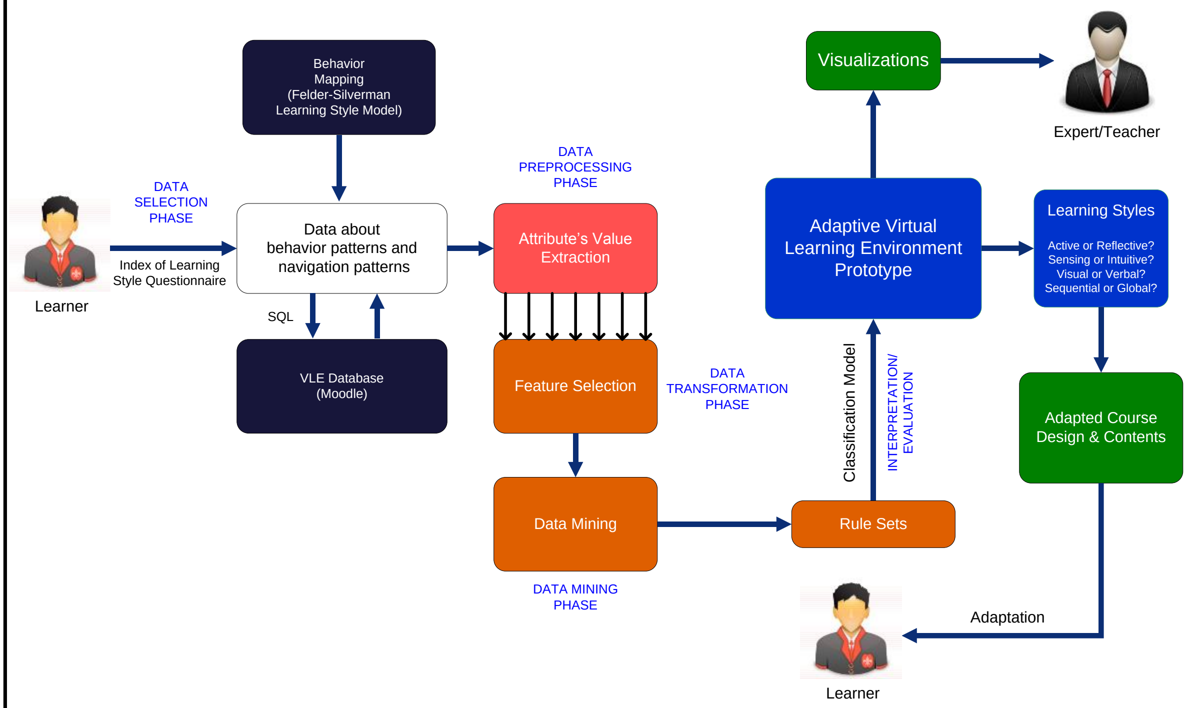



*Figure 2.5 Conceptual Framework*

These derived variables together with the results of the Index of Learning style questionnaire was transformed into fields, assigned with proper data attributes, and stored into a file. All data field was organized to form a rational data set. Feature selection technique was implemented to find the most meaningful attributes for processing and analysis. This phase is critical for it extracts useful information and features from the existing data.

The data mining phase included artificial intelligence analysis for predictive or classification purposes. Different classification algorithm technique was applied to find the most accurate model to build a predictive or classification model of the student's learning styles in Virtual Learning Environment. An open source data mining software package such as WEKA, was used to perform data analysis on the derived datasets to uncover the most accurate classification model that was used on the software prototype. Moreover, the most accurate classification model was utilized on the software prototype to provide adaptation to the course design and contents of student course by serving their preferred learning objects based from the results of their classified learning styles. Visualization features was also incorporated to the prototype for the experts or teachers for in depth understanding of the student's learning styles. This feature was a valuable software feature for the experts or teachers in order to easily visualized learner's behavior and navigational patterns through the usage of varieties of charts and graphs.

# Chapter 3

# RESEARCH METHODOLOGY

This chapter describes the research approach and methodology of the study. Specifically it presents the design of the study, method and techniques, the respondents of the study, the instrument of the study, the developmental model, data processing and statistical treatment that was applied in the study.

## Design of the Study

This section provides information about the design of the study. Although VLE (eg. Moodle, BlackBoard) provides already quite comprehensive tracking mechanisms, some features are still necessary in order to track all information that the researcher aimed at while investigating the study. For investigating the behavior of the student's behavior with respect to their learning styles, the ILS questionnaire (Felder & Soloman, 1997) was used. The ILS questionnaire will be introduced in more detail in the subsequent section.

## Learning Object Types

In most Virtual Learning Environment, learning objects can be created but for the study, the learning object has to be distinguished with respect to its characteristics and an additional description of the learning object is quite necessary. In most cases, this differentiation and additional descriptions are not supported by most Virtual Learning Environments. To address this issue, it must provide the possibility for teachers and course developers to specify information about the created learning material by use of additional description. As an example, teachers and course developers are provided with the opportunity to specify whether the material is a concrete material, abstract material or visual material. Furthermore, quizzes are made in general without additional descriptions as to what it truly represents, such as a self-assessment test or exercises. Self-assessment tests focus on theoretical issues and can be used to check whether a learner understand the learning material. While the purpose of these two types of test is different, their structure is quite similar. Therefore, it is a necessity to distinguish between these types by the use of some additional descriptions. These features are useful in order to effectively track student's behavior in a Virtual Learning Environment.

**Description of the Course**

The study is based on data from a Moodle course of Computer Programming 1 which is taught for the freshmen students for Computer Technology courses in Southern Luzon State University. The Moodle course is composed of five (5) sections that include seventy nine (79) learning objects. There are different exercises that allow students to practice their programming skills. Self-assessment tests were also provided for each chapter overall. Students also were encouraged to use the forums in order to interact and solve problems with other students during the course. This particular course was selected for the investigation of individual learning styles because it is found to have large number of enrolled students in the Moodle Course and the structure of the course is most appropriate for the selected learning style model.

**Index of Learning Styles Questionnaire**

The Index of Learning Style (ILS) questionnaire (See Appendix A) is developed for identifying learning styles based on FSLSM and consists of 44 questions (Felder & Soloman, 1997). As mentioned in the literature, according to FSLSM each learning styles are expressed by values between +11 to -11 per dimension, with steps of +/-2. This range comes from the 11 questions that are presented for each dimension. When answering a question, for instance, with an active preference, +1 is added to the value of the active/reflective dimension, whereas an answer for a reflective preference decreases the value by 1. Therefore, each question is answered either with a value of +1 (answer a) or -1 (answer b). Answer 'a' corresponds to the preference for the first pole of each dimension (active, sensing, visual or sequential) and answer 'b' to the second pole of each dimension (reflective, intuitive, verbal, or global).

The ILS questionnaire is an often used and well-investigated instrument to identify learning styles. Felder and Spurlin (2005) provided an overview of studies dealing with analyzing the response data of the ILS questionnaire regarding the distribution of preferences for each dimension as well as with verifying the reliability and validity of the instrument. Various studies (Van Zwanenberg, Wilkinson & Anderson, 2000; Viola et al., 2007) have proven that the questionnaires' validity and reliability to infer learning styles are accurate. Furthermore, Felder and Spurlin concluded that the ILS questionnaire is a very reliable and valid instrument suitable for identifying learning styles according to FSLSM.

**Methods and Techniques Used**

The study utilized data mining techniques in order to classify learning styles on Virtual Learning Environment using different classification methods to empirically compare the accuracy and find the best data model for the classification results on learning styles identification. The data-driven approach uses sample data in order to build a model for classifying learning styles from the relevant behavior of the learners. This approach aims at building a model that imitates or mimics the ILS questionnaire. The advantage of using a data-driven approach is that the model has the possibility to be very accurate due to the use of real data. A representative set of data is used to build a model that can be used on one hand to identify learning styles from data of the same course.

**Data Collection Method**

The study used the acquisition of data coming from the Virtual Learning Environment database. Specifically, the data from student's logs and activities on the Virtual Learning Environment was carefully examined. The student's learning styles was obtained by using the Index of Learning Styles (ILS) questionnaires that was answered by the students who are enrolled and completed the target course. Also, an evaluation instrument was formulated in order to evaluate the developed prototype of an adaptive Virtual Learning Environment based on quality characteristics of the ISO 20150 software quality model consisting of criteria which include functionality, reliability and usability.

**Population and Sample of the Study**

The subject of the study were consists of 507 Computer Technology students who successfully completed the Computer Programming 1 course during the academic year 2012 to 2015. These set of students were also enrolled with the corresponding Moodle Course during those periods.

**Development Methodology**

The researcher utilized the steps of Knowledge Discovery in Databases and CRISP-DM methodologies for this study. The life cycle of a data mining project as defined by CRISP-DM consists of six phases and the knowledge discovery in database consists of nine steps.

**CRISP-DM**

**A. Knowledge in the Domain**

This step involves understanding and defining goal of the end users, where knowledge discovery process took place and other relevant prior knowledge. The researcher focused on the educational domain specifically on learning style identification. The study determined the characteristics of student's learning styles and the applicability of classification algorithms in learning style classification.

**B. Selection and Addition**

This step involves the selection of the needed attributes to be performed based on goals. This phase identified the data that were needed and its availability. For each student, behavior activities were collected and categorized based on the attributes which represent the student's characteristics based on Felder-Silverman Learning Style Model.

**C. Preprocessing and Cleansing**

Data reliability was enhanced at this stage. It included data cleansing by removing unwanted attributes, handling missing values, and removal of outliers or inconsistent data. The researcher specifically used aggregate functions in SQL (Structured Query Language) commands as the data processing technique to query relevant and extract data values from the Virtual Learning Environment database.

**D. Data Transformation**

In this stage, the generation of better data for the data mining was prepared and developed. The data were transformed into a proper format using data preprocessing technique of a data mining tool. The generated comma separated values (CSV) were converted into an Attribute Relation Format (ARFF) file which can be recognized by the Waikato Knowledge Analytics (WEKA) to generate data model for classification.

**E. Data Mining Phase**

**1. Business Understanding**

There is a two-step process of data classification. The training sets of data were determined by analyzing a set of training databases instance until a data model was built that describes a predetermined set of class labels. Furthermore, the generated models are applied to test data in order to determine the classification rate of the model.

### 2. Data Understanding

Considering pertaining relevant behavior for the identification process of learning styles is an important issue. The selection of incorporated features and patterns of behavior is based on two parameters: Primarily, the patterns of behavior need to be relevant for classifying and detecting learning styles based on selected learning style model and that VLE can gather information about the behavioral patterns must be as high as possible. In order to determine the requirements, behaviors and patterns were derived based from characteristics of learners according to the Felder-Silverman Learning Style Model (Felder & Silverman, 1998).

For each of the four learning style dimensions of FSLSM, relevant behavior patterns were selected, which were based on commonly used types of learning objects in learning systems. These patterns mainly consider how often a student visits particular types of learning objects, how often they are viewing or posting in a forum, how often they perform self-assessment test, how often they reviewed their answers when the exercise are graded and their navigational patterns. The next section describes the selection of behaviors

#### 2.1 Relevant Behaviors for Processing Dimension (Active/Reflective)

Active learners are characterized as learners who prefer to process information by doing something with the learned material, the most notable pattern of behavior of an active learner is that they have the strong tendency to discussed and interact with other learners. On the other hand, reflective learners prefer to think about the learning and work alone. With regards to discussing and explaining, communication learning object such as a forum can give indications about the student's preferences for active or reflective learning. While active learners are expected to post more often in a forum, reflective learner's tendencies are supposed to prefer to participate passively by visiting a forum but rarely posting by themselves. Therefore, the number of views and the number of postings can be used as patterns for classifying active and reflective learning style.

Another pattern of substance according to the FSLSM with regards to active learners is that they tend to attempt more self-assessment tests. A self-assessment test in general is a type of exam where the result is not graded but it is also important in order for the learner to assess their knowledge on a particular topic. Since reflective learners like to think about the material and reflect about it, they are expected to visit more learning objects of a textual-based context and reflect about it.

### 2.2 Relevant Behaviors for Perception Dimension (Sensing/Intuitive)

Sensing learners tends to repeatedly visit concrete learning materials that contains facts, data and when a learning object is being linked to real life context, whereas intuitive learners prefer to view or visit abstract learning material that contains theories and their underlying meanings, histories, glossaries, syntax, and concepts. Therefore, the number of visits on these kinds of learning objects serves as a pattern. On the other hand, intuitive learners supposed tendencies are to highly visit learning objects such as an example as a supplementary material. Therefore, the number of visits on these kinds of learning object tends to be higher for an intuitive learner. Another characteristic of intuitive learner is that they work carefully and slowly. With respect to the preference for working carefully, intuitive learners tend to be careful and tend to review their answers more when performing a test especially when it is being graded. The pattern can be conceived by the number of attempted answer reviews they made in an exercise before attempting to submit their answers.

**2.3 Relevant Behaviors for Input Dimension (Visual/Verbal)**

Accordingly, verbal learners preference on a learning object is composed mostly of words or texts, they tend to like communication with others and discussions. Therefore, verbal learner's tendencies are to use the forum, thus a high number of forum postings can indicate a verbal learning style. On the opposite end, visual learners learn best from what they actually see. Therefore, they tend to view more learning objects that usually contains graphics such as diagrams, charts, and pictures. Video presentations also are highly preferred by visual learners while verbal learners are expected to visit a learning object of textual-based types.

**2.4 Relevant Behaviors for Understanding Dimension (Sequential/Global)**

Sequential learners are more comfortable with details, whereas global learners tend to be good in seeing the overall picture and connections to other fields. Because of this kind of behavior, global learners are interested in getting the “big picture” and an overview. Course outlines are especially important to them whereas sequential learners tend to skip these kinds of learning objects. A high number of visits spent on chapter outlines, course overview or chapter overview page indicate a global learning style. The navigational patterns of learners when using a VLE can be used to differentiate sequential or global learning style as well. While sequential learners tend to go through the course step by step in a linear way, global learners tend to learn in large gaps by skipping learning objects and jumping to more complex and advanced learning objects. Therefore, the navigational patterns can be seen as an indicator to differentiate the two styles.

### 2.5 Navigational Pattern Sequence Data Collection

Navigational patterns refers to how learners navigate through the course and in which order they visit certain types of learning objects. In a study by Imra et al. (2016) on personalized learning recommendation system, they have proposed identification of navigational sequence pattern using Euclidean distance to compute the similarity and difference between learners based on their navigational characteristics. The formula to calculate the Euclidean distance between navigational sequences is shown in Equation 1.

**Equation 1.** Euclidean Distance, n-dimensional space

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_i - q_i)^2 + \cdots + (p_n - q_n)^2}.$$

With this equation, we can infer the navigational patterns of students in a Virtual Learning Environment by analyzing and computing their navigation sequence distance values. In a similar research by Benlarmi (2003) on dynamic learning modeler, they have used approximately thirty (30) navigational sequences to cluster similarities between students navigational behavior in a hypermedia courseware. In accordance to previous studies the navigational distance values in order to distinguish a user that are navigating sequentially or navigating globally can be tracked when accessing the course.

**3. Data Processing and Transformation**

The raw data extracted from the Virtual Learning Environment's database were cleaned by extracting only the significant fields using SQL scripts to avoid nulls and missing values. The extracted data were transformed in an MS Excel file and then saved to a format that was recognized by a data mining tool. These files will be prepared in order to be compatible with the SPSS and WEKA tools in building the model.

**4. Pattern Discovery**

In this phase, different mining classification techniques were tested in order to infer the students learning style. The datasets are analyzed into a data mining tool such as WEKA that implements different classification algorithms. This study compared accuracy of several classification algorithms using the detailed classification table results. The result for each data mining model will be evaluated in order to determine the best data model that will be incorporated in the prototype of adaptive Virtual Learning Environment for different learning styles.

**5. Evaluation**

The model evaluation is an integral part of the model development process. It aids in finding the best model that represent the data and how well the chosen model will work in the future. The common way to evaluate a particular model is to verify their performances on the test datasets. Evaluation of the model can be identified by empirically obtaining the number of correct predictions to the total number of predictions. Comparison techniques of the derived model will illustrate its accuracy and it is an iterative process in which all competing models are evaluated based on accuracy. If accuracy of the model is too low, the model is considered under fit and when the accuracy is too high the model is considered to be over fit (Nisbet, Elder & Miner, 2009).

The quality of classification was evaluated using the Receiver Operating Characteristic (ROC) and Area under the Curve (AUC) plots to measure the accuracy and quality of the model. The ROC plot is similar to the gain or lift charts in that they provide a means of comparison between the qualities of classifications of different models. As can be seen in Figure 3.1, the ROC plot shows false positive rate (1-specifity) on X-axis, the probability of target =1 when its true value is 0, against true positive rate (sensitivity) on Y-axis, the probability of target =1 when its true value is 1. Ideally, the curve will climb quickly toward the top-left portion of the plot; meaning a higher quality of classification of predicted cases. The diagonal line is for a random model and the closer the curve comes to the 45-degree diagonal of the ROC space, the lower the accuracy of classification of the model. Area under the ROC curve is often used as a measure of quality of the classification methods.

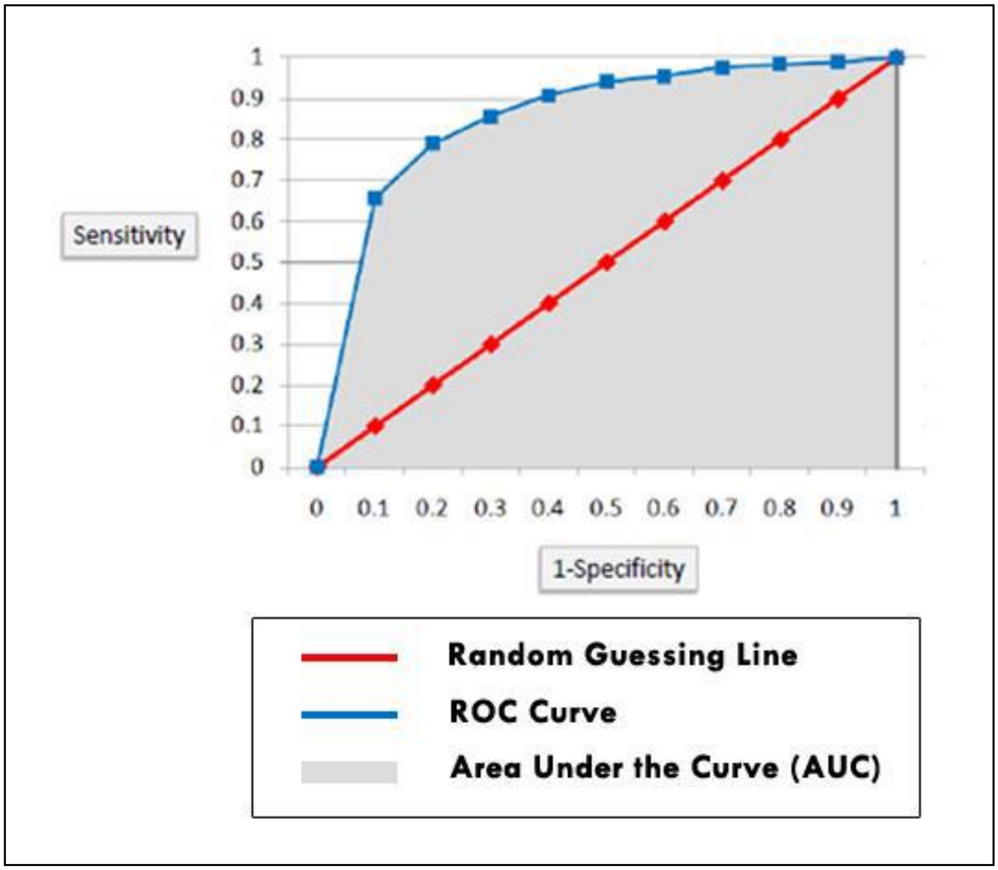



*Figure 3.1 Receiver operating characteristic and area under the curve plot*

A random classifier has an area under the curve of 0.5, while AUC for a perfect classifier is equal to 1. In practice, most of the accurate classification models have an AUC between 0.5 and 1. A rough guide for classifying the quality of classification of the area under the curve is based on the traditional academic point system as shown in Table 3.1. (Mehdi et al, 2011).

**Table 3.1** Traditional Academic Point System

| Range | Description |
|---|---|
| .90 -1.00 | Excellent (A) |
| .80 - .90 | Good (B) |
| .70 - .80 | Fair (C) |
| .60 - .70 | Poor (D) |
| .50 - .60 | Fail (F) |

Another evaluation measure of classification accuracy in data mining is the Cohen's Kappa Equivalent. It is a coefficient which measures the inter-rater agreement for qualitative categorical items. This measurement was applied to also measure the classification accuracy when performing classification in data mining. Kappa statistics was used to assess the accuracy of any particular measuring cases. Cohen's kappa Equivalent values are shown in Table 3.2.

**Table 3.2** Cohen's Kappa Equivalent Values

| Kappa Score | Equivalent |
|---|---|
| 0.81 - 1.00 | Perfect |
| 0.61 - 0.80 | Substantial |
| 0.41 - 0.60 | Moderate |
| 0.21 - 0.40 | Fair |
| 0.01 - 0.20 | Slight |
| <= 0 | None |

**Software Methodology**

The Scrum approach has been developed for managing the software development process. It is an empirical approach applying the ideas of process control theory to software methodology resulting in an approach that reintroduces the ideas of flexibility, adaptability and productivity. The main idea of Scrum is that systems development involves several environmental variables (eg. Requirements, time frame, resources, and technology) that is likely to change during the process. This makes the development process to require flexibility of the systems development process for it to be able to respond to the changes. Most Virtual Learning Environment Systems that have been developed utilize the Scrum software methodology (Schwaber & Beedle, 2002). Scrum process includes three phases: pre-game, development and post-game.

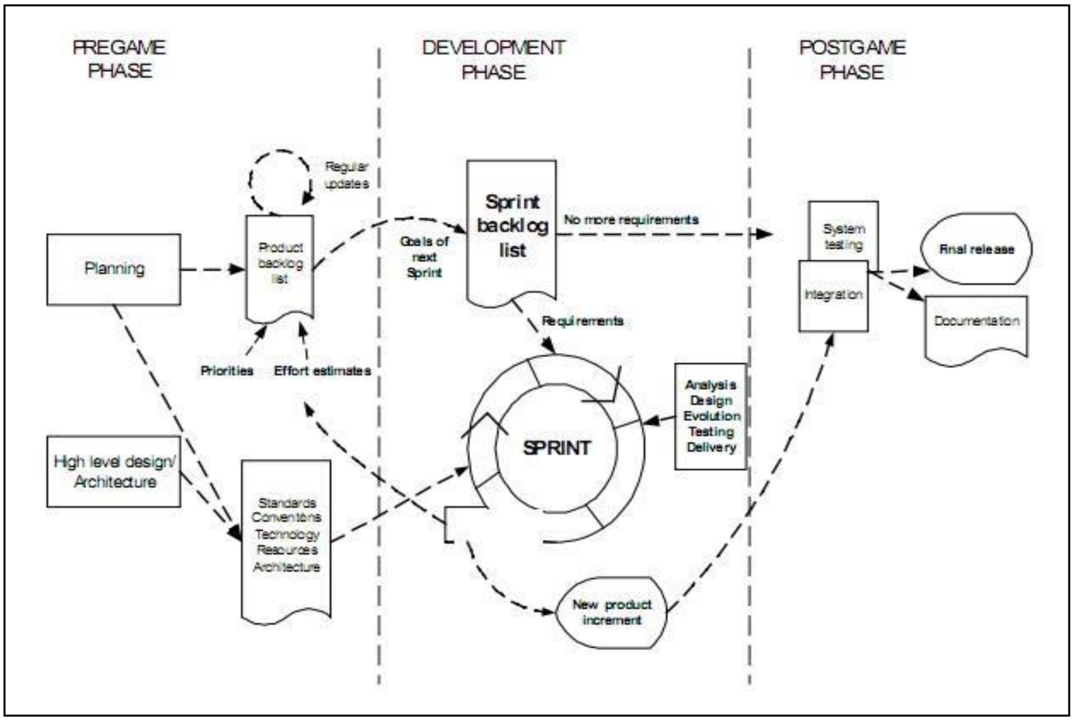



*Figure 3.2 Scrum Process*

The pre-game phase includes two sub-phases: Planning and Architecture/High Level Design (Figure 3.2). Planning includes the definition of the system being developed. A Product Backlog list will be created containing all the requirements that are currently known. The requirements are prioritized and the effort needed for their implementation is estimated. Planning also includes the definition of the project, tools and other resources. In every iteration the updated product backlog is reviewed to gain commitment for the next iteration.

In the architecture phase, the high level design of the software including the architecture will be planned based on the current items in the Product backlog. In case of an enhancement to existing software, the changes needed for implementing the backlog items are identified along with the problems that it may cause. A design review for the implementation and decisions are made on the basis of this review. In addition, preliminary plans for the contents of releases are prepared. The development phase (also known as the game phase) is the agile part of the Scrum approach. This phase is treated as a “black box” where the unpredictable is expected. The different environmental and technical variables (such as time frame, quality, requirements, resources, implementation technologies, tools, and even development methods) identified in Scrum. In the development phase, the software is developed in Sprints. Sprints are iterative cycles where the functionality is developed or enhanced to produce new increments. Each Sprint includes the traditional phases of software development: requirements, analysis, design, evolution and delivery phases. The architecture and the design of the system evolve during the Sprint development.

The post-game phase contains the closure of the release. This phase is entered when an agreement has been made that the environmental variables such as the requirements are completed. In this case, no more items and issues can be found nor can any new ones be invented. The system is now ready for the release and the preparation for this is done during the post-game phase, including the tasks such as the integration, system testing and documentation.

**Software Evaluation Instrument**

A software evaluation instrument was formulated to evaluate the prototype. The instrument for evaluation was based on quality characteristics of the ISO/IEC 20510 software quality model consisting of criteria which include functional suitability, performance efficiency, compatibility, usability, reliability, security, maintainability and portability. External quality was used to measure the characteristics of the prototype. Due to the complexity of measurements for some criteria, the evaluation focused only on functionality, reliability and usability of the prototype (Azuma, 2004). The functionality requirements provide decision criteria that contribute in deciding the priority of each function when the software product is used under specific condition. It focused on accuracy and interoperability. The reliability requirements focused on recoverability and fault tolerance. Finally, the usability requirements focused on operability and learnability of the product (Kim, 2014).

According to Chua and Dyson (2004), the first three characteristics (Functionality, Reliability, and Usability) can be easily assessed, while the remaining characteristics are difficult to measure unless done by highly trained IT professionals (Valenti et. al, 2002). Thus the study focused only on the software evaluation using the first three characteristics. Based on the criteria (Functionality, Reliability and Usability), a software quality questionnaire was created using questions from existing questionnaires. The questionnaire's composition consists of 15 questions as shown in Table 3.3.

**Table 3.3** Composition of the Software Quality Questionnaire

| Instrument | Reference | Criteria | No. of Adopted Items |
|---|---|---|---|
| IBM Computer Usability Satisfaction Questionnaires | Lewis (1995) | Functionality | 5 |
| | Lewis (1995) | Usability | 5 |
| | Lewis (1995) | Reliability | 3 |
| DEC System Reliability Scale | Tullis (2004) | Reliability | 2 |

The evaluation was quantified using a five-point Likert Scale as shown in Table 3.4. The score in the scales used the average weights assigned to the particular response made by the respondents. To interpret the rating of the experts on the scale, the following intervals and other corresponding descriptions for the software prototype acceptability were used.

**Table 3.4** Software Evaluation Five-Point Likert Scale

| Range | Interpretation |
|---|---|
| 4.51 – 5.00 | Highly Acceptable |
| 3.51 – 4.50 | Acceptable |
| 2.51 – 3.50 | Uncertain |
| 1.51 – 2.50 | Unacceptable |
| 1.00 – 1.50 | Highly Unacceptable |

# Chapter 4

# RESULTS AND DISCUSSIONS

The aim of this chapter is to present the classification results of student's learning styles based on the features and values that are extracted from their Virtual Learning Environment log and interaction data, as well as the prototype software implementation of Adaptive Virtual Learning Environment for Different Learning styles. To review, the following research questions that this chapter aims to address are the following:

1. How learning styles are classified using learner's behavior in Virtual Learning Environment?
2. How Virtual Learning Environment adapt to the different learning styles of the learners?
3. How classifications of learning styles affect the course design and contents of a Virtual Learning Environment?

## Results and Analysis

Answering the research questions entails addressing three aspects: (1) Selection of the appropriate learning style model for classifying learner's learning styles in a Virtual Learning Environment, (2) Identification of relevant behavior patterns and navigational patterns of the learners in a Virtual Learning based from the selected Learning Style Model, and (3) Mapping of relevant behaviors of the learners in a Virtual Learning Environment to their corresponding learning styles.

**Learning Style Model Selection**

In order to classify learning styles of student's behavior in a Virtual Learning Environment, it is significant to select the appropriate learning style model that best fit in analyzing student's behavior in a Virtual Learning Environment. There are multitude of different learning style models including Kolb, Honey and Mumford, and Felder and Silverman. Each one of them proposes different descriptions and classifications of learning styles. In this study, the learning style model selected is the Felder-Silverman learning style model (FSLSM). The reason for selecting the particular learning style model is that various learning style models classify learners into a few groups, whereas Felder and Silverman describes the learning style of a learner in more detail, more distinguished between preferences on its four dimensions. Another critical factor in selecting the learning style model for this study is that the Felder and Silverman Learning Style model is highly based on tendencies, indicating that learners has a high preference for certain behaviors. Furthermore, FSLSM is used most of the time in research related to learning styles in advanced technologies such as a Virtual Learning Environment.

Based from the related literature and various studies, the Felder Model is the most appropriate for e-learning courseware. These are confirmed by conducting a comparison of learning style models with respect to the application to E-Learning and Web-based learning systems and results suggested FSLSM as the most appropriate learning style model. Moreover, a study by Litzinger et al. (2007) to assess the reliability, factor structure, and construct validity of the

FSLSM through its Index of Learning Style (ILS) questionnaire revealed and proved that it has internal consistency reliability ranging from 0.55 to 0.77 across the four learning style scales of the ILS questionnaire which proves of its high reliability.

**Context, Participants and Learning Style Questionnaire**

The study is based on data sets from Computer Programming 1 Course which is taught to freshmen students for Computer Technology course in Southern Luzon State University. Aside from traditional classroom setup, the course is supplemented by a Moodle course set-up to be accessed in the intranet of the campus that is composed of five chapters and includes varieties of learning objects ranging from textual, visual, video, concrete and abstract learning materials. There are also different exercises that allow students to assess their programming knowledge and understanding. Self-Assessments tests were also provided for each chapter overall. Students were also encouraged to use the forums in order to interact and solve problems with other students during the duration of the course. This particular course was selected for the investigation of individual learning styles for it is found to have a large number of enrolled students in the Moodle course.

This particular study used the acquisition of data coming from the VLE database. Specifically, the data from student's logs and activities on the VLE were carefully examined. The student's learning styles that are used in the data sets are obtained by using the Index of Learning Styles (ILS) questionnaires (See Appendix A) that are provided in the Felder-Silverman Learning Style Model.

These learning style questionnaires were answered by the students who are previously enrolled and completed the selected course.

A total of five hundred forty seven (547) students who are registered and completed the Computer Programming 1 course were traced to be able to answer the ILS questionnaires. However, only five hundred and seven (507) students were able to fill the ILS questionnaire to determine their learning styles. Each question in the questionnaire was carefully explained to the students and they have been given ample amount of time to answer the questionnaire to avoid contaminating the data. Table 4.1 shows the learning styles' distribution for all dimensions of the FSLSM without considering the degree of style preference.

**Table 4.1** Distribution of the learning styles of the students based from ILS questionnaires

| Dimension | Processing | | Perception | | Input | | Understanding | |
|---|---|---|---|---|---|---|---|---|
| Learning Style | Active | Reflective | Sensing | Intuitive | Visual | Verbal | Sequential | Global |
| No. of Students | 244 | 263 | 348 | 159 | 388 | 119 | 250 | 257 |
| Total | 507 | | 507 | | 507 | | 507 | |

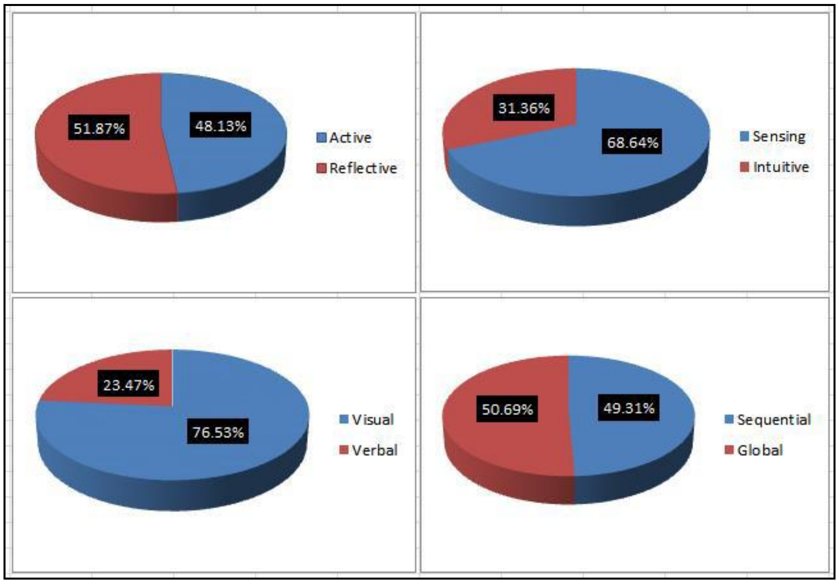



*Figure 4.1 Distribution of learning styles of students for each dimension of FSLSM*

Figure 4.1 shows the distribution of students' reported learning styles in percentages for each dimension of FSLSM. From the analysis of the Index of Learning Style (ILS) questionnaire collected from five hundred seven (507) students, it reveals that at the processing dimension of FSLSM there are 263 (51.87%) students that have a reflective learning style while 244 (48.13%) students have an active learning style. This manifests that students learning styles in the processing dimension is fairly balanced. The perception dimension reveals that 348 (68.64%) students have a sensing learning style. This means that most students prefers learning objects that are based from real facts and data, and a learning object that is linked to real life situations. At the input dimension, the data collected also reveals that 388 (76.53%) of students prefers learning objects that mostly contains graphics such as pictures, charts, diagrams and video presentation materials. Finally, the data reveals that students' learning style in the understanding dimension is fairly balanced with 257 (50.69%) students with global and 250 (49.31%) students with sequential learning styles.

**Mapping of Learning Styles and Learner's Behavior in Virtual Learning Environment**

In this section, a mapping between learning styles and learner's behavior are presented through their relevant interaction logs in the Virtual Learning Environment. The goal of this section is to define the features that can be extracted from the Virtual Learning Environment logs which correspond to the learning style behavior of the learners. Table 4.2 provides the list of the learning style mapping of relevant learner's behavior on a Virtual Learning Environment.

The features were mapped according to the relevant behaviors and navigational patterns of the students based from the Felder-Silverman Learning Style Model in Chapter 3 (p. 63). These sets of relevant behaviors were extracted from the VLE database to construct the data sets.

**Table 4.2** Learning Style Mapping of Relevant Behaviors of Learners Based from FSLSM

| Learning Style | Relevant Behavior | Attribute Name | Attribute Value |
|---|---|---|---|
| Active | Post more often in discussion forum | forum_posts | no. of posting in forum |
| | Perform more self-assessment tests | self_assessment | no. of completed assessment tests |
| Reflective | Passively participates in forum and frequently reading post but rarely posting by themselves | forum_view | no. of viewed posts in forum |
| | Prefers learning material presented in texts or audio | text_materials | no. of visits |
| Sensing | Pefers learning material with facts, data, metaphors, analogy (concrete materials) | concrete_materials | no. of visits |
| | Prefers examples | examples | no. of visits |
| Intuitive | Prefers learning material with definitions, theories, syntax, abstract concepts, flowcharts (abstract materials) | abstract_materials | no. of visits |
| | Prefers to review answers in graded exercise tests | exercises_rev | no. of attempted answer reviews |
| Visual | Prefers learning materials supplemented with pictures, diagrams, graphs | visual_materials | no. of visits |
| | Prefers learning materials presented in a video presentation | video_materials | no. of visits |
| Verbal | Prefers learning material presented in texts and audio | text_materials | no. of visits |
| | Post more often in discussion forum | forum_post | no. of posting in discussion |
| Sequential | Prefers to go through the course step by step (linear way) | nav_pattern_distance | sequence of navigational patttern |
| Global | Prefers overviews, outlines | course_overviews | no. of visits |
| | Prefers to learn in large leaps by skipping learning material & jumping to more complex materials (non-linear way) | nav_pattern_distance | sequence of navigational patttern |

**Data Preprocessing, Transformation and Attribute Value Extraction**

Every logs and activities of all students are recorded in the Virtual Learning Environment database. Primarily, VLE such as Moodle provides a module for extraction of user logs and activities for a specific course by exporting to varieties of file formats such as Comma separated values (*.csv), Microsoft Excel (*.xlsx), HTML Table, JavaScript Object Notation (*.json) and OpenDocument (*.ods). The table is comprised of data labels such as ‘Time’, ‘User Full Name’, ‘Affected User’, ‘Event Context’, ‘Component’, ‘Event Name’, ‘Description’, ‘Origin’ and ‘IP Address’.

| User full name | Affected user | Event context | Component | Event name | Description |
|---|---|---|---|---|---|
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Discussion viewed | The user with id '2235' has viewed the discussi |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Post created | The user with id '2235' has created the post wit |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Some content has been posted. | The user with id '2235' has posted content in th |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Discussion viewed | The user with id '2235' has viewed the discussi |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Course module viewed | The user with id '2235' viewed the 'forum' activit |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Discussion created | The user with id '2235' has created the discuss |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Some content has been posted. | The user with id '2235' has posted content in th |
| Chantrea Feliche Acero | - | Forum: COPRO1 2015 Forum | Forum | Course module viewed | The user with id '2235' viewed the 'forum' activit |
| Chantrea Feliche Acero | - | Course: Computer Programming 1 | System | Course viewed | The user with id '2235' viewed the course with i |
| Moodle Admin | - | Course: Computer Programming 1 | System | Course viewed | The user with id '2' viewed the course with id '2' |
| Chantrea Feliche Acero | - | Other | Forum | Discussion viewed | The user with id '2235' has viewed the discussi |
| Chantrea Feliche Acero | - | Other | Forum | Discussion viewed | The user with id '2235' has viewed the discussi |
| Chantrea Feliche Acero | - | Other | Forum | Course module viewed | The user with id '2235' viewed the 'forum' activit |
| Chantrea Feliche Acero | - | Course: Computer Programming 1 | System | Course viewed | The user with id '2235' viewed the course with i |
| Moodle Admin | - | Other | Forum | Discussion viewed | The user with id '2' has viewed the discussion v |
| Moodle Admin | - | Other | Forum | Course module viewed | The user with id '2' viewed the 'forum' activity wi |
| Moodle Admin | - | Other | Forum | Discussion deleted | The user with id '2' has deleted the discussion |
| Moodle Admin | - | Other | Forum | Post deleted | The user with id '2' has deleted the post with id |
| Moodle Admin | - | Other | Forum | Discussion viewed | The user with id '2' has viewed the discussion v |
| Moodle Admin | - | Other | Forum | Course module viewed | The user with id '2' viewed the 'forum' activity wi |
| Moodle Admin | - | Other | Forum | Discussion created | The user with id '2' has created the discussion |
| Moodle Admin | - | Other | Forum | Some content has been posted. | The user with id '2' has posted content in the fo |
| Moodle Admin | - | Other | Forum | Course module viewed | The user with id '2' viewed the 'forum' activity wi |
| Moodle Admin | - | Other | Forum | Course module viewed | The user with id '2' viewed the 'forum' activity wi |

g Files / Types / Reduced Log Files (Orig) / Reduced Log Files (Copy) / Navigation Sequence / Euclidean D Calculation

*Figure 4.2 Raw log data of Computer Programming 1 (Moodle) course*

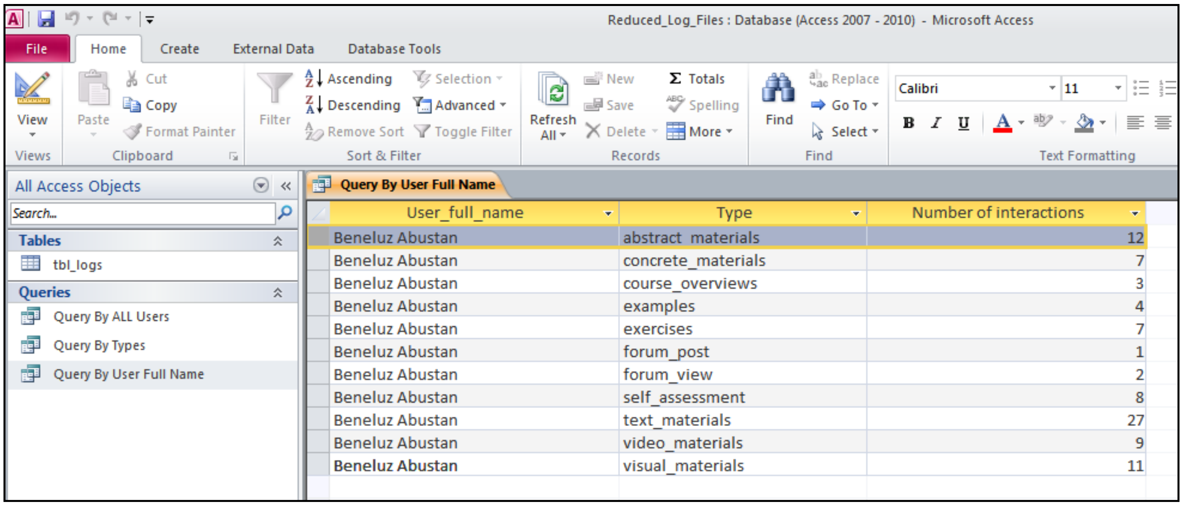
Figure 4.2 shows the raw log files of the students for the selected course. The data preprocessing phase was performed by reducing the log file which was cleaned by removing all unnecessary data such as ‘Time’, ‘Affected User’, ‘Component’, ‘Origin’ and ‘IP address’. Interaction logs of each target students were extracted to produce a reduced log file that only contains the data labels of ‘User Full Name’, ‘Event Context’, ‘Event Name’ and ‘Type’.

Figure 4.3 depicts an excerpt of a reduced log file that contains 52,815 rows of extracted student logs and activities for the course that were used in classification of individual learning styles in the study. As can be seen also in the figure, a 'Learning Object Type' field has been created in order to identify as to what type of learning object each particular student interacts with. Identification of learning object type in the course was also mapped in order to identify as to what kind of learning object each truly represents based on learning object literature types whether textual learning materials, visual learning materials, abstract learning materials, concrete learning materials and examples. It is a necessity to distinguish these learning object types in order to effectively create data sets in inferring student's learning styles. Full results of learning object type identification by education field experts can be seen in Appendix B.

| User full name | Event context | Event name | Learning Object Type |
|---|---|---|---|
| Beneluz Abustan | Page: Chapter 1 Overview | Course module viewed | course_overviews |
| Beneluz Abustan | Page: C++ Terminology | Course module viewed | abstract_materials |
| Beneluz Abustan | Page: Assignment Statements | Course module viewed | text_materials |
| Beneluz Abustan | Page: Assignment Statements | Course module viewed | text_materials |
| Beneluz Abustan | Page: Literals | Course module viewed | text_materials |
| Beneluz Abustan | Page: Literals | Course module viewed | text_materials |
| Beneluz Abustan | Page: Naming Constants | Course module viewed | text_materials |
| Beneluz Abustan | Page: Arithmetic Operators and Expressions | Course module viewed | text_materials |
| Beneluz Abustan | Page: Arithmetic Operators and Expressions | Course module viewed | text_materials |
| Beneluz Abustan | Page: Type Casting | Course module viewed | text_materials |
| Beneluz Abustan | Page: Output Using cout | Course module viewed | visual_materials |
| Beneluz Abustan | Page: New Lines in Output | Course module viewed | visual_materials |
| Beneluz Abustan | Page: Input using cin | Course module viewed | video_materials |
| Beneluz Abustan | Quiz: Exercise 1 | Quiz attempt reviewed | exercises_rev |
| Beneluz Abustan | Quiz: Exercise 1 | Quiz attempt reviewed | exercises_rev |
| Beneluz Abustan | Quiz: Self Assessment 1 | Quiz attempt submitted | self_assessment |
| Beneluz Abustan | Quiz: Self Assessment 1 | Quiz attempt submitted | self_assessment |
| Beneluz Abustan | Glossary: Glossary 1 | Course module viewed | abstract_materials |
| Beneluz Abustan | Glossary: Glossary 1 | Course module viewed | abstract_materials |
| Beneluz Abustan | Glossary: Glossary 1 | Course module viewed | abstract_materials |
| Beneluz Abustan | Glossary: Glossary 1 | Course module viewed | abstract_materials |
| Beneluz Abustan | Page: Precedence Rules | Course module viewed | concrete_materials |
| Beneluz Abustan | Page: Compound Statements | Course module viewed | text_materials |
| Beneluz Abustan | Page: Multiway IF - ELSE Statement | Course module viewed | text_materials |
| Beneluz Abustan | Page: Multiway IF - ELSE Statement | Course module viewed | text_materials |
| Beneluz Abustan | Page: The conditional operator | Course module viewed | text_materials |

*Figure 4.3 Reduced log data for the Computer Programming 1 (Moodle) Course*

The next phase in the construction of the data sets is data transformation. The reduced log data in Microsoft Excel format is transformed and converted to a Microsoft Access file (*.accdb) format in order to easily aggregate the total number of interaction a particular learner to each learning objects. An aggregate SQL commands was used to extract the needed values for data mining and analysis. Derived variables was extracted through calculating and accumulating variable data such as number of views, number of visits, number of posts, and number of exercises answer review attempts, number of completed assessment test to name a few.




| User_full_name | Type | Number of interactions |
|---|---|---|
| Beneluz Abustan | abstract_materials | 12 |
| Beneluz Abustan | concrete_materials | 7 |
| Beneluz Abustan | course_overviews | 3 |
| Beneluz Abustan | examples | 4 |
| Beneluz Abustan | exercises | 7 |
| Beneluz Abustan | forum_post | 1 |
| Beneluz Abustan | forum_view | 2 |
| Beneluz Abustan | self_assessment | 8 |
| Beneluz Abustan | text_materials | 27 |
| Beneluz Abustan | video_materials | 9 |
| Beneluz Abustan | visual_materials | 11 |

*Figure 4.4 Aggregated number of interaction of a particular learner to a learning object*

Figure 4.4 illustrates the result of aggregated data for a particular learner using SQL queries. The final phase in the construction of data sets is to arrange the derived values of number of interactions of the student to a specific learning object. It was arranged and categorized based from the learning behavior pattern mapping in Table 4.2. These can be seen in Figures 4.5 to 4.8.

| No. | Student | forum_post | forum_view | self_assesment | text_materials | PROCESSING |
|---|---|---|---|---|---|---|
| 1 | ABUSTAN, BENELUZ | 1 | 2 | 8 | 27 | ACTIVE |
| 2 | ABUAN, SIDNEY JANE | 11 | 6 | 3 | 0 | REFLECTIVE |
| 3 | ABULAR, MA. FREDA MAE | 21 | 10 | 7 | 29 | ACTIVE |
| 4 | ABULENCIA, APPLE GEM | 9 | 2 | 8 | 1 | ACTIVE |
| 5 | ABUSTAN, AUDREY CASSIE | 4 | 3 | 8 | 17 | ACTIVE |
| 6 | ACERO, CHANTREA FELICHE | 15 | 11 | 0 | 14 | ACTIVE |
| 7 | ADAO, ANTONETTE | 22 | 0 | 6 | 4 | ACTIVE |
| 8 | AGUILA, ELAINE | 0 | 6 | 0 | 4 | REFLECTIVE |
| 9 | ALCANTARA, CHRISTINE JADE | 9 | 7 | 8 | 7 | ACTIVE |
| 10 | ALCANTARA, GABRIEL EMMANUEL | 12 | 5 | 3 | 22 | REFLECTIVE |
| 11 | ALCANTARA, RHEALENE | 6 | 11 | 2 | 7 | REFLECTIVE |
| 12 | ALCOREZA, RONALD | 5 | 12 | 1 | 38 | REFLECTIVE |
| 13 | ALFONSO, ELDRICH CLARK | 14 | 16 | 2 | 19 | REFLECTIVE |
| 14 | ALMIRAÑEZ, JOHN MERJAN | 5 | 5 | 4 | 11 | ACTIVE |
| 15 | ALONDRES, DHARRENZ | 1 | 17 | 1 | 31 | REFLECTIVE |
| 16 | ANARETA, MARIGOLD | 4 | 9 | 1 | 18 | REFLECTIVE |
| 17 | AÑOSO, KHATE NESLYN T. | 0 | 2 | 2 | 26 | ACTIVE |
| 18 | ARCILLA, ASHLEY MAY | 20 | 11 | 7 | 26 | ACTIVE |
| 19 | AVELLANEDA, JOHN KIRBY | 13 | 9 | 5 | 27 | ACTIVE |
| 20 | AZORES, RENNALYN | 8 | 18 | 2 | 3 | REFLECTIVE |
| 21 | BAEL, AILEEN | 13 | 8 | 2 | 20 | REFLECTIVE |
| 22 | BALURAN, GLAIZA | 7 | 9 | 3 | 9 | REFLECTIVE |
| 23 | BISCO, ALLEANDRO | 23 | 4 | 0 | 33 | ACTIVE |
| 24 | BORINES, VINZE GERMEL | 4 | 11 | 2 | 32 | REFLECTIVE |

*Figure 4.5 Excerpt of final data set construction (Processing Dimension)*

| No. | Student | concrete_materials | abstract_materials | examples | exercises_rev | PERCEPTION |
|---|---|---|---|---|---|---|
| 1 | ABUSTAN, BENELUZ | 7 | 12 | 4 | 7 | INTUITIVE |
| 2 | ABUAN, SIDNEY JANE | 7 | 6 | 6 | 9 | SENSING |
| 3 | ABULAR, MA. FREDA MAE | 8 | 7 | 2 | 6 | INTUITIVE |
| 4 | ABULENCIA, APPLE GEM | 18 | 11 | 10 | 9 | SENSING |
| 5 | ABUSTAN, AUDREY CASSIE | 18 | 7 | 5 | 4 | SENSING |
| 6 | ACERO, CHANTREA FELICHE | 16 | 3 | 12 | 2 | SENSING |
| 7 | ADAO, ANTONETTE | 11 | 5 | 11 | 4 | SENSING |
| 8 | AGUILA, ELAINE | 3 | 14 | 2 | 4 | INTUITIVE |
| 9 | ALCANTARA, CHRISTINE JADE | 10 | 4 | 10 | 7 | SENSING |
| 10 | ALCANTARA, GABRIEL EMMANUEL | 4 | 7 | 6 | 13 | INTUITIVE |
| 11 | ALCANTARA, RHEALENE | 16 | 12 | 9 | 7 | SENSING |
| 12 | ALCOREZA, RONALD | 10 | 9 | 8 | 1 | SENSING |
| 13 | ALFONSO, ELDRICH CLARK | 12 | 8 | 12 | 5 | SENSING |
| 14 | ALMIRAÑEZ, JOHN MERJAN | 12 | 7 | 3 | 1 | SENSING |
| 15 | ALONDRES, DHARRENZ | 7 | 9 | 3 | 4 | INTUITIVE |
| 16 | ANARETA, MARIGOLD | 15 | 14 | 13 | 6 | SENSING |
| 17 | AÑOSO, KHATE NESLYN T. | 7 | 7 | 9 | 8 | SENSING |
| 18 | ARCILLA, ASHLEY MAY | 15 | 11 | 14 | 9 | SENSING |
| 19 | AVELLANEDA, JOHN KIRBY | 6 | 16 | 8 | 4 | INTUITIVE |
| 20 | AZORES, RENNALYN | 10 | 14 | 12 | 16 | INTUITIVE |
| 21 | BAEL, AILEEN | 7 | 9 | 11 | 6 | SENSING |
| 22 | BALURAN, GLAIZA | 15 | 2 | 3 | 8 | SENSING |
| 23 | BISCO, ALLEANDRO | 16 | 5 | 14 | 4 | SENSING |
| 24 | BORINES, VINZE GERMEL | 7 | 10 | 11 | 9 | SENSING |

*Figure 4.6 Excerpt of final data set construction (Perception Dimension)*

| No. | Student | visual_materials | video_materials | text_materials | forum_posts | INPUT |
|---|---|---|---|---|---|---|
| 1 | ABUSTAN, BENELUZ | 11 | 9 | 27 | 1 | VISUAL |
| 2 | ABUAN, SIDNEY JANE | 7 | 11 | 0 | 11 | VISUAL |
| 3 | ABULAR, MA. FREDA MAE | 16 | 9 | 29 | 21 | VISUAL |
| 4 | ABULENCIA, APPLE GEM | 20 | 8 | 1 | 9 | VISUAL |
| 5 | ABUSTAN, AUDREY CASSIE | 30 | 9 | 17 | 4 | VISUAL |
| 6 | ACERO, CHANTREA FELICHE | 3 | 19 | 14 | 15 | VISUAL |
| 7 | ADAO, ANTONETTE | 6 | 14 | 4 | 22 | VISUAL |
| 8 | AGUILA, ELAINE | 22 | 16 | 4 | 0 | VISUAL |
| 9 | ALCANTARA, CHRISTINE JADE | 4 | 10 | 7 | 9 | VERBAL |
| 10 | ALCANTARA, GABRIEL EMMANUEL | 21 | 14 | 22 | 12 | VISUAL |
| 11 | ALCANTARA, RHEALENE | 20 | 12 | 7 | 6 | VISUAL |
| 12 | ALCOREZA, RONALD | 22 | 21 | 38 | 5 | VISUAL |
| 13 | ALFONSO, ELDRICH CLARK | 22 | 19 | 19 | 14 | VISUAL |
| 14 | ALMIRAÑEZ, JOHN MERJAN | 4 | 13 | 11 | 5 | VISUAL |
| 15 | ALONDRES, DHARRENZ | 13 | 10 | 31 | 1 | VERBAL |
| 16 | ANARETA, MARIGOLD | 13 | 6 | 18 | 4 | VERBAL |
| 17 | AÑOSO, KHATE NESLYN T. | 25 | 8 | 26 | 0 | VISUAL |
| 18 | ARCILLA, ASHLEY MAY | 17 | 19 | 26 | 20 | VISUAL |
| 19 | AVELLANEDA, JOHN KIRBY | 28 | 12 | 27 | 13 | VISUAL |
| 20 | AZORES, RENNALYN | 30 | 10 | 3 | 8 | VISUAL |
| 21 | BAEL, AILEEN | 3 | 11 | 20 | 13 | VISUAL |
| 22 | BALURAN, GLAIZA | 29 | 10 | 9 | 7 | VISUAL |
| 23 | BISCO, ALLEANDRO | 15 | 10 | 33 | 23 | VISUAL |
| 24 | BORINES, VINZE GERMEL | 4 | 7 | 32 | 4 | VERBAL |

*Figure 4.7 Excerpt of final data set construction (Input Dimension)*

| No. | Student | course_overviews | nav_euclidean_distance | UNDERSTANDING |
|---|---|---|---|---|
| 1 | ABUSTAN, BENELUZ | 3 | 5.29 | SEQUENTIAL |
| 2 | ABUAN, SIDNEY JANE | 2 | 6.48 | SEQUENTIAL |
| 3 | ABULAR, MA. FREDA MAE | 3 | 6.08 | SEQUENTIAL |
| 4 | ABULENCIA, APPLE GEM | 5 | 8.83 | SEQUENTIAL |
| 5 | ABUSTAN, AUDREY CASSIE | 3 | 3.74 | GLOBAL |
| 6 | ACERO, CHANTREA FELICHE | 0 | 5.39 | SEQUENTIAL |
| 7 | ADAO, ANTONETTE | 2 | 4.90 | SEQUENTIAL |
| 8 | AGUILA, ELAINE | 2 | 12.45 | GLOBAL |
| 9 | ALCANTARA, CHRISTINE JADE | 0 | 7.21 | SEQUENTIAL |
| 10 | ALCANTARA, GABRIEL EMMANUEL | 3 | 4.90 | SEQUENTIAL |
| 11 | ALCANTARA, RHEALENE | 1 | 4.24 | SEQUENTIAL |
| 12 | ALCOREZA, RONALD | 3 | 4.47 | GLOBAL |
| 13 | ALFONSO, ELDRICH CLARK | 2 | 4.80 | SEQUENTIAL |
| 14 | ALMIRAÑEZ, JOHN MERJAN | 3 | 11.49 | GLOBAL |
| 15 | ALONDRES, DHARRENZ | 3 | 7.21 | GLOBAL |
| 16 | ANARETA, MARIGOLD | 2 | 4.00 | SEQUENTIAL |
| 17 | AÑOSO, KHATE NESLYN T. | 3 | 4.24 | SEQUENTIAL |
| 18 | ARCILLA, ASHLEY MAY | 2 | 5.39 | SEQUENTIAL |
| 19 | AVELLANEDA, JOHN KIRBY | 4 | 3.61 | SEQUENTIAL |
| 20 | AZORES, RENNALYN | 3 | 4.12 | GLOBAL |
| 21 | BAEL, AILEEN | 3 | 6.63 | SEQUENTIAL |
| 22 | BALURAN, GLAIZA | 3 | 5.29 | SEQUENTIAL |
| 23 | BISCO, ALLEANDRO | 3 | 6.63 | SEQUENTIAL |
| 24 | BORINES, VINZE GERMEL | 5 | 7.14 | SEQUENTIAL |

*Figure 4.8 Excerpt of final data set construction (Understanding Dimension)*

An excerpt of the final data set construction is depicted in Figure 4.5, 4.6, 4.7, and 4.8. An additional data field was created to accommodate the reported learning styles of each student based from their answers from the Index of Learning Style Questionnaire. The results of the questionnaire served as the class labels of each student in terms of their learning styles for each learning dimensions of the selected learning style model. The final data sets were used in data mining.

**Feature Selection**

To determine the best features or attributes for determining the learning styles of the students in each dimension, attribute selection was used. Filtering method using Information Gain attribute evaluation was selected. The objective of feature selection technique testing is to empirically confirm and improve the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data (Guyon, 2003). The results of feature selection for each learning style dimension are discussed in detail in the next sections.

Based on the learning style mapping of relevant behaviors of learners in the Processing dimension of the Felder-Silverman Learning Style Model as can be seen in Table 4.2, a total of fourteen (14) possible attributes were tested using feature selection method. By applying data preprocessing using Information Gain Attribute Evaluation, significant predictors were extracted from each of the mapped attributes for each learning style dimensions. Summary of feature selection results can be seen below.

**Table 4.3** Results of Feature Selection for each FSLSM Dimension Attributes

| | Information Gain | Significant? |
|---|---|---|
| **Attributes** | **Rank Value** | **(yes/no)** |
| forum_view | 0.449 | yes |
| self_asssement | 0.338 | yes |
| forum_post | 0.267 | yes |
| textual_materials | 0 | no |
| | **Information Gain** | **Significant?** |
| **Attribute** | **Rank Value** | **(yes/no)** |
| concrete_materials | 0.3533 | yes |
| exercises_rev | 0.2413 | yes |
| examples | 0.1071 | yes |
| abstract_materials | 0.0939 | yes |
| | **Information Gain** | **Significant?** |
| **Attribute** | **Rank Value** | **(yes/no)** |
| video_materials | 0.382 | yes |
| visual_materials | 0.269 | yes |
| forum_post | 0 | no |
| textual_materials | 0 | no |
| | **Information Gain** | **Significant?** |
| **Attribute** | **Rank Value** | **(yes/no)** |
| course_overview | 0.2851 | yes |
| nav_pattern_distance | 0.0399 | yes |

Based from the results, eleven (11) attributes have been found to be significant such as forum_view, self_assesment, forum_post, concrete_materials, exercises_rev, examples, abstract_materials, video_materials, visual_materials, course_overview and nav_pattern_distance. These are the significant attributes for their respective learning dimension in classifying learning styles.

**J48 Decision Tree Performance in Classification**

To derive the results of data mining, classification algorithms were used. WEKA was utilized to classify students learning styles. The data sets were tested with J48 decision tree classifier. J48 classifier is amongst the most powerful and reliable decision tree classifiers (Kaur, 2014). The study considered accuracy rate as the main criterion for determining the most appropriate data mining technique. The results of the performance evaluation are shown in Tables 4.4, 4.5, 4.6 and 4.7 as correctly and incorrectly classified instances generated by WEKA. A 10-fold cross validation method to estimate the accuracy rates of each technique was used. Additional criteria such as Precision which can be thought of as a measure of classifier exactness, F-Measure that conveys the balance between the precision and recall, Kappa statistics that is used to assess the accuracy of any particularly measuring cases, confusion matrix for analyzing how well the best classier can recognized tuples of different classes that can be seen in Table 4.9 and receiver operating characteristic (ROC) curve and Area under the Curve (AUC) plots are also evaluated for the classification model that has the highest accuracy to determine its goodness of fit (See Figures 4.8, 4.9, 4.10 & 4.11).

As can be seen in the performance tables, the J48 classifier demonstrates a reasonably high performance of classification accuracy across the four learning style dimension of the Felder-Silverman Learning Style Model. It is noted that sometimes, correctly classified instances can be insensitive to a class distribution. Therefore, when selecting the best technique, precision rates for each class and the ROC area values must be considered. The most optimal classifier should have receiver operating characteristics (ROC) values that approach a value of 1. By considering the overall results of classification accuracy, as shown in the other learning style dimension, it is J48 decision tree classifier that was the most appropriate method for the datasets.

**Table 4.4** Performance in Processing Dimension (Active/Reflective)

| J48 Decision Tree Classifier | |
|---|---|
| **Correctly Classified Instances** | **92.50%** |
| **Incorrectly Classified Instances** | 7.49% |
| **Kappa Statistics** | 0.849 |
| **Precision** | 0.933 |
| **Recall** | 0.925 |
| **F-Measure** | 0.925 |

Table 4.4 summarizes the results based on correctly and incorrectly classified instances, kappa statistics, precision, and f-measure. From Table 4.4, it can be seen that classification tree algorithm of J48 attained an accuracy of 92.50%. Kappa score from the J48 algorithm is at 0.849 which shows that the accuracy of the classification is 'Perfect' based from Cohen's Kappa Equivalent Value that can be seen in Table 3.2 (p. 70). Weighted Average precision scores of 0.993 and weighted average F-measure scores of 0.925 for the J48 algorithm suggest that both scores approaches a value of 1 and it is deem accurate.

**Table 4.5** Performance in Perception Dimension (Sensing/Intuitive)

| J48 Decision Tree Classifier | |
|---|---|
| **Correctly Classified Instances** | **88.16%** |
| **Incorrectly Classified Instances** | 11.83% |
| **Kappa Statistics** | 0.699 |
| **Precision** | 0.891 |
| **Recall** | 0.882 |
| **F-Measure** | 0.875 |

Table 4.5 summarizes the results based on correctly and incorrectly classified instances, kappa statistics, precision, and f-measure. From Table 4.5, it can be seen that classification tree algorithm of J48 attained an accuracy of 88.16%/ Kappa score from the J48 algorithm is at 0.6994 which shows that the accuracy of the classification is 'Substantial'. Weighted Average precision scores of 0.891 and weighted average F-measure scores of 0.875 for the J48 algorithm suggest that both scores approaches a value of 1 and it is deem accurate.

**Table 4.6** Performance in Input Dimension (Visual/Verbal)

| **J48 Decision Tree Classifier** | |
|---|---|
| **Correctly Classified Instances** | **86.58%** |
| **Incorrectly Classified Instances** | 13.41% |
| **Kappa Statistics** | 0.677 |
| **Precision** | 0.901 |
| **Recall** | 0.866 |
| **F-Measure** | 0.873 |

Table 4.6 summarizes the results based on correctly and incorrectly classified instances, kappa statistics, precision, and f-measure. From Table 4.6, it can be seen that classification tree algorithm of J48 attained an accuracy of 86.58%. Kappa score from the J48 algorithm is at 0.677 which shows that the accuracy of the classification is 'Substantial'. Weighted Average precision scores of 0.852 and weighted average f-measure scores of 0.854 for the J48 algorithm suggest that both scores are accurate.

**Table 4.7** Performance in Understanding Dimension (Sequential/Global)

| J48 Decision Tree Classifier | |
|---|---|
| **Correctly Classified Instances** | **82.44%** |
| **Incorrectly Classified Instances** | 17.55% |
| **Kappa Statistics** | 0.647 |
| **Precision** | 0.844 |
| **Recall** | 0.824 |
| **F-Measure** | 0.822 |

Table 4.7 summarizes the results based on correctly and incorrectly classified instances, kappa statistics, precision, and f-measure. From Table 4.7, it can be seen that J48 algorithm attained an accuracy of 82.44%. Kappa score from the J48 algorithm is at 0.647 which shows that the accuracy of the classification is 'Substantial'. Weighted Average precision scores of 0.844 and weighted average F-measure scores of 0.822 for the J48 algorithm suggest that both scores are accurate.

**Confusion Matrix Results of the J48 Decision Tree**

The table below (Table 4.8) is a representation of the learning styles confusion matrix table for the J48 Decision Tree Classifier. The confusion matrix is a useful tool for analyzing how well a classifier can recognize tuples of different classes (Han, 2006).

**Table 4.8** Confusion Matrix for J48 Classification Technique for All Dimensions

| PROCESSING DIMENSION (ACTIVE/REFLECTIVE) | | | | |
|---|---|---|---|---|
| **Actual Value** | **Predicted Value** | | **Percentage** | **Average Percentage** |
| | Active | Reflective | | |
| Active | 208 | 36 | 85.246% | **92.505%** |
| Reflective | 2 | 261 | 99.240% | |
| **PERCEPTION DIMENSION (SENSING/INTUITIVE)** | | | | |
| **Actual Value** | **Predicted Value** | | **Percentage** | **Average Percentage** |
| | Intuitive | Sensing | | |
| Intuitive | 104 | 55 | 65.409% | **88.166%** |
| Sensing | 5 | 343 | 98.563% | |
| **INPUT DIMENSION (VISUAL/VERBAL)** | | | | |
| **Actual Value** | **Predicted Value** | | **Percentage** | **Average Percentage** |
| | Visual | Verbal | | |
| Visual | 327 | 61 | 84.278% | **86.588%** |
| Verbal | 7 | 112 | 94.118% | |
| **UNDERSTANDING DIMENSION (SEQUENTIAL/GLOBAL)** | | | | |
| **Actual Value** | **Predicted Value** | | **Percentage** | **Average Percentage** |
| | Sequential | Global | | |
| Sequential | 120 | 54 | 70.000% | **82.445%** |
| Global | 27 | 306 | 94.550% | |

**Classification Quality of J48 Decision Tree using ROC and AUC Plots**

The receiver operating characteristic (ROC) chart is similar to the gain or lift charts in that they provide a means of comparison between classification models. As explained in the previous chapter, the ROC chart shows false positive rate (1-specificity) on X-axis, the probability of target = 1 when its true value is 0, against true positive rate (sensitivity) on Y-Axis, the probability of target = 1 when its true value is 1. Ideally, the curve will climb quickly toward the top-left meaning the model correctly predicted the cases.

The diagonal line is for a random model and the closer the curve comes to the 45-degree diagonal of the ROC Space, the less accurate the model. Area under the curve (AUC) under the ROC curve is often used as a measure of quality of the classification models.

To further test the classification quality of the J48 classification model, a total of four (4) ROC curve plots have been generated for each learning style dimension using the KnowledgeFlow feature in WEKA.

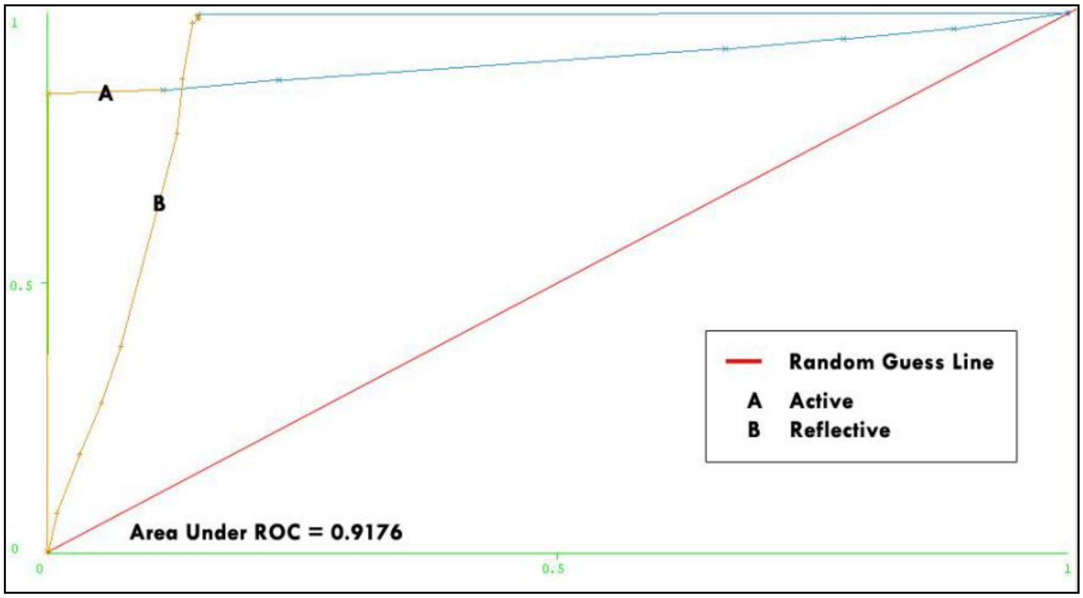



*Figure 4.9 ROC and AUC plot generated in WEKA for processing dimension*

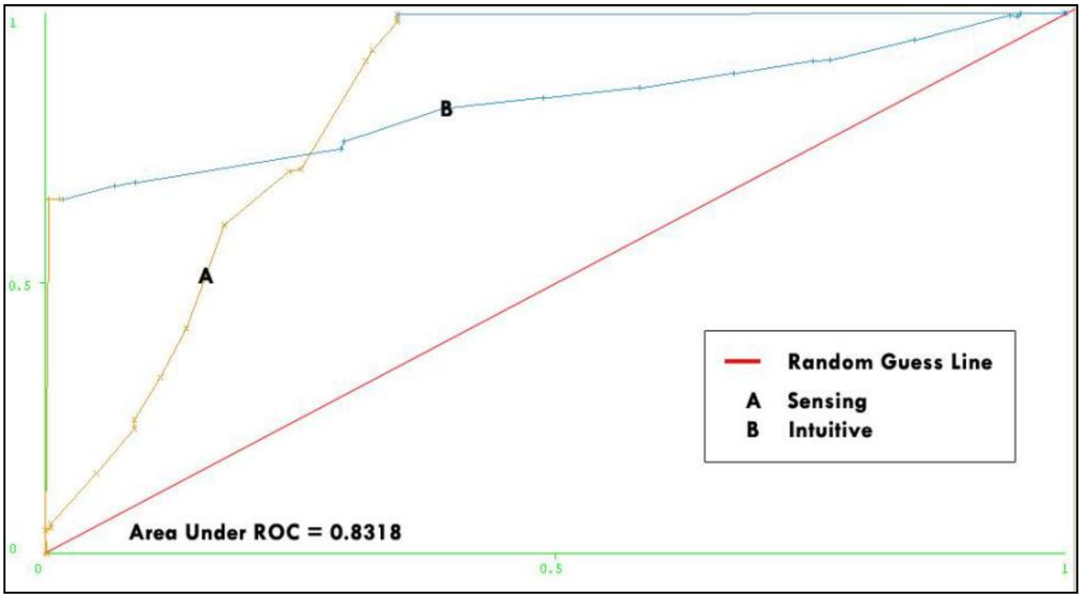



*Figure 4.10 ROC and AUC plot generated in WEKA for perception dimension*

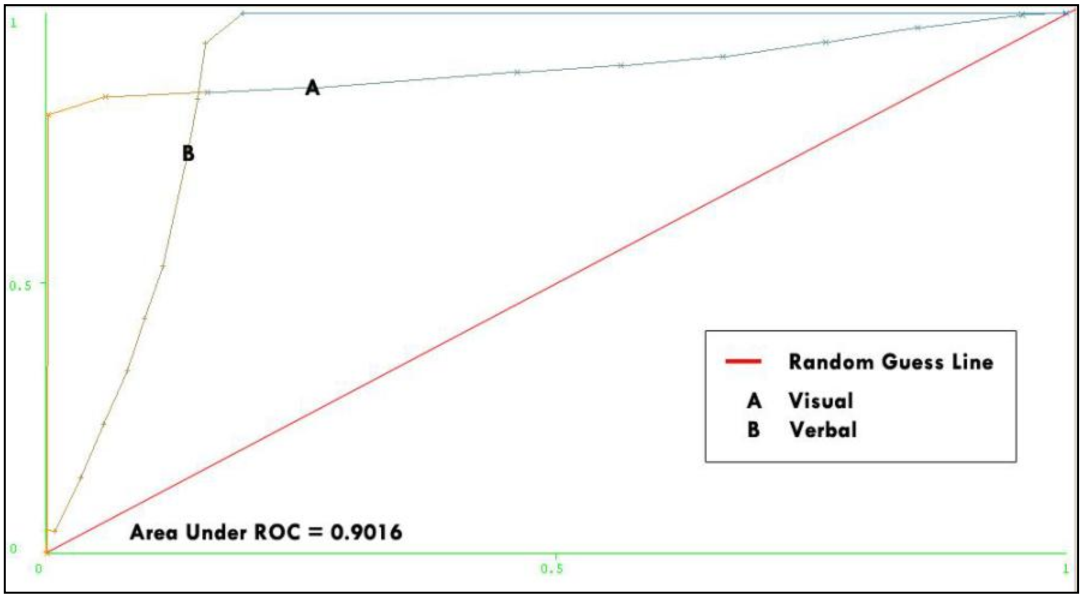



*Figure 4.11 ROC and AUC plot generated in WEKA for input dimension*

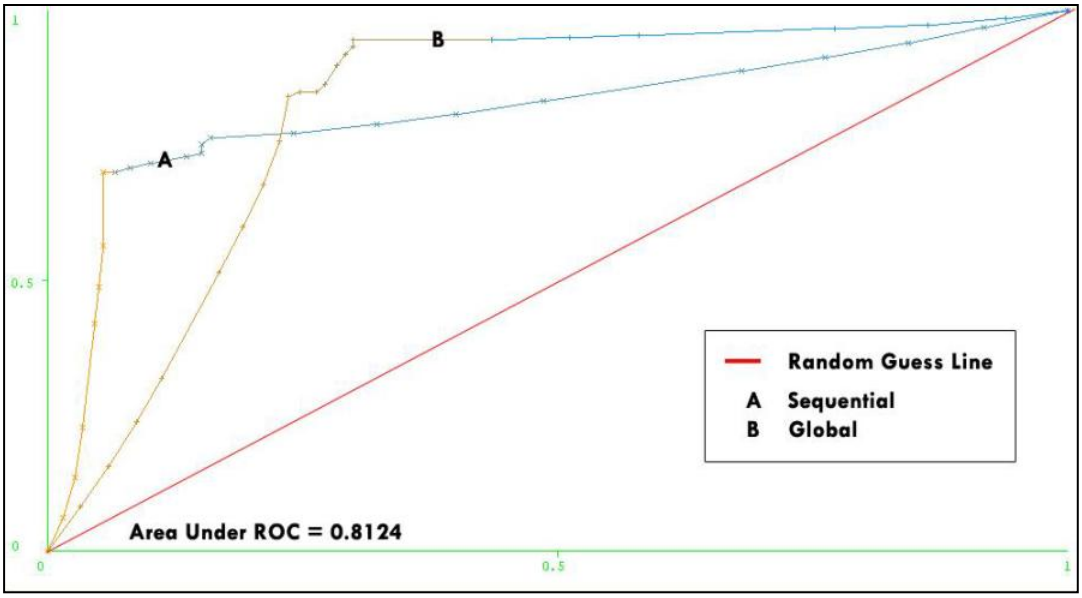



*Figure 4.12 ROC and AUC plot generated in WEKA for understanding dimension*

Figures 4.9, 4.10, 4.11 and 4.12 suggests that the ROC curves for all learning style dimensions did not fall below the random guessing line threshold of 0.5 which suggests that the quality of classification is well beyond random guessing or classification did not happen by chance only. Furthermore, the values obtained from the Area under the Curve (AUC) plots are 0.9176 (Excellent) for processing dimension, 0.8318 (Good) for perception dimension, 0.9016 (Excellent) for input dimension and 0.8124 (Good) for the understanding dimension (Refer to Table 3.1, p. 70). Average AUC scores across all four dimensions are 0.86585 that signifies that the model provides a good fit and accuracy. Having determined that the J48 classifier was the best fit for the classification purposes of learning styles from the collective empirical results of correctly classified instances, kappa statistics, precision, f-measure, confusion matrices, receiver operating characteristics plots and area under the curve values, the rules generated and extracted from the J48 classification algorithm was used in the prototype of adaptive Virtual Learning Environment for different learning styles. The sets of rules extracted from the J48 classification technique are shown in the proceeding section.

**Rules Extracted from the J48 Classification Model**

J48 models are easy to understand as the rules that are derived from the technique have a very straightforward interpretation. J48 classifier is amongst the most powerful and reliable decision tree classifiers (Kaur, 2014). By tracing the path from the root node to a leaf node in the generated decision tree, classification rules can be extracted. From the results of classification using the J48 technique, Table 4.10 summarizes all the sets of classification rules extracted for the four learning styles dimension of Felder Silverman Learning Style Model.

Based from the extracted rules from the J48 algorithm, the number of times a student performs self-assessment tests; the most likely a student to have an active learning style. This piece of information is in congruency with the study by Graf (2007) on semantic grouping of learners within the Active/Reflective dimension of the FSLSM using correlations. In the study, active learners are group of individuals that are fond of trying things out, they like learning by trial and error and they prefer to work actively with the learning material such as completing a self-assessment tests. The preference for the semantic group regarding working carefully and slowly can be seen from the behavior when exercises are specifically graded. Learners who are careful with details tends to check their answers more carefully and to make more revisions on their answers during exercises. From the extracted rules of the Sensing/Reflective dimension, the root node of the decision tree is the number of times a learners review their answer on exercises  (a test that is graded), this piece of information agrees again to the semantic grouping using correlations performed by Graf (2007).

In the Visual/Verbal learning dimension, it is noted that interaction with video and visual type of learning objects highly differentiates a visual and verbal learner.  Finally, the Sequential/Global dimension rule sets are parallel to the description of a sequential learner that prefers navigating the course sequentially rather than sporadically as suggested in the study by Graf (2007). This can be observed by the small Euclidean distance values of their navigational patterns.

**Table 4.9** Sets of Classification Rules from J48 Classification Model

| PROCESSING DIMENSION | | |
|---|---|---|
| **Rules** | **Active/Reflective** | **Instances** |
| IF (self_assessment) > 3 | Active | 129 |
| IF (self_assessment) <= 3 , AND (forum_post) > 14 | Active | 52 |
| IF (self_assessment) <= 3 , AND (forum_post) <= 14, AND (forum_view) <= 4 | Reflective | 26 |
| IF (self_assessment) <= 3 , AND (forum_post) <= 14, AND (forum_view) > 4 | Reflective | 300/37 |
| **Summary:** Number of Leaves: 4, Size of the Tree: 7 | | |
| **PERCEPTION DIMENSION** | | |
| **Rules** | **Sensing/Intuitive** | **Instances** |
| IF (exercises_rev) > 12 | Intuitive | 59 |
| IF (exercises_rev) <= 12, AND (concrete_materials) <= 4 | Intuitive | 24 |
| IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) > 14 | Intuitive | 19 |
| IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) > 4 | Sensing | 345/42 |
| IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) <= 2 | Intuitive | 6 |
| IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) > 2, AND (concrete_materials) > 6 | Sensing | 49/5 |
| IF (exercises_rev) <= 12, AND (concrete_materials) > 4, AND (abstract_materials) <= 14, AND (examples) <= 4, AND (examples) > 2, AND (concrete_materials) <= 6 | Intuitive | 5/1 |
| **Summary:** Number of Leaves: 7, Size of the Tree: 13 | | |
| **INPUT DIMENSION** | | |
| **Rules** | **Visual/Verbal** | **Instances** |
| IF (video_materials) > 12 | Visual | 235 |
| IF (video_materials) <= 12, AND (visual_materials) > 13 | Visual | 87 |
| IF (video_materials) <= 12, AND (visual_materials) <= 13 | Verbal | 185/66 |
| **Summary:** Number of Leaves: 3, Size of the Tree: 5 | | |
| **UNDERSTANDING DIMENSION** | | |
| **Rules** | **Sequential/Global** | **Instances** |
| IF (course_overviews) > 2 | Global | 275/59 |
| IF (course_overviews) <= 2, AND (nav_pattern_distance) > 8 | Global | 42/15 |
| IF (course_overviews) <= 2, AND (nav_pattern_distance) <= 8 | Sequential | 190/14 |
| **Summary:** Number of Leaves: 3, Size of the Tree: 5 | | |

### Adaptive Course Design and Contents

The third research question addresses the issue of adapting course design and contents to match the learning styles of the learners. Once the rule sets for each learning styles are known, these rule sets can be integrated in a Virtual Learning Environment to generate and present adaptive course design and contents. The study adopted an architectural model for an adaptive Virtual Learning Environment (See Figure 2.4) and within this study; a prototype for an Adaptive Virtual Learning Environment for different learning styles was developed. An adaptive learning system that is able to provide content information in a way that adapts to different learning styles of the learners.

Adaptation features indicate how a course can change for each learner with different learning styles. These features are based on the types of learning objects presented and refer to the sequence and the availability of presented learning objects. Adaptation features is classified into two groups, namely adaptive content presentation and adaptive navigation support. Adaptive navigation support is based on links and includes features such as adaptive sorting, hiding and placement of links. Adaptive presentation includes adaptation features based on content such as dynamic content presentation.

For the purpose of analysis, a partial list of student data who utilized the Adaptive Virtual Learning Environment prototype was extracted. The observed data were deemed sufficient enough to make generalized results. Table 4.10 shows 5 out of 30 students who utilized the adaptive virtual learning environment prototype.

**Table 4.10** Partial List of Data Extracted and their Inferred Learning Styles

| No. | Name | forum_view | self-assessment | forum_post | concrete_materials | text_materials | exercises_rev | examples | abstract_materials | video_materials | visual_materials | course_overviews | nav_pattern_distance | LEARNING STYLE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Vladimir | 0 | 4 | 0 | 3 | 10 | 0 | 1 | 3 | 2 | 8 | 2 | 21.54 | Active/Intuitive/Verbal/Global |
| 2 | Jennadel | 0 | 0 | 0 | 7 | 2 | 2 | 3 | 0 | 2 | 15 | 1 | 4.69 | Reflective/Sensing/Visual/Sequential |
| 3 | Aldrin | 0 | 1 | 1 | 4 | 3 | 0 | 2 | 4 | 2 | 11 | 0 | 21.52 | Reflective/Intuitive/Verbal/Global |
| 4 | Maria Bhea | 1 | 1 | 1 | 8 | 4 | 1 | 1 | 1 | 2 | 12 | 1 | 4.9 | Reflective/Sensing/Visual/Sequential |
| 5 | Bianca Mae | 1 | 4 | 2 | 7 | 4 | 0 | 5 | 1 | 1 | 2 | 1 | 47.36 | Active/Sensing/Verbal/Sequential |

Student's interaction to each learning objects are recorded in the VLE log files. Based from that number of interactions, the system inferred their learning styles accordingly to the four learning style dimensions of the FSLSM. For course design and content adaptation feature comparison, student 'Vladimir' and student 'Jennadel' was compared for they have exactly the opposite learning styles.

According to FSLSM, active learners prefer to learn by trying things out and doing something actively. Therefore, navigation wise, self-assessment tests are presented at the beginning of each chapter for active learners and after the learning materials for reflective learners as can be seen in Figure 4.13. In contrast, reflective learners prefer to learn by reflecting on the learning material and thinking things through. Therefore, the number of learning object asking for active learning behavior such as self-assessment test is decreased.

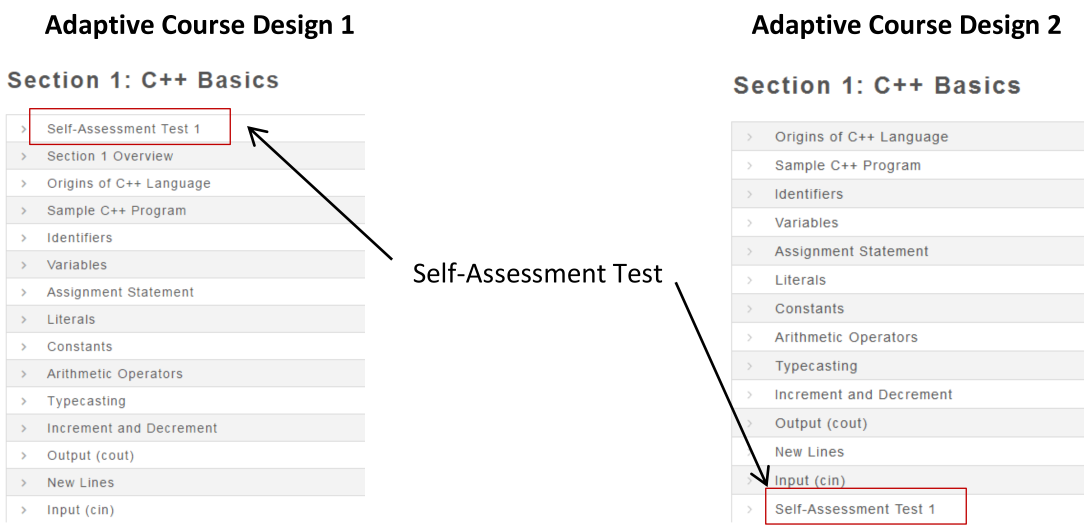



*Figure 4.13 Self-Assessment Test placements for Active and Reflective Learners*

Content wise, simulation encourages active learners as opposed to reflective learners that prefer to learn by reflecting on the learning material and thinking things through.

Sensing learners prefer to learn concrete learning materials such as data and facts as well as like to learn when a learning material is linked to real-life situations. Therefore, the contents of learning materials are supplemented by these kinds of context for a sensing learner. Moreover, sensing learners prefer to solve problems by already learned approaches. Therefore, providing task such as exercises and self-assessment test only after the learning material is highly recommended. On the other hand, intuitive learners like challenges and therefore task like self-assessment tests are recommended to be presented before the learning material. Since intuitive learners prefer to learn abstract material, supplementary abstract context in the learning content is highly recommended such as definitions, concepts, syntax, flow charts and theories. These can be seen in Figure 4.14.

Visual learners prefer learning materials that are supplemented with pictures, diagrams, charts, animations and videos. Therefore, providing learning contents with graphical content is highly recommended. On the opposite end, verbal learners prefer learning materials that are purely on a textual content in nature.

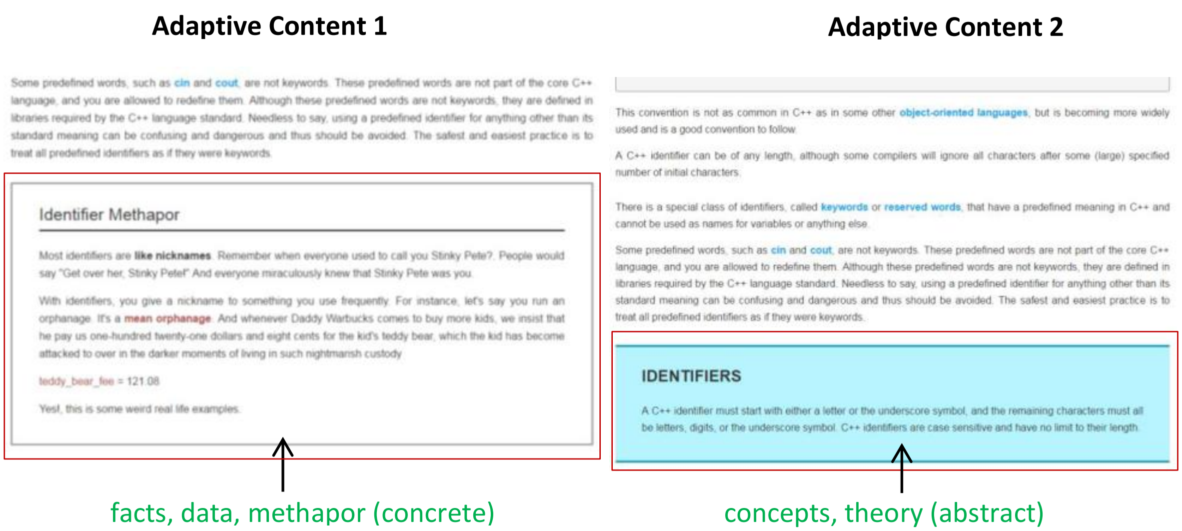



*Figure 4.14 Learning Content Adaptations for Sensing and Intuitive Learner*

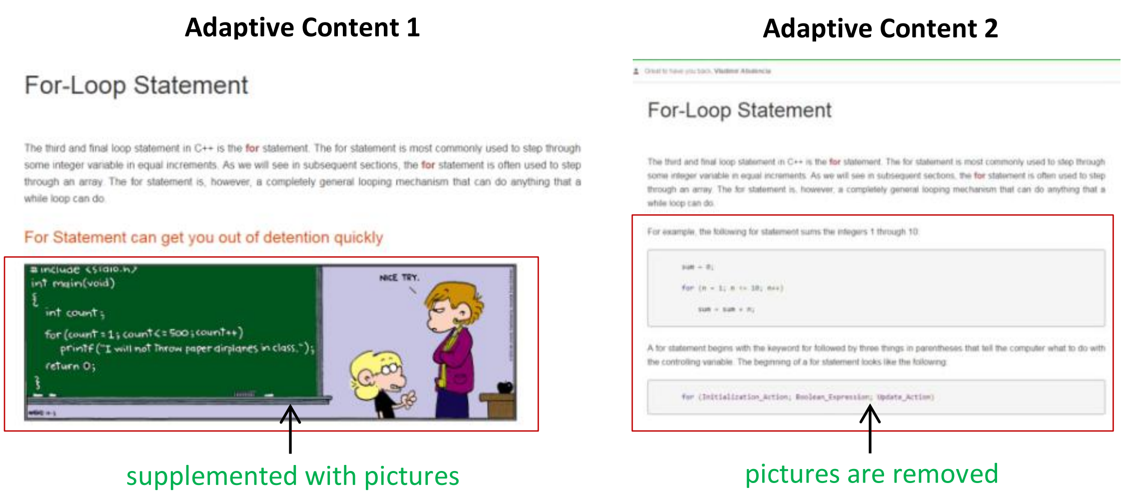



*Figure 4.15 Learning Content Adaptations for Visual and Verbal Learners*

Verbal learner’s strength lies by focusing on explanations by written or spoken sentences. Therefore pictures and diagram are mostly removed from a learning object for a verbal learner as can be seen in Figure 4.15.

Finally, since sequential learners prefer to learn in linear steps with a linear increase of complexity; they are more interested in a predefined learning path than in getting the overview of the whole course. Course overviews are not that important to them. It is also recommended for sequential learners to limit the number of accessible learning objects so that they can entirely focus on the requisite learning materials before moving on to the next learning materials. In contrast, for global learners it is very important to get the big picture of the course.  This is supported by providing chapter overviews at the start of each chapter or sections.Furthermore, global learners tend to be poor in using partial knowledge. Therefore, navigation wise, limit from navigation jumps to complex learning material is removed from this particular learner. These are demonstrated in Figure 4.16.

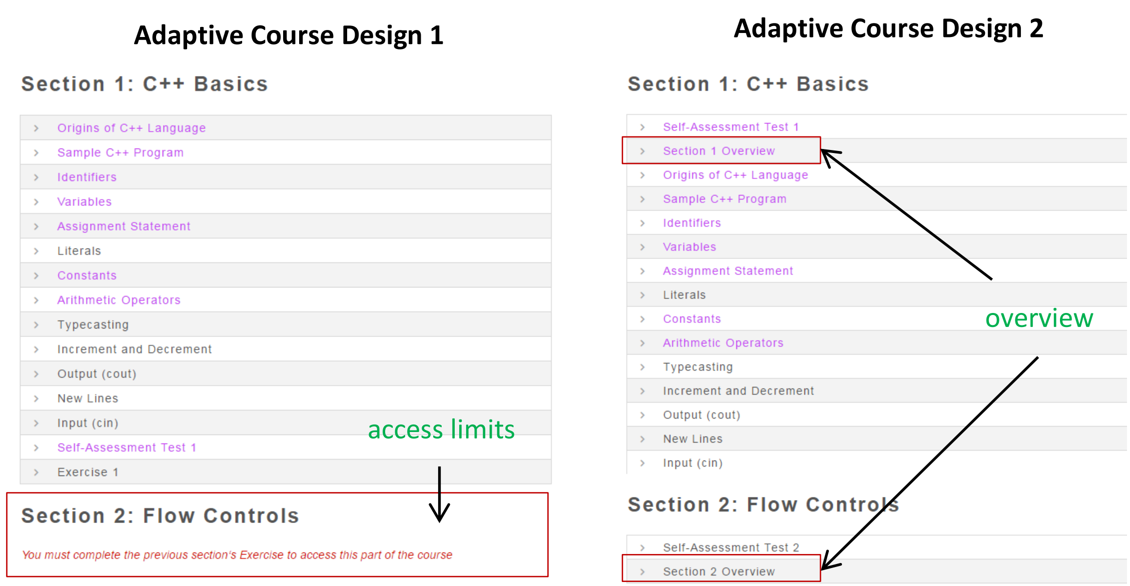



*Figure 4.16 Learning Object Access Limits of Sequential and Global Learners*

# Chapter 5

# SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter further summarizes the work conducted and the results in the previous chapter. In the next subsection, a summary of the performed research is given and the contributions of this work are highlighted. Consequently, limitations of the research are described and conclude with discussion on future research.

## Summary

The objective of the study was to develop a framework to be used in classification of student's learning styles and to create a prototype for an Adaptive Virtual Learning Environment. Most Virtual Learning Environment primarily focuses on aiding, supplementing and supporting teachers in creating, administrating, and managing e-learning courses. Most systems provide very little, or in most cases, no adaptation for learners. On the other hand, adaptive system support learners by providing course designs that specifically matches their needs and characteristics but these are rarely used in real practice due to their lack of support for teachers. Another objective of this study was to develop a prototype of a Virtual Learning Environment with capabilities and functionalities of providing adaptation for different learning styles based on the Felder-Silverman Learning Style Model (FSLSM).

In order to provide the necessary adaptation based on learning styles in a Virtual Learning Environment, the learning styles of each learner must be known at first hand. Therefore, an automatic student modeling approach for classification of learning styles from the relevant behaviors and actions of the learners was developed. For each of the four learning style dimension of the FSLSM, relevant patterns of behavior were mapped-out and selected. For deducing learning styles from the learners, a data-driven approach using different classification algorithms such as logistic regression, naïve bayes, conjunctive rule and J48 decision tree were compared and evaluated (See Appendix E). The evaluation results showed that the decision tree (J48) achieved higher accuracy results in classifying learning styles with high precision. Hence, the evaluation results can be seen as a suitable instrument for classification and detection of learning styles in a Virtual Learning Environment.

Once learning styles classifications are known, adaptation can be provided in a Virtual Learning Environment. Within the realms of this study, a framework for providing adaptive course in Virtual Learning Environment was developed. This framework was implemented by developing an Adaptive Virtual Learning Environment to automatically generate and present courses that are tailored fit to a student's learning styles. By creating an adaptive Virtual Learning Environment, teachers can continue holding courses with adaptation by using the advantages of a Virtual Learning Environment. On the other hand, learners are supported in learning by being provided with course design and contents that fit their respective individual learning styles.

**Conclusions**

The objective of this study was as follows:

1. To determine the relevant behaviors of students as attributes that are used in classification of student's learning styles in Virtual Learning Environment.

   Relative to this objective, the research question asked: *How learning styles are classified using student's behavior in Virtual Learning Environments?*

To be able to classify learning styles based on student's behavior in a Virtual Learning Environment, it is appropriate to select one from a multitude of existing learning style models that is the best fit in analyzing student's behavior in a Virtual Learning Environment. In this particular study, the Felder-Silverman Learning Style Model (FSLSM) was selected for the reason that this particular learning's style model classifies learners in a more detailed and distinguished features between preferences on its four dimension. The most critical factor for selecting this particular learning style model for this study is that the Felder and Silverman Learning Style model is highly based on tendencies, indicating that learners has a high preference for certain behaviors. In addition, the learning style model is specifically designed in advanced technologies such as a Virtual Learning Environment (Carver et al, 1999). Moreover, the learning style reliability, factor structure, and construct validity of the FSLSM through its Index of Learning Style (ILS) questionnaire revealed and proved that is has a consistent reliability based from the study by Litzinger et al. (2007). Attributes of each learning style dimensions were mapped according to the relevant behaviors and literature of the selected Felder-Silverman Learning Style Model.

2. To determine what classification technique accurately measures the classification of student's learning styles in a Virtual Learning Environment.

   Relative to this objective, the research question asked: *"How Virtual Learning Environments adapt to the different learning styles of the students?*

An adaptation strategy was necessary in order to provide adaptation to a Virtual Learning Environment. Extraction of learner's behaviors in a Virtual Learning Environment were possible by collecting each learner's log files in a Virtual Learning Environment's database and collecting each of the student's learning styles thru questionnaires to extract hidden predictive information from the data collected. Data sets from a total of five hundred seven (507) out of the possible five hundred forty seven (547) students who completed the Computer Programming 1 course were collected. Specifically, the data from student's logs and activities on the supplementary Virtual Learning Environment were carefully extracted and examined. A total of 52,815 rows of extracted user logs and activities for the particular course were used in classification of individual learning styles in the study. The student's learning styles which served as the class labels are obtained by using the Index of Learning Styles (ILS) questionnaires that are answered by the students who are enrolled and completed the selected course.

Different feature selection techniques such as Logistic Regression using Forward Likelihood Ratio (LR), Correlation-Based Feature Subset selection and Filtering method using Information Gain attribute evaluation was used to determine the best subset of features or attributes for determining the learning styles of the students in each learning style dimensions (See Appendix C). The data sets were tested with various classification algorithms that include Logistic Regression, Naïve Bayes, Conjunctive Rule and J48 Tree classifier (See Appendix E). The study have considered accuracy rate, f-measure, kappa statistics, confusion matrices, receiver operating characteristics (ROC) and Area under the Curve (AUC) plots to evaluate the classification quality of models. Based from the collective results, J48 classification algorithm yielded the highest average classification accuracy of 87.42% across all learning style dimensions and the rule sets derived from the algorithm (See Appendix F) was integrated to the developed Adaptive Virtual Learning Environment prototype.

3. To extend the capability of Virtual Learning Environments to adapt its course design based on the classification of student's learning styles.

   Relative to this objective, the research question asked: *"How classifications of learning styles affect the course design and contents of a Virtual Learning Environment?"*

Developing learning objects and making them accessible to the learners is not enough, it is more significant and critical that knowledge materials are tailored towards various learning characteristics of learners based from their individual learning styles. The study adopted a system architecture model of an adaptive Virtual Learning Environment system and developed a prototype of an Adaptive Learning Environment for different learning styles. A system that is capable in adapting and providing content information in a way that adapts to learning styles or preference of the learners.

**Recommendations**

The study is far from being perfect and it still has plenty of space for further improvements that future researchers might want to consider and follow through:

1. Develop new model using different data mining algorithms.
2. Build new model with increased number of data sets.
3. Explore on other potential attributes that may contribute to a more accurate classification of learning styles.
4. Consider the degree of learning style preferences to fine tune the classifications of learning styles.
5. Printing of reports of student learning styles could also be implemented in future prototype as this would be a valuable feature for reporting purposes.
6. Conduct a future investigation on the relationship between adapted learning environment and its relationship to student's academic performance.

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# Appendices

## Appendix A

## Index of Learning Styles (ILS) Questionnaire *

**Respondent Name:** ____________________________

**Dear Respondent,**

This questionnaire will be used to gather information about your learning style preferences. The responses you provide in this questionnaire will be kept confidential. Thank you very much for taking the time to answer this questionnaire.

**Directions:**

Encircle your answer to every question on the ILS scoring sheet. Please choose ONLY ONE (1) answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently.

1. I understand something better after I

   a. try it out.
   b. think it through.

2. I would rather be considered

   a. realistic.
   b. innovative.

3. When I think about what I did yesterday, I am most likely to get
   a. a picture
   b. words.

4. I tend to
   a. understand details of a subject but may be fuzzy about its overall structure.
   b. understand the overall structure but may be fuzzy about details.

5. When I am learning something new, it helps me to
   a. talk about it.
   c. think about it.

6. If I were a teacher, I would rather teach a course
   a. that deals with facts and real life situations.
   b. that deals with ideas and theories.

7. I prefer to get new information in
   a. pictures, diagrams, graphs, or maps.
   b. written directions or verbal information.

8. Once I understand
   a. all the parts, I understand the whole thing.

   b. the whole thing, I see how the parts fit.

9. In a study group working on difficult material, I am more likely to
   a. jump in and contribute ideas.
   b. sit back and listen.

10. I find it easier
    a. to learn facts.
    b. to learn concepts.

11. In a book with lots of pictures and charts, I am likely to
    a. look over the pictures and charts carefully.
    b. focus on the written text.

12. When I solve math problems
    a. I usually work my way to solutions one step at a time.
    b. I often just see the solutions but then have to struggle to figure out the steps to get to them

13. In classes I have taken
    a. I have usually gotten to know many of the students.
    b. I have rarely gotten to know many of the students.

14. In reading nonfiction, I prefer
    a. something that teaches me new facts or tells me how to do something
    b. something that gives me new ideas to think about.

15. I like teachers
    a. who put a lot of diagrams on the board.
    b. who send a lot of time explaining.

16. When I'm analyzing a story or a novel
    a. I think of the incidents and try to put them together to figure out the themes.
    b. I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.

17. When I start a homework problem, I am more likely to
    a. start working on the solution immediately.
    b. try to fully understand the problem first.

18. I prefer the idea of
    a. certainty.
    b. theory.

19. I remember best
    a. what I see.
    b. what I hear.

20. It is more important to me that an instructor
    a. layout the material in clear sequential steps.
    b. give me an overall picture and relate the material to other subjects.

21. I prefer to study
    a. in a study group.
    b. alone.

22. I am more likely to be considered.
    a. careful about the details of my work.
    b. creative about how to do my work.

23. When I get directions to a new place, I prefer
    a. a map
    b. written instructions.

24. I learn
    a. at a fairly regular pace. If I study hard, I will “get it”.
    b. in fits and starts. I’ll be totally confused and then suddenly it all “clicks”.

25. I would rather first
    a. try things out.
    b. think about how I’m going to do it.

26. When I am reading for enjoyment, I like writers to
    a. clearly say what they mean.
    b. says things in creative, interesting ways.

27. When I see a diagram or sketch in class, I am most likely to remember
    a. the picture.
    b. what the instructor said about it.

28. When considering a body of information, I am more likely to
    a. focus on details and miss the big picture.
    b. try to understand the big picture before getting into the details.

29. I more easily remember
    a. something I have done.
    b. something I have thought a lot about.

30. When I have to perform a task, I prefer to
    a. master one way of doing it.
    b. come up with new ways of doing it.

31. When someone is showing me data, I prefer
    a. charts or graphs.
    b. text summarizing the results.

32. When writing a paper, I am more likely to
    a. work on (think about or write) the beginning of the paper and progress forward.
    b. work on (think about or write) different parts of the papter and then order them.

33. When I have to work on a group project, I first want to
    a. have “group brainstorming” where everyone contributes ideas.
    b. brainstorm individually and then come together as a group to compare ideas.

34. I consider it higher praise to call someone
    a. sensible.
    b. imaginative.

35. When I meet people at a party, I am more likely to remember
    a. what they looked like.
    b. what they said about themselves.

36. When I am learning a new subject, I prefer to
    a. stay focused on that subject, learning as much about it as I can.
    b. try to make connections between that subject and related subject.
37. I am more likely to be considered
    a. outgoing.
    b. reserved.

38. I prefer courses that emphasize
    a. concrete material (facts, data)
    b. abstract material (concepts, theories)

39. For entertainment, I would rather
    a. watch television.
    b. read a book.

40. Some teachers start their lectures with an outline of what they will cover. Such outlines are
    a. somewhat helpful to me.
    b. very helpful to me.

41. The idea of doing homework in groups, with one grade for the entire group,
    a. appeals to me.
    b. does not appeal to me.

42. When I am doing long calculations,
    a. I tend to repeat all my steps and check my work carefully.
    b. I find checking my work tiresome and have to force myself to do it.

43. I tend to picture places I have been
    a. easily and fairly accurately.
    b. with difficulty and without much detail.

44. When solving problems in a group, I would be more likely to
    a. think of the steps in the solution process.
    b. think of possible consequences or applications of the solution in a wide range of areas.

## ILS SCORING SHEET

1. Put “1’s in the appropriate spaces in the table below (e.g. if you answered “a” to Question 3, put a “1” in Column A by Question 3).

2. Total the columns and write the totals in the indicated spaces.

3. For each of the four scales, subtract the smaller total from the larger one. Write the difference (1 to 11) and the letter (a or b) for which the total was larger on the bottom line.

   For example, if under “ACT/REF” you had 4 “a” and 7 “b” responses, you would write “3b” on the bottom line under that heading.

4. On the next page, mark "X"s above your scores on each of the four scales.

| ACT/REF | | | SNS/INT | | | VIS/VRB | | | SEQ/GLO | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Q | a | b | Q | a | b | Q | a | b | Q | a | b |
| 1 | ___ | ___ | 2 | ___ | ___ | 3 | ___ | ___ | 4 | ___ | ___ |
| 5 | ___ | ___ | 6 | ___ | ___ | 7 | ___ | ___ | 8 | ___ | ___ |
| 9 | ___ | ___ | 10 | ___ | ___ | 11 | ___ | ___ | 12 | ___ | ___ |
| 13 | ___ | ___ | 14 | ___ | ___ | 15 | ___ | ___ | 16 | ___ | ___ |
| 17 | ___ | ___ | 18 | ___ | ___ | 19 | ___ | ___ | 20 | ___ | ___ |
| 21 | ___ | ___ | 22 | ___ | ___ | 23 | ___ | ___ | 24 | ___ | ___ |
| 25 | ___ | ___ | 26 | ___ | ___ | 27 | ___ | ___ | 28 | ___ | ___ |
| 29 | ___ | ___ | 30 | ___ | ___ | 31 | ___ | ___ | 32 | ___ | ___ |
| 33 | ___ | ___ | 34 | ___ | ___ | 35 | ___ | ___ | 36 | ___ | ___ |
| 37 | ___ | ___ | 38 | ___ | ___ | 39 | ___ | ___ | 40 | ___ | ___ |
| 41 | ___ | ___ | 42 | ___ | ___ | 43 | ___ | ___ | 44 | ___ | ___ |

**Total (sum X's in each column)**

| ACT/REF | | SNS/INT | | VIS/VRB | | SEQ/GLO | |
|---|---|---|---|---|---|---|---|
| a | b | a | b | a | b | a | b |
| ___ | ___ | ___ | ___ | ___ | ___ | ___ | ___ |

**(Larger – Smaller) + Letter of Larger (see below*)**

| | | | |
|---|---|---|---|
| _____ | _____ | _____ | _____ |

*Example: If you totaled 3 for a and 8 for b, you would enter 5b in the space below.

## ILS REPORT FORM

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ACT** | 11a | 9a | 7a | 5a | 3a | 1a | 1b | 3b | 5b | 7b | 9b | 11b | **REF** |
| **SEN** | 11a | 9a | 7a | 5a | 3a | 1a | 1b | 3b | 5b | 7b | 9b | 11b | **INT** |
| **VIS** | 11a | 9a | 7a | 5a | 3a | 1a | 1b | 3b | 5b | 7b | 9b | 11b | **VRB** |
| **SEQ** | 11a | 9a | 7a | 5a | 3a | 1a | 1b | 3b | 5b | 7b | 9b | 11b | **GLO** |

If your score on a scale is 1-3, you are fairly well balanced on the two dimensions of that scale.

If your score on a scale is 5 or 7, you have a moderate preference for one dimension of the scale and will learn more easily in a teaching environment which favors that dimension.

If your score on a scale is 9 or 11, you have a very strong preference for one dimension of the scale. You may have real difficulty learning in an environment which does not support that preference.

# Appendix B

## Summary of Learning Object Type Mapping by Education Experts For Computer Programming 1 Moodle Course

| Evaluators | | | |
|---|---|---|---|
| **No.** | **Experts** | **Educational Attainment** | **Designation (SLSU)** |
| 1 | Teresita V. De la Cruz | Doctor of Education | Dean, College of Education |
| 2 | Ricaryl Catherine P. Cruz | Doctor of Education | Dean, Graduate School |
| 3 | Clarrisa D. Maguyon | Doctor of Education | Director of Instruction |

| Learning Object Types | | |
|---|---|---|
| **No.** | **Learning Object Type** | **Description** |
| 1 | overview | The learning object is a chapter overview or chapter outline |
| 2 | video | The learning object is a video presentation |
| 3 | abstract | The learning object context is abstract in nature |
| 4 | concrete | The learning object context is concrete in nature |
| 5 | visual | The learning object is presented with pictures, diagrams or graphs |
| 6 | textual | The learning object is presented in textual form |
| 7 | example | The learning object is primarily composed of example |
| 8 | exercise | The learning object is a type of quiz that is graded |
| 9 | self-assessment | The learning object is a type of quiz that is not graded |
| 10 | forum | The learning object is used for discussion |

| Mapping of Learning Objects for Chapter 1 (C++ Basics) | | | | |
|---|---|---|---|---|
| **Learning Object (Topic Title)** | **Expert 1** | **Expert 2** | **Expert 3** | **Overall Evaluation** |
| Page: Chapter 1 Overview | overview | overview | overview | overview |
| Page: Origins of the C++ Language | video | video | video | video |
| Page: C++ Terminology | abstract | abstract | abstract | abstract |
| Page: A Sample C++ Program | example | example | example | example |
| Page: Identifiers | visual | visual | visual | visual |
| Page: Variables | visual | abstract | visual | visual |
| Page: Assignment Statements | abstract | textual | textual | textual |
| Page: Literals | textual | textual | abstract | textual |
| Page: Naming Constants | textual | textual | textual | textual |
| Page: Arithmetic Operators and Expressions | textual | textual | textual | textual |
| Page: Type Casting | textual | concrete | textual | textual |
| Page: Increment and Decrement Operators | textual | textual | textual | textual |
| Page: Output Using cout | visual | visual | visual | textual |
| Page: New Lines in Output | visual | visual | visual | visual |
| Page: Input using cin | video | video | video | video |
| Quiz: Exercise 1 | exercise | exercise | exercise | exercise |
| Quiz: Self Assessment 1 | self-assessment | self-assessment | self-assessment | self-assessment |
| Glossary: Glossary 1 | abstract | abstract | abstract | abstract |

| Mapping of Learning Objects for Chapter 2 (Flow of Control) | | | | |
|---|---|---|---|---|
| **Learning Object (Topic Title)** | **Expert 1** | **Expert 2** | **Expert 3** | **Overall Evaluation** |
| Page: Chapter 2 Overview | overview | overview | overview | overview |
| Page: Building Boolean Expressions | visual | visual | visual | visual |
| Page: Precedence Rules | textual | concrete | concrete | concrete |
| Page: IF - ELSE Statement | visual | visual | visual | visual |
| Page: Compound Statements | textual | textual | textual | textual |
| Page: Nested Statements | visual | concrete | visual | visual |
| Page: Multiway IF - ELSE Statement | abstract | textual | textual | textual |
| Page: The Switch Statement | visual | visual | visual | visual |
| Page: The conditional operator | textual | textual | textual | textual |
| Page: The WHILE and DO - WHILE Statements | video | video | video | video |
| Page: The FOR Statement | visual | visual | visual | visual |
| Page: BREAK and CONTINUE Statement | concrete | concrete | concrete | concrete |
| Page: Nested Loops | textual | textual | textual | textual |
| Page: Example - Loop Program | example | example | example | examples |
| Quiz: Exercise 2 | exercise | exercise | exercise | exercises |
| Quiz: Self Assessment 2 | self-assessment | self-assessment | self-assessment | self-assessment |
| Glossary: Glossary 2 | abstract | abstract | abstract | abstract |

| Mapping of Learning Objects for Chapter 3 (Function Basics) | | | | |
|---|---|---|---|---|
| **Learning Object (Topic Title)** | **Expert 1** | **Expert 2** | **Expert 3** | **Overall Evaluation** |
| Page: Chapter 3 Overview | overview | overview | overview | overview |
| Page: Predefined Functions that return a Value | textual | textual | concrete | textual |
| Page: Predefined void Functions | textual | textual | textual | textual |
| Page: A random number generator | example | example | textual | example |
| Page: Defining functions that return a value | textual | example | textual | textual |
| Page: Alternate Form for Function Declarations | textual | textual | textual | textual |
| Page: Example - A rounding function | example | example | concrete | example |
| Page: Preconditions and Postconditions | concrete | concrete | concrete | concrete |
| Page: Recursive Functions | video | video | video | video |
| Page: Local Variables | concrete | textual | concrete | concrete |
| Page: Procedural Abstraction | video | video | video | video |
| Page: Global Constants and Global Variables | visual | visual | visual | visual |
| Page: Blocks | concrete | concrete | concrete | concrete |
| Page: Nested Scopes | concrete | concrete | concrete | concrete |
| Quiz: Exercise 3 | exercise | exercise | exercise | exercise |
| Quiz: Self Assessment 3 | self-assessment | self-assessment | self-assessment | self-assessment |
| Glossary: Glossary 3 | abstract | abstract | abstract | abstract |

| Mapping of Learning Objects for Chapter 4 (Arrays) | | | | |
|---|---|---|---|---|
| **Learning Object (Topic Title)** | **Expert 1** | **Expert 2** | **Expert 3** | **Overall Evaluation** |
| Page: Chapter 4 Overview | overview | overview | overview | overview |
| Page: Declaring and Referencing Arrays | video | video | video | video |
| Page: Use for Loop with Arrays | video | video | video | video |
| Page: Arrays in Memory | visual | concrete | visual | visual |
| Page: Initializing Arrays | video | video | video | video |
| Page: Indexed Variables as Function Arguments | textual | textual | textual | textual |
| Page: Entire Arrays as Function Arguments | concrete | textual | textual | textual |
| Page: The const Parameter Modifier | textual | textual | textual | textual |
| Page: Example - Functions that return an Array | example | example | example | example |
| Page: Production Graph | example | example | example | example |
| Page: Partially filled Arrays | textual | textual | textual | textual |
| Page: Example - Searching an Array | example | example | example | example |
| Page: Multidimensional Array Basics | video | video | video | video |
| Page: Multidimensional Array Parameters | abstract | textual | textual | textual |
| Page: Example - Two Dimensional Array Grading Program | example | example | example | example |
| Quiz: Exercise 4 | exercise | exercise | exercise | exercise |
| Quiz: Self Assessment 4 | self-assessment | self-assessment | self-assessment | self-assessment |
| Glossary: Glossary 4 | abstract | abstract | abstract | abstract |

| Mapping of Learning Objects for Chapter 5 (Structures and Classes) | | | | |
|---|---|---|---|---|
| **Learning Object (Topic Title)** | **Expert 1** | **Expert 2** | **Expert 3** | **Overall Evaluation** |
| Page: Chapter 5 Overview | overview | overview | overview | overview |
| Page: Structure Types | video | video | video | video |
| Page: Structure as Function Arguments | visual | visual | visual | visual |
| Page: Use Hierarchical Structure | visual | visual | concrete | visual |
| Page: Initializing Structures | visual | visual | visual | visual |
| Page: Defining Classes and Member Functions | textual | textual | textual | textual |
| Page: Encapsulation | visual | visual | abstract | visual |
| Page: Public and Private Member | textual | textual | textual | textual |
| Page: Accessor and Mutator Functions | textual | textual | textual | textual |
| Page Separate Interface and Implementation | textual | textual | textual | textual |
| Page: Structure versus Classes | concrete | textual | concrete | concrete |
| Quiz: Exercise 5 | exercise | exercise | exercise | exercise |
| Quiz: Self Assessment 5 | self-assessment | self-assessment | self-assessment | self-assessment |
| Glossary: Glossary 5 | abstract | abstract | abstract | abstract |

# Appendix C

## Full Results of Feature Selection for the Data Sets

## Using Different Techniques

## I. Processing Dimension (Active/Reflective)

### A. Logistic Regression (*Forward - Likelihood Ratio*)

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | forum_view | .422 | .038 | 122.461 | 1 | .000 | 1.526 |
| | Constant | -3.469 | .332 | 109.202 | 1 | .000 | .031 |
| Step 2[b] | forum_post | -.193 | .024 | 64.590 | 1 | .000 | .824 |
| | forum_view | .462 | .045 | 103.515 | 1 | .000 | 1.588 |
| | Constant | -2.043 | .377 | 29.343 | 1 | .000 | .130 |
| Step 3[c] | forum_post | -.207 | .028 | 53.126 | 1 | **.000** | .813 |
| | forum_view | .443 | .051 | 75.728 | 1 | **.000** | 1.557 |
| | self_assesment | -.585 | .085 | 47.228 | 1 | **.000** | .557 |
| | Constant | -.274 | .468 | .341 | 1 | .559 | .761 |

a. Variable(s) entered on step 1: forum_view.

b. Variable(s) entered on step 2: forum_post.

c. Variable(s) entered on step 3: self_assesment.

### B. Subset Evaluation (*CfsSubsetEval, BestFirst, 10-Fold Cross Validation*)

=== Attribute selection 10 fold cross-validation (stratified), seed: 1 ===

| **Number of folds (%)** | **Attribute** |
|---|---|
| 10 (100 %) | 1 forum_post |
| 10 (100 %) | 2 forum_view |
| 10 (100 %) | 3 self_assesment |
| 0 (0 %) | 4 text_materials |

### C. Information Gain Attribute Evaluation (*InfoGainAttributeEval, Ranker, Use full training set*)

=== Attribute Selection on all input data ===

Attribute Evaluator (supervised, Class (nominal): 5 PROCESSING):
Information Gain Ranking Filter

| **Ranked** | **Attributes** |
|---|---|
| 0.449 | 2 forum_view |
| 0.338 | 3 self_assesment |
| 0.267 | 1 forum_post |
| 0 | 4 text_materials |

## II. Perception Dimension (Sensing/Intuitive)

### A. Logistic Regression (*Forward - Likelihood Ratio*)

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | concrete_materials | .392 | .039 | 102.530 | 1 | .000 | 1.480 |
| | Constant | -2.642 | .323 | 66.965 | 1 | .000 | .071 |
| Step 2[b] | concrete_materials | .402 | .044 | 83.887 | 1 | .000 | 1.495 |
| | exercises_rev | -.237 | .034 | 47.114 | 1 | .000 | .789 |
| | Constant | -.847 | .417 | 4.135 | 1 | .042 | .429 |
| Step 3[c] | concrete_materials | .403 | .045 | 81.401 | 1 | .000 | 1.496 |
| | examples | .107 | .038 | 7.929 | 1 | .005 | 1.113 |
| | exercises_rev | -.229 | .035 | 43.067 | 1 | .000 | .795 |
| | Constant | -1.768 | .541 | 10.697 | 1 | .001 | .171 |
| Step 4[d] | concrete_materials | .408 | .045 | 80.727 | 1 | **.000** | 1.503 |
| | abstract_materials | -.077 | .032 | 5.798 | 1 | **.016** | .926 |
| | examples | .111 | .039 | 8.251 | 1 | **.004** | 1.118 |
| | exercises_rev | -.230 | .035 | 43.135 | 1 | **.000** | .794 |
| | Constant | -1.143 | .601 | 3.618 | 1 | .057 | .319 |

### B. Subset Evaluation (*CfsSubsetEval, BestFirst, 10-Fold Cross Validation*)

=== Attribute selection 10 fold cross-validation (stratified), seed: 1 ===

| **Number of folds (%)** | **Attribute** |
|---|---|
| 10 (100 %) | 1 concrete_materials |
| 10 (100 %) | 2 abstract_materials |
| 10 (100 %) | 3 examples |
| 10 (100 %) | 4 exercise_rev |

### C. Information Gain Attribute Evaluation (*InfoGainAttributeEval, Ranker, Use full training set*)

=== Attribute Selection on all input data ===

Attribute Evaluator (supervised, Class (nominal): 5 PERCEPTION):
Information Gain Ranking Filter

| **Ranked** | **Attributes** |
|---|---|
| 0.3533 | 1 concrete_materials |
| 0.2413 | 4 exercise_rev |
| 0.1071 | 3 examples |
| 0.0939 | 2 abstract_materials |

## III. Input Dimension (Visual/Verbal)

### A. Logistic Regression (*Forward - Likelihood Ratio*)

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | video_materials | .448 | .047 | 90.027 | 1 | .000 | 1.565 |
| | Constant | -3.473 | .453 | 58.889 | 1 | .000 | .031 |
| Step 2[b] | visual_materials | .225 | .032 | 48.327 | 1 | **.000** | 1.252 |
| | video_materials | .462 | .056 | 68.480 | 1 | **.000** | 1.588 |
| | Constant | -6.102 | .691 | 77.953 | 1 | .000 | .002 |

a. Variable(s) entered on step 1: video_materials.

b. Variable(s) entered on step 2: visual_materials.

### B. Subset Evaluation (*CfsSubsetEval, BestFirst, 10-Fold Cross Validation*)

=== Attribute selection 10 fold cross-validation (stratified), seed: 1 ===

| **Number of folds (%)** | **Attribute** |
|---|---|
| 10 (100 %) | 1 visual_materials |
| 0 (100 %) | 2 text_materials |
| 10 (100 %) | 3 video_materials |
| 0 (100 %) | 4 forum_posts |

### C. Information Gain Attribute Evaluation (*InfoGainAttributeEval, Ranker, Use full training set*)

=== Attribute Selection on all input data ===

Attribute Evaluator (supervised, Class (nominal): 5 INPUT):
Information Gain Ranking Filter

| **Ranked** | **Attributes** |
|---|---|
| 0.382 | 3 video_materials |
| 0.269 | 1 visual_materials |
| 0 | 4 forum_post |
| 0 | 2 text_materials |

## IV. Understanding Dimension (Sequential/Global)

### A. Logistic Regression (*Forward - Likelihood Ratio*)

**Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | course_overviews | -.768 | .075 | 103.454 | 1 | .000 | .464 |
| | Constant | 2.118 | .229 | 85.394 | 1 | .000 | 8.312 |
| Step 2[b] | course_overviews | -.810 | .079 | 106.289 | 1 | **.000** | .445 |
| | nav_pattern_distance | -.205 | .047 | 18.816 | 1 | **.000** | .815 |
| | Constant | 3.486 | .404 | 74.490 | 1 | .000 | 32.654 |

a. Variable(s) entered on step 1: course_overviews.

b. Variable(s) entered on step 2: nav_pattern_distance.

### B. Subset Evaluation (*CfsSubsetEval, BestFirst, 10-Fold Cross Validation*)

=== Attribute selection 10 fold cross-validation (stratified), seed: 1 ===

| **Number of folds (%)** | **Attribute** |
|---|---|
| 10 (100 %) | 1 course_overviews |
| 10 (100 %) | 2 nav_pattern_distance |

### C. Information Gain Attribute Evaluation (*InfoGainAttributeEval, Ranker, Use full training set*)

=== Attribute Selection on all input data ===

Attribute Evaluator (supervised, Class (nominal): 3 UNDERSTANDING):
Information Gain Ranking Filter

| **Ranked** | **Attributes** |
|---|---|
| 0.2851 | 1 course_overviews |
| 0.0399 | 2 nav_pattern_distance |

# Appendix D

## Full Classification Performance Results for J48 Decision Tree Classifier

## I. Processing Dimension (Active/Reflective)

### === Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: Processing Dimension
Instances: 507
Attributes: 5
forum_posts
forum_view
self_assesment
text_materials
PROCESSING

Test mode: 10-fold cross-validation

### === Classifier model (full training set) ===

Number of Leaves : 4
Size of the Tree : 7

Time taken to build model: 0.03 seconds

### === Stratified cross-validation ===
### === Summary ===

| | | |
|---|---|---|
| **Correctly Classified Instances** | 469 | 92.5077% |
| **Incorrectly Classified Instances** | 38 | 7.4951% |
| **Kappa statistic** | 0.8491 | |
| **Mean absolute error** | 0.1281 | |
| **Root mean squared error** | 0.2549 | |
| **Relative absolute error** | 25.6643% | |
| **Root relative squared error** | 51.0124% | |
| **Total Number of Instances** | 507 | |

### === Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class |
|---|---|---|---|---|---|---|---|
| | 0.852 | 0.008 | 0.99 | 0.852 | 0.916 | 0.918 | ACTIVE |
| | 0.992 | 0.148 | 0.879 | 0.992 | 0.932 | 0.918 | REFLECTIVE |
| **Weighted Avg.** | 0.925 | 0.08 | 0.933 | 0.925 | 0.925 | 0.918 | |

### === Confusion Matrix ===

| | Active | Reflective |
|---|---|---|
| **Active** | 208 | 36 |
| **Reflective** | 2 | 261 |

## II. Perception Dimension (Sensing/Intuitive)

### === Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: Perception Dimension
Instances: 507
Attributes: 5
concrete_materials
abstract_materials
examples
exercises_rev
PERCEPTION

Test mode: 10-fold cross-validation

### === Classifier model (full training set) ===

Number of Leaves : 7
Size of the Tree : 13

Time taken to build model: 0.01 seconds

### === Stratified cross-validation ===
### === Summary ===

| | | |
|---|---|---|
| **Correctly Classified Instances** | 447 | 88.1657% |
| **Incorrectly Classified Instances** | 60 | 11.8343% |
| **Kappa statistic** | 0.6994 | |
| **Mean absolute error** | 0.1882 | |
| **Root mean squared error** | 0.316 | |
| **Relative absolute error** | 43.6885% | |
| **Root relative squared error** | 68.1137% | |
| **Total Number of Instances** | 507 | |

### === Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class |
|---|---|---|---|---|---|---|---|
| | 0.654 | 0.014 | 0.954 | 0.654 | 0.776 | 0.832 | INTUITIVE |
| | 0.986 | 0.346 | 0.862 | 0.986 | 0.920 | 0.832 | SENSING |
| **Weighted Avg.** | 0.882 | 0.242 | 0.891 | 0.882 | 0.875 | 0.832 | |

### === Confusion Matrix ===

| | Intuitive | Sensing |
|---|---|---|
| **Intuitive** | 104 | 55 |
| **Sensing** | 5 | 343 |

## III. Input Dimension (Visual/Verbal)

### === Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: Input Dimension
Instances: 507
Attributes: 5
visual_materials
video_materials
INPUT

Test mode: 10-fold cross-validation

### === Classifier model (full training set) ===

Number of Leaves : 3
Size of the Tree : 5

Time taken to build model: 0.02 seconds

### === Stratified cross-validation ===
### === Summary ===

| | | |
|---|---|---|
| **Correctly Classified Instances** | 439 | 86.5878% |
| **Incorrectly Classified Instances** | 68 | 13.4122% |
| **Kappa statistic** | 0.6774 | |
| **Mean absolute error** | 0.17 | |
| **Root mean squared error** | 0.295 | |
| **Relative absolute error** | 47.2262% | |
| **Root relative squared error** | 69.5993% | |
| **Total Number of Instances** | 507 | |

### === Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class |
|---|---|---|---|---|---|---|---|
| | 0.843 | 0.059 | 0.979 | 0.843 | 0.906 | 0.902 | VISUAL |
| | 0.941 | 0.157 | 0.647 | 0.941 | 0.767 | 0.902 | VERBAL |
| **Weighted Avg.** | 0.866 | 0.082 | 0.901 | 0.866 | 0.873 | 0.902 | |

### === Confusion Matrix ===

| | Visual | Verbal |
|---|---|---|
| **Visual** | 327 | 61 |
| **Verbal** | 7 | 112 |

## IV. Understanding Dimension (Sequential/Global)

### === Run information ===

| | |
|---|---|
| Scheme: | weka.classifiers.trees.J48 -C 0.25 -M 2 |
| Relation: | Understanding Dimension |
| Instances: | 507 |
| Attributes: | 3 |
| | course_overviews |
| | nav_pattern_distance |
| | UNDERSTANDING |
| Test mode: | 10-fold cross-validation |

### === Classifier model (full training set) ===

Number of Leaves : 3
Size of the Tree : 5

Time taken to build model: 0.01 seconds

### === Stratified cross-validation ===
### === Summary ===

| | | |
|---|---|---|
| **Correctly Classified Instances** | 418 | 82.4458% |
| **Incorrectly Classified Instances** | 89 | 17.5542% |
| **Kappa statistic** | 0.6477 | |
| **Mean absolute error** | 0.2743 | |
| **Root mean squared error** | 0.3716 | |
| **Relative absolute error** | 54.8608% | |
| **Root relative squared error** | 74.3356% | |
| **Total Number of Instances** | 507 | |

### === Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | ROC Area | Class |
|---|---|---|---|---|---|---|---|
| | 0.700 | 0.054 | 0.926 | 0.700 | 0.797 | 0.812 | SEQUENTIAL |
| | 0.946 | 0.300 | 0.764 | 0.946 | 0.845 | 0.812 | GLOBAL |
| **Weighted Avg.** | 0.824 | 0.179 | 0.844 | 0.824 | 0.822 | 0.812 | |

### === Confusion Matrix ===

| | Sequential | Global |
|---|---|---|
| **Sequential** | 175 | 75 |
| **Global** | 14 | 243 |

## Appendix E

## Comparative Performance Results of Classification using Different Techniques

| Performance in Processing Dimension (Active/Reflective) | | | | |
|---|---|---|---|---|
| | Simple Logistic | Naïve Bayes | Conjunctive Rule | J48 |
| **Correctly Classified Instances** | 85.99% | 89.34% | 75.14% | 92.50% |
| **Incorrectly Classified Instances** | 14.01% | 10.65% | 24.85% | 7.49% |
| **Kappa statistic** | 0.719 | 0.786 | 0.497 | 0.849 |
| **Mean absolute error** | 0.226 | 0.156 | 0.330 | 0.128 |
| **Root mean squared error** | 0.311 | 0.2838 | 0.409 | 0.254 |
| **Relative absolute error** | 45.34% | 31.32% | 66.14% | 25.66% |
| **Root relative squared error** | 62.42% | 56.79% | 81.86% | 51.01% |
| **Precision** | 0.861 | 0.895 | 0.766 | 0.933 |
| **Recall** | 0.860 | 0.893 | 0.751 | 0.925 |
| **F-Measure** | 0.860 | 0.893 | 0.746 | 0.925 |
| **Total Number of Instances** | 507 | 507 | 507 | 507 |

| Performance in Perception Dimension (Sensing/Intuitive) | | | | |
|---|---|---|---|---|
| | Simple Logistic | Naïve Bayes | Conjunctive Rule | J48 |
| **Correctly Classified Instances** | 81.65% | 82.24% | 68.63% | 88.16% |
| **Incorrectly Classified Instances** | 18.34% | 17.75% | 31.36% | 11.83% |
| **Kappa statistic** | 0.550 | 0.586 | 0 | 0.699 |
| **Mean absolute error** | 0.263 | 0.236 | 0.430 | 0.188 |
| **Root mean squared error** | 0.356 | 0.350 | 0.464 | 0.316 |
| **Relative absolute error** | 61.21% | 54.82% | 100.00% | 43.68% |
| **Root relative squared error** | 76.79% | 75.58% | 99.99% | 68.11% |
| **Precision** | 0.812 | 0.822 | 0.471 | 0.891 |
| **Recall** | 0.817 | 0.822 | 0.686 | 0.882 |
| **F-Measure** | 0.811 | 0.822 | 0.559 | 0.875 |
| **Total Number of Instances** | 507 | 507 | 507 | 507 |

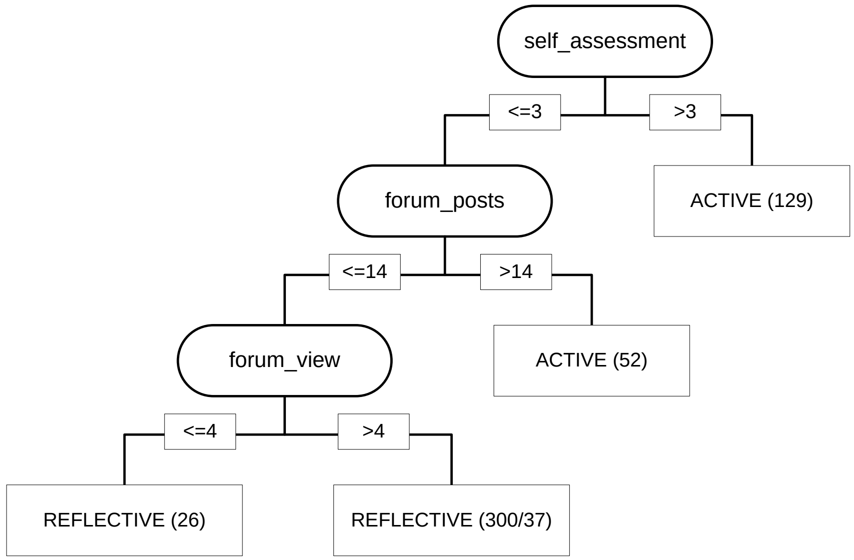
| Performance in Input Dimension (Visual/Verbal) | | | | |
|---|---|---|---|---|
| | Simple Logistic | Naïve Bayes | Conjunctive Rule | J48 |
| **Correctly Classified Instances** | 85.79% | 85.99% | 76.52% | 86.58% |
| **Incorrectly Classified Instances** | 14.20% | 14.00% | 23.47% | 13.41% |
| **Kappa statistic** | 0.582 | 0.634 | 0 | 0.677 |
| **Mean absolute error** | 0.205 | 0.164 | 0.359 | 0.170 |
| **Root mean squared error** | 0.302 | 0.295 | 0.423 | 0.295 |
| **Relative absolute error** | 57.06% | 45.66% | 99.77% | 47.22% |
| **Root relative squared error** | 71.29% | 69.94% | 100.00% | 69.59% |
| **Precision** | 0.852 | 0.872 | 0.586 | 0.901 |
| **Recall** | 0.858 | 0.860 | 0.765 | 0.866 |
| **F-Measure** | 0.854 | 0.864 | 0.664 | 0.873 |
| **Total Number of Instances** | 507 | 507 | 507 | 507 |

| Performance in Understanding Dimension (Sequential/Global) | | | | |
|---|---|---|---|---|
| | Simple Logistic | Naïve Bayes | Conjunctive Rule | J48 |
| **Correctly Classified Instances** | 80.27% | 74.95% | 81.26% | 82.44% |
| **Incorrectly Classified Instances** | 19.72% | 25.04% | 18.73% | 17.55% |
| **Kappa statistic** | 0.605 | 0.500 | 0.624 | 0.647 |
| **Mean absolute error** | 0.383 | 0.330 | 0.287 | 0.274 |
| **Root mean squared error** | 0.426 | 0.407 | 0.385 | 0.371 |
| **Relative absolute error** | 76.72% | 66.19% | 57.53% | 54.86% |
| **Root relative squared error** | 85.26% | 81.57% | 77.07% | 74.33% |
| **Precision** | 0.804 | 0.758 | 0.826 | 0.844 |
| **Recall** | 0.803 | 0.750 | 0.813 | 0.824 |
| **F-Measure** | 0.802 | 0.748 | 0.810 | 0.822 |
| **Total Number of Instances** | 507 | 507 | 507 | 507 |

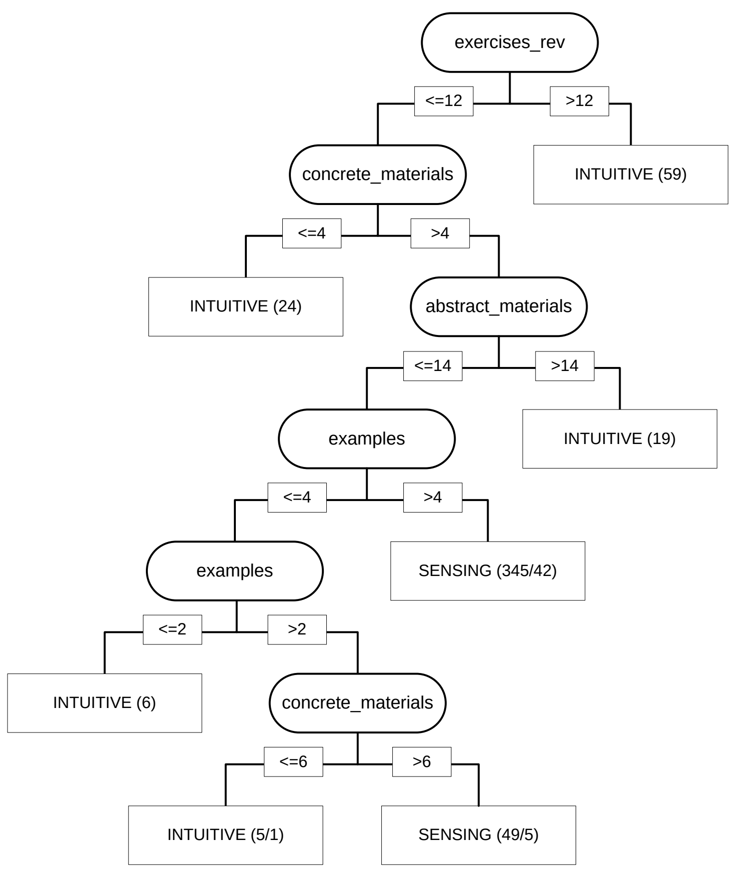
## Appendix F

## Rule Sets Derived from J48 Decision Tree Classifier

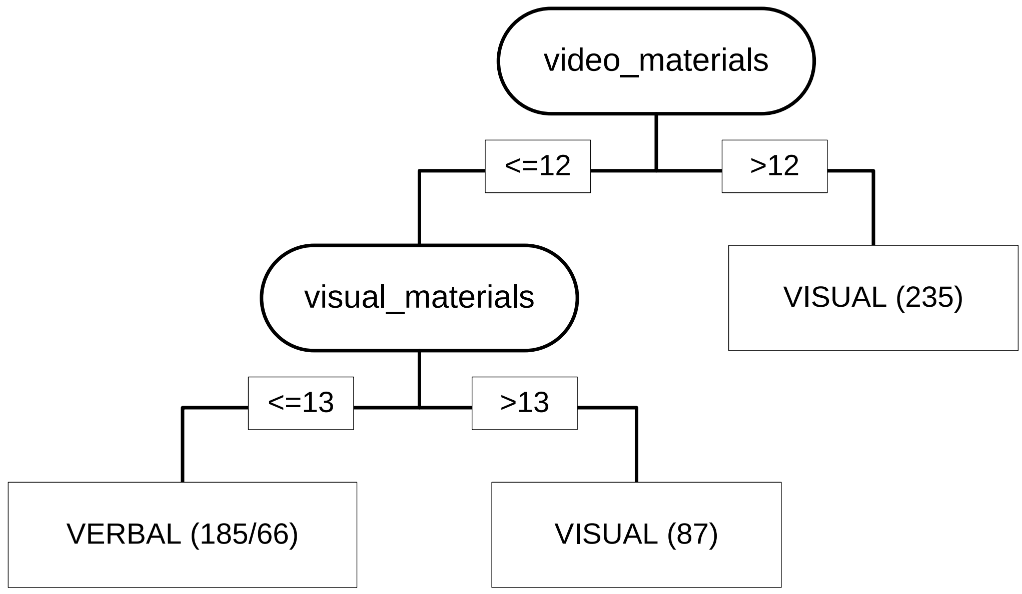
### I. Processing Dimension (Active/Reflective)



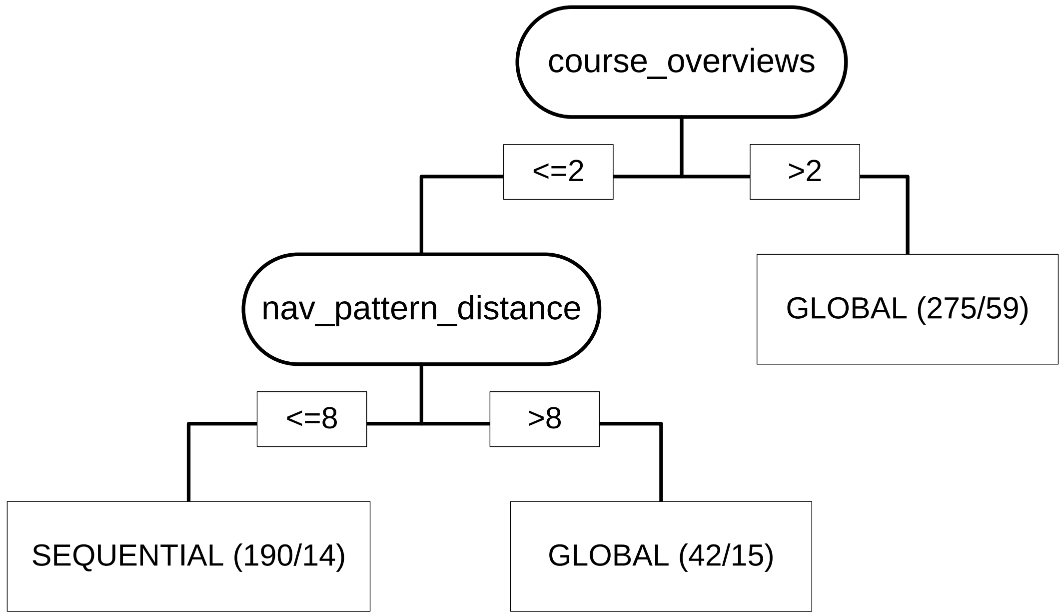

### II. Perception Dimension (Sensing/Intuitive)



**III. Input Dimension (Visual/Verbal)**




**IV. Understanding Dimension (Sequential/Global)**



## Appendix G

## Software Quality Survey

**Name of Respondent (Optional):** ____________________________________
**College/University/Industry:** ____________________________________

**Dear Respondents,**

I am Renato R. Maaliw III, a DIT student from AMA Computer University, Project 8, Quezon City and currently conducting my dissertation entitled **"Adaptive Virtual Learning Environment for Different Learning Styles Using J48 Decision Tree"**. In lieu of this, may I ask a little of your time to test and evaluate the system based from its functionality, usability and reliability. The responses you provide in this questionnaire will be kept confidential. Thank you very much.

Rate the following characteristics of the system by placing a check (✓) mark on the space provided.

**5** - Highly Acceptable
**4** - Acceptable
**3** - Uncertain
**2** - Unacceptable
**1** - Highly Unacceptable

| No. | Functionality | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|
| 1 | The organization of information on the system screens is clear. | | | | | |
| 2 | It is easy to find the information I needed. | | | | | |
| 3 | The information is effective in helping me complete the tasks and scenarios. | | | | | |
| 4 | Information (such as on-screen messages) provided with this system is clear. | | | | | |
| 5 | The system has all the features and capabilities I expect it to. | | | | | |
| | **Usability** | | | | | |
| 6 | Overall, I am satisfied with how easy it is to use the system. | | | | | |
| 7 | It was simple to use the system. | | | | | |
| 8 | I can effectively complete my work using the system. | | | | | |
| 9 | It was easy to learn to use the system. | | | | | |
| 10 | The interface of the system is pleasant. | | | | | |
| | **Reliability** | | | | | |
| 11 | The system gives error messages that clearly tells me how to fix the problems | | | | | |
| 12 | Whenever I make mistakes using the system, I recover easily and quickly | | | | | |
| 13 | The system generates correct and accurate results | | | | | |
| 14 | The system provides error messages in wrong data entries | | | | | |
| 15 | The system is free from system error and crashes | | | | | |

## Appendix H

### Software Quality Evaluation Results (ISO/IEC 20510)

| Functionality | Weighted Mean | Interpretation |
|---|---|---|
| The organization of information on the system screens is clear. | 4.50 | Highly Acceptable |
| It is easy to find the information I needed. | 4.40 | Acceptable |
| The information is effective in helping me complete the tasks and scenarios. | 4.60 | Highly Acceptable |
| Information (such as on-screen messages) provided with this system is clear. | 4.40 | Acceptable |
| The system has all the features and capabilities I expect it to. | 4.30 | Acceptable |
| **Average Weighted Mean** | **4.44** | **Acceptable** |

| Usability | Weighted Mean | Interpretation |
|---|---|---|
| Overall, I am satisfied with how easy it is to use the system. | 4.70 | Highly Acceptable |
| It was simple to use the system. | 4.80 | Acceptable |
| I can effectively complete my work using the system. | 4.60 | Highly Acceptable |
| It was easy to learn to use the system. | 4.50 | Acceptable |
| The interface of the system is pleasant. | 4.50 | Acceptable |
| **Average Weighted Mean** | **4.62** | **Highly Acceptable** |

| Reliability | Weighted Mean | Interpretation |
|---|---|---|
| The system gives error messages that clearly tells me how to fix the problems | 4.40 | Acceptable |
| Whenever I make mistakes using the system, I recover easily and quickly | 4.40 | Acceptable |
| The system generates correct and accurate results | 4.50 | Highly Acceptable |
| The system provides error messages in wrong data entries | 4.70 | Highly Acceptable |
| The system is free from system error and crashes | 4.60 | Highly Acceptable |
| **Average Weighted Mean** | **4.52** | **Highly Acceptable** |

| Overall Weighted Mean for Software Evaluation | | |
|---|---|---|
| **Criteria** | **Weighted Mean** | **Interpretation** |
| Functionality | 4.44 | Acceptable |
| Usability | 4.62 | Acceptable |
| Reliability | 4.52 | Highly Acceptable |
| **Average Weighted Mean** | **4.51** | **Highly Acceptable** |

# CURRICULUM VITAE

# RENATO R. MAALIW III

150 A. Bonifacio St.
Lucban, Quezon, Philippines
rmaaliw@slsu.edu.ph


| | |
|---|---|
| Date of Birth | **December 9, 1982** |
| Place of Birth | **Lucban, Quezon** |
| Citizenship | **Filipino** |
| Civil Status | **Married** |
| Gender | **Male** |

| | |
|---|---|
| 2016 – present | **ASSISTANT PROFESSOR III**<br>Southern Luzon State University<br>Lucban, Quezon, Philippines |
| 2012 – 2015 | **INSTRUCTOR II**<br>Southern Luzon State University<br>Lucban, Quezon, Philippines |
| 2010 – 2011 | **INSTRUCTOR I**<br>Southern Luzon State University<br>Lucban, Quezon, Philippines |
| 2006 – 2009 | **CONTRACTUAL INSTRUCTOR**<br>Southern Luzon State University<br>Lucban, Quezon, Philippines |
| 2005 – 2006 | **FRONT-END WEB DEVELOPER**<br>i2Sys Systems Inc.<br>Makati City, Philippines |

## EDUCATION

2013 – 2017 **Doctor in Information Technology**
AMA University
Quezon City, Philippines

2011 – 2012 **Professional Teaching Certification Program**
Leon Guinto Memorial College
Atimonan, Quezon, Philippines

2008 – 2010 **Master in Information Technology**
Manuel S. Enverga University Foundation
Lucena City, Philippines

1999 – 2005 **Bachelor of Science in Computer Engineering**
AMA University
Quezon City, Philippines

## ELIGIBILITY AND CERTIFICATION

2014 **Certified Web Developer**
BrainBench International

2014 **Certified Computer Programmer**
BrainBench International

2013 **Licensed Professional Teacher (LPT)**
Professional Regulation Commission

2013 **Level 1 IT Professional Certification (IT Passport)**
Philippine National IT Standards (PhilNITS) Foundation

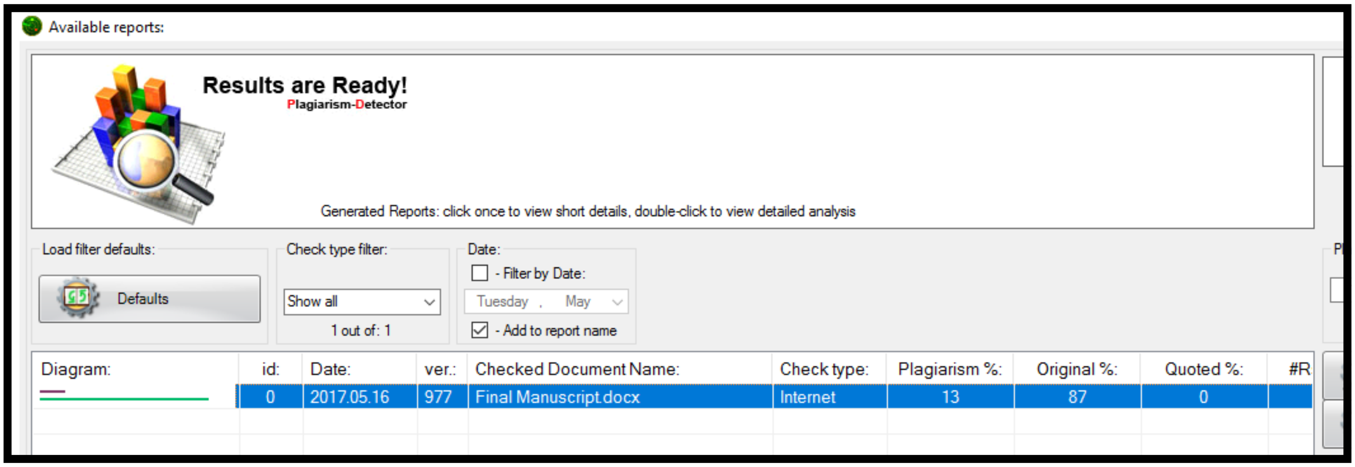
2012 **Zend Certified PHP Engineer (ZCPE)**
RogueWave Software (Zend)

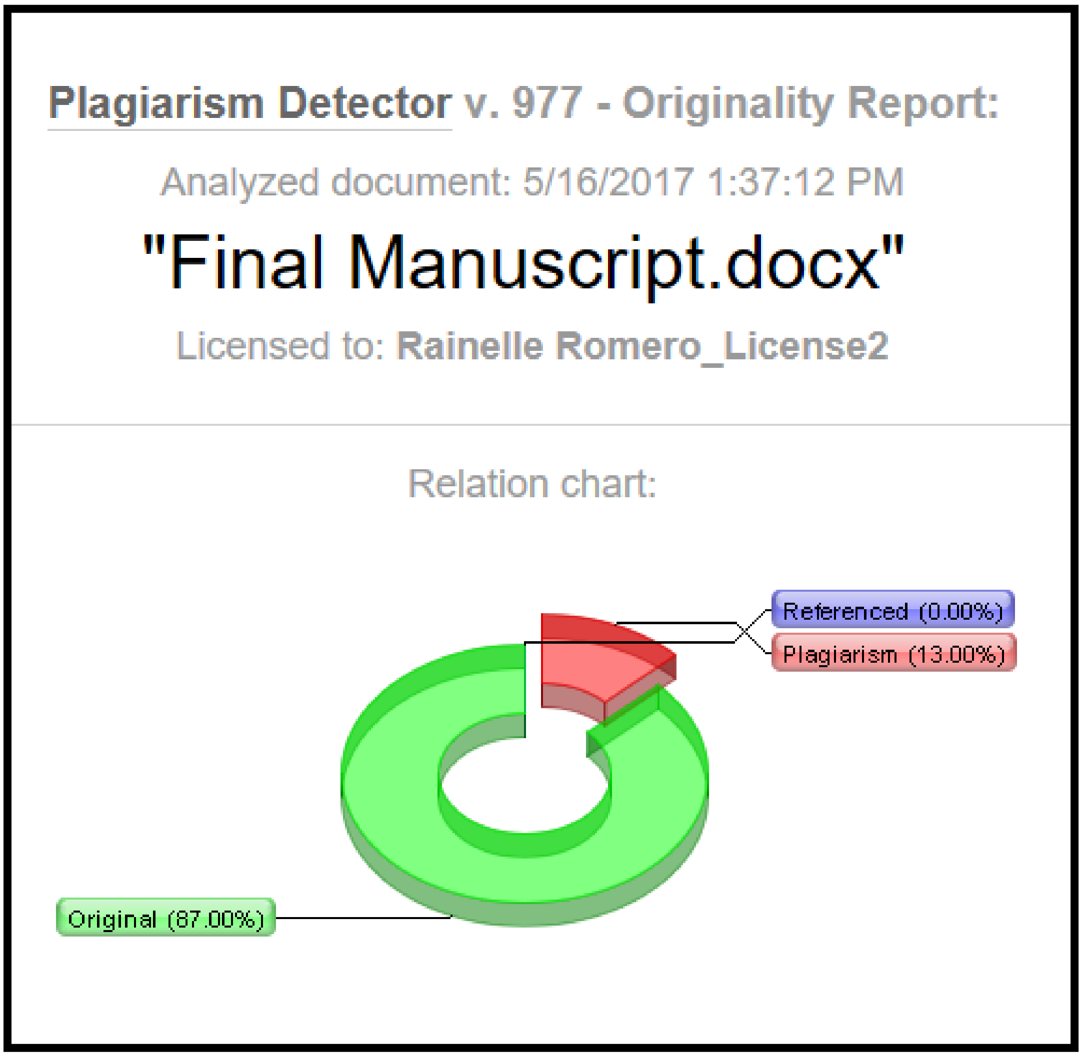
2009 **Career Service Professional**
Civil Service Commission

## PROJECT AND PORTFOLIO

CodeCanyon **https://codecanyon.net/user/peanutcode/portfolio**

# PLAGIARISM REPORT




**Plagiarism Detector** v. 977 - Originality Report: