CONTEXT-AWARE FRAMEWORK FOR MODELING A LEARNER

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DECLARATION

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ABSTRACT

Given the growing use of mobile devices, there is an increasing interest in the potential for supporting the mobile learners. Therefore, many researches have been conducted in the field of Technology Enhanced Learning (TEL) in the past decade. Context awareness and adaptability are two key enablers for intelligent systems that provide effective recommendations to users to optimize their learning process in the Technology Enhanced Learning (TEL) filed.

This research developed a framework that enables context aware recommendations for an optimized learning process through identification of learning styles, categorization of the learners to the appropriate group and providing context aware learning recommendations based on the categorization. In this work we have identified the useful contextual information and developed a complete learner model by collecting, storing and modeling the identified contextual information. The contextual information is captured and filtered through a simple mobile app, which is a mobile interface to the Moodle learning management system. The proposed model is implemented on the Moodle learning management system and the system can be extended to provide recommendations for enhanced learning experience to the learners. The developed system is evaluated using a sample dataset collected over a period of one week of Moodle access by twenty users for fifty topics related to computer science. The evaluation results show that the developed model can effectively categorize the users.

ACKNOWLEDGEMENT

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LIST OF ABBREVIATIONS

Abbreviation	**Description**
GRLSS	Grasha-Reichmann Learning Style Scales
ILS	Index of Learning Styles
LMS	Learning Management System
LSQ	Learning Styles Questionnaire
TEL	Technology Enhanced Learning
VAK	Visual, Auditory, Kinesthetic
VARK	Visual, Auditory, Reading, Kinesthetic

1 INTRODUCTION

1.1 Introduction / Problem Background

There is a great interest in using Learning Management Systems (LMS) in many universities, educational institutes, and some colleges and even in some large organizations. These software systems are currently used by administration for management purposes, tracking, report generation and for cost-saving purposes; by instructors to deliver learning materials, conduct exams, tests & quizzes, track students' performance, collect assignments, manage grades and marks, and as a communication tool; moreover, by students to collect learning materials, enroll for courses, plan their courses, track their performance, etc. The courses conducted in those institutes can be entirely online or blended with traditional education. These technology-enhanced learning platforms can be further improved to provide an advanced learning experience for students.

Learners are different from one to another and hence their learning patterns are different, some students understand theoretical kinds of stuff and others by doing exercises, some like to see visual things, other like to hear lectures, etc. Lots of research have been done on learning styles, learner characteristics and their influence on the learning process. Moreover, instructors also exhibit different techniques, some focus on theories while others focus on applications, some lecture others do discussions, etc. researchers have found that if learning method didn't match to teaching method, students become bored, inattentive and as consequences, they perform poorly in exams and even in worst cases dropout from institutes. On other hand, lecturers become less confident about their teaching and become disinclined to conduct classes and making the situation even worse.

Adaptive learning techniques are the solution to this problem. However, in most cases, LMSs provides no adaptivity to support differences in individual learning styles. With the advancement of mobile technologies and smart-phones, people spend more time on mobile devices. This enables the capturing more and more contextual information about the user using the mobile devices. This contextual information are different from one person to another and hence can be used to identify classes of people with similar characteristics.

1.2 Problem Statement

In this research, we focus on developing a learner modeling technique to classify learners according to their preferred and most effective learning styles. The developed model will help adaptive learning systems to cater students with most preferable teaching methods.

1.3 Research Objectives

The main objectives of this research are to:

1. Identify relevant contextual information that can be captured to build a learner model.
2. Define and build a learner model based on the captured context.
3. Classify learners utilizing the developed model.

1.4 Research Approach

The contextual information that can be used to classify the learners were identified through a thorough analysis of literature, device capabilities and LMS functionalities. Then, different learner models were reviewed and four learner models, namely; Felder-Silverman model [1], VARK model [2] [3], Grasha-Reichmann model [4], Dunn and Dunn Model [5] were selected based on the identified contextual information and the input requirements of these models. Then, the suitability of the identified contextual information as an indicator for each learning style model was evaluated through hypothesis testing. Based on the results of hypothesis testing, we have developed efficient learner classification models for each learning style. The context capturing mechanisms and the VARK model with classification capabilities were implemented on the Moodle LMS. Finally, the implemented system was evaluated using a sample dataset collected through a mobile app.

1.5 Research Outcomes

The two main outcomes of this research are an identification of appropriate contextual information (indicators) for the learner classification and developing an appropriate classification model for each learning style. In addition, we have implemented the context capturing mechanism and the learner classification model for the VARK model on the Moodle LMS. These results can be used by LMS developers to provide better recommendations for the learners in their LMSs. In addition, as the implementation of the classification model is available for Moodle LMS, future research can utilize the implementation to provide effective recommendations for the learners. In the long term, this work would result in enhanced learner support in LMSs with optimized learner performance through effective recommendations.

1.6 Outline of the Rest of the Thesis

In the second chapter, we discuss literature review and background work has been carried out so far by researchers. The discussion in chapter two is divided into two different research areas, the first domain is the educational field and the second domain is context-aware computing. In the discussion about the educational field, different intelligence types, learning processes, different learning styles and counter-arguments on learning style theories are discussed and, in next section context awareness and similar systems are discussed.

In the third chapter, the methodology carried out in this research is discussed and it consists of the selection of an appropriate LMS, identification of relevant contextual information, development of models for learning style detection and a classification model for categorization of learners.

In the fourth chapter, the implementation procedure is discussed and it consists of the extension of Moodle LMS for incorporating learning style detection and development of the mobile app for context capturing and filtering.

In the fifth chapter, results of this research are discussed. It contains results for identification of indicators, parameters of the developed models and sample classification results for test samples.

In the sixth chapter, conclusion which contains an evaluation of this research and the research areas for future works related to this research is discussed.

In the next section a list of references in the order in which they appear in this thesis is listed.

2 LITERATURE REVIEW

This chapter provides the literature analysis of different learning models, learner characteristics and similar research work. Section 2.1 gives details on learner profiles and how comprehensive learner profiles are developed considering learning styles into account. In section 2.2 counter-arguments against learning style models are discussed. In section 2.3 context awareness is discussed and in Section 2.4 related systems to this research work are discussed.

2.1 What is a Learner Profile?

A learner profile is a dynamic document/tool/system which contains comprehensive and personalized information about a learner, it helps educators to provide a better academic experience to each individual irrespective of diversity observed in different students, and also it supports students in understanding themselves so that they can make decisions along their learning career.

Following sections are usually included in a learner profile.

1) Demographic Information.
    a. Personal identification.
    b. Family information.
    c. Other notes (e.g. notes on medical/psychological conditions, economic conditions, etc.)

2) Academic Information.
    a. Test scores.
    b. Indicators from analysis of academic performance.
    c. Academic achievements / failures.
    d. Teachers’ notes.

3) Characteristic Information.
    a. Learning styles.
    b. Skills and strengths.
    c. Habits
    d. Strategies.

4) Learning Interests / Divers.
    a. Dreams, goals and their current state.
    b. Driving factors.
    c. Career plans.

Our focus in this research is *‘Learning styles’* mentioned in the above 3rd section. Development of a model to properly identify learning styles helps educators to provide the most effective learning methodology for students.

2.1.1 Types of intelligence

Human beings possess various cognitions and aptitudes, and they are present in different scales from one individual to another. Researchers have conducted studies over the years to identify nature of the human brain, differences exist in individuals, psychological states, various cognitions pertaining to humans and etc. The following sections describe various studies carried out by researchers to identify the existence of different types of intelligence.

2.1.1.1 Theory of multiple intelligences

In 1983 Howard Gardner introduced the theory of multiple intelligence with his publication [6]. He suggests that intelligence is a brain-based predisposition and different individuals tend to exhibit different types of intelligence at different scales and combinations. Even though Gardner initially published the theory of multiple intelligence as a study of human mind and psychology, sooner educational institutes, teachers, training communities grasped the model as it is directly influenced to the educational field. Initially, he identified 7 types of intelligence and later he added another one, and also discuss the possibility of the existence of the 9th one in 1999. Table 2.1 summarizes the 8 types of intelligence proposed by Gardner.

Table 2.1 - Types of Learning Aptitude

Aptitudes	Description
Verbal-Linguistic	Competence to use language
Logical-Mathematical	Logical/mathematical competence to use reason, number and logic
Interpersonal	Interpersonal competence to communicate with others
Intrapersonal	Intrapersonal competence to self-reflect
Spatial	Spatial competence to perceive the visual
Musical-Rhythmic	Musical competence to create and compose music
Bodily-Kinesthetic	Kinesthetic competence to handle objects skillfully
Naturalistic	Naturalist competence to realize flora and fauna

1) **Linguistic:**

The competency in using words very effectively whether orally or writing. This ability includes proper manipulation of words, syntax, and structure of a language, ability to excel in multi-languages, a proper understanding of the semantics of a language, understanding of phonology and sounds of a language and ability to speak properly. Individuals who are in professions like orator, narrator, editor, journalist, poet, announcers, presenters used to observe possession of linguistic intelligence significantly.

2) **Logical-mathematical:**

The competency in using numbers and reasoning effectively. This includes the ability to work with numbers such as in accounting, statistics, mathematics, ability to understand logic, formulas, and science. Mathematician, accountant, statistician, scientist, lawyer, computer programmer are examples for professionals who directly influenced by logical-mathematical intelligence.

3) **Spatial:**

This competency is the ability to perceive visual-spatial information, process and act upon them effectively. Individuals with better spatial intelligence possess higher sensitivity towards shapes, colors, space utilization, and styles. They can combine these elements to develop creative designs. Hunters, soldiers, scout, guide, decorators, artists, architects possess spatial intelligence in an exceptional amount.

4) **Bodily-kinesthetic:**

Competence in expressing ideas and feelings using own body and competence physical skills. This includes the ability to express facial expressions, body languages and physical skills like strength, balance, speed, precision, endurance, dexterity and flexibility. Peoples like sportsman, athletes, actors, dancers, surgeons, mechanics, sculptors, and craftsman possess high bodily-kinesthetic intelligence.

5) **Musical:**

Competence in apprehending, discriminating, creating and performing musical ideas. This includes awareness of rhythm, pitch, tones, melody, ability to play musical instruments, ability to sing, compose music, and etc. Musicians, composers, singers, musical instrument performers are believed to possess higher musical intelligence.

6) **Interpersonal:**

Competence in sensing the emotional status, moods, intentions, feelings of other people, and competence in expressing or hide one's emotional status, moods, and etc. to others. This includes better identification of facial expressions, gestures, body language, voice and actions of others and ability in expressing facial expressions, gestures and etc. to others. People like counselors, psychiatrist, teachers, mentors, leaders, priests possess higher interpersonal skills.

7) **Intrapersonal:**

Competence in identifying self-reflect. This includes the better understanding of self-knowledge, inner moods, strengths and weaknesses, intentions, desires, temperaments and etc.

8) **Naturalist:**

Competence in recognizing and understanding natural phenomena like raining, earthquakes, volcanos, clouds, thundering & lighting etc. This also includes the ability to identify flora and fauna, species around one's environment.

2.1.1.2 Triarchic theory of intelligence

Similarly, Robert Sternberg identified three types of intelligence [7] (refer Table 2.2) in 1985 which he proposed observable in different combinations and scales in each individual. His proposed theory of human intelligence trends towards a cognitive approach rather than a behavioristic perspective.

Table 2.2 - Types of Intelligence

Intelligence	Description
Componential – Analytical Intelligence	Involves planning, monitoring, reflection and transfer
Practical - Contextual Intelligence	Involves selecting and shaping real-world environments and experiences
Experiential - Creative Intelligence	Involves developing, applying new ideas, and creating solutions

1) **Componential – Analytical Intelligence:**

This form of intelligence is characterized by the analytical nature of the brain. People with high analytical skills are good at problem-solving due to their high capacity of abstract thinking, knowledge gathering and evaluation skills. They generally are said to be book smart and have higher IQ level.

Key characteristics:

Analyze, Critique, Evaluate, Contrast, Assess, Judge, Compare, Inspect, Interpret, Estimate, Memorize and etc.

2) **Practical - Contextual Intelligence**

This involves the ability to apply knowledge and skills, and ability to cope with problems with the lessons learned from past experiences. People with higher practical intelligence can conformably deal with everyday tasks in the best possible manner, they are smart with handling multiple tasks and learn well from experiences, they are flexible and can adapt to any environment in a short period of time and smart at changing the environment around them accordingly to best suit them.

Key characteristics:

Apply, Practice, Experience, Use, Implement, Observe, Employ, Use, Try out, Engage and etc.

3) **Experiential - Creative Intelligence**

This is the ability to innovate. People with higher experiential intelligence use knowledge and experience to deal with new problems, extend and optimize existing solutions. These kind of individuals are good observers and seek problems that others usually don't notice, and start thinking out of the box to find an innovative solution, they are very attentive, and curious in nature.

Key characteristics:

Invent, Imagine, Predict, Discover, Create, Come up with, Contrive, Devise and etc.

2.1.2 Learning process

Learning is not a thing that can be acquired immediately, it is a constructive process and have to go through a series of stages. Identifying the stage where each student is will help the educators to adjust their teaching process and improve the effectiveness of learning.

2.1.2.1 Domains of learning

In 1948, an assembly of American Psychological Association led Benjamin Bloom, an American educational psychologist to develop a method of classification for thinking behaviors which were believed to be very important for the learning process. Eventually, they proposed a taxonomy of three domains [8] (refer Table 2.3).

Table 2.3 - Types of Thinking Behaviors

Domain	Description
Cognitive Domain	Knowledge based domain consists of 6 taxonomies proposed by Benjamin Bloom.
Affective Domain	Attitudinal based domain consists of 5 taxonomies proposed by David Krathwohl.
Psychomotor Domain	Skills based domain consists of 6 sub taxonomies proposed by Anita Harrow.

2.1.2.2 Bloom's taxonomy (cognitive domain)

In 1956, Bloom published a book, '*Taxonomy of Educational Objectives* [9]' explaining the cognitive domain of above mentioned 'Domains of Learning', in 2001 a group of educational specialists and psychologist published a revision to Bloom's taxonomy titled 'A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives [10] '.

Table 2.4 illustrates the hierarchical components of the Bloom's Taxonomy in the arrangement order in which they are sorted from simpler to complex functions.

Table 2.4 - Hierarchical Components of the Bloom's Taxonomy

Component	Description
Remembering	Ability to retrieve previously learned information from memory.
Understanding	Ability to construct the meaning of a learned thing.

Applying	Ability to apply learned material to a novel situation
Analyzing	Ability to break learned materials to their constituent parts, understand the structure of components & their interconnection relationship.
Evaluating	Ability to make judgments about ideas based on criteria & standards.
Creating	Ability to gather components together to create a whole.

2.1.2.3 Krathwohl’s taxonomy (affective domain)

The affective domain was published later in 1964 [11] and in this domain, the way of dealing with things emotionally is discussed. Table 2.5 includes the objectives of the affective domain listed in a hierarchical manner in which they are ordered from simpler to complex feeling.

Table 2.5 - Objectives of the Affective Domain

Component	Description
Receiving	Willingness to receive existing ideas, phenomena o materials.
Responding	Active attention & motivation towards phenomena.
Valuing	Interest in a phenomena and worth or value attached towards.
Organization	Enthusiasm in organizing values, contrasting differences, resolving conflicts in ideas and phenomena.
Characterization	Refers to the highest internalization building up a consistent philosophy of life.

2.1.2.4 Harrow's taxonomy (psychomotor domain)

This domain was introduced by Harrow, A.J. in 1972 [12] and it describes physical actions ranging from involuntary movements to interpretive movements. Followings are the components of the taxonomy organized in an order from simpler to complex (refer Table 2.6).

Table 2.6 - Components of the Harrow's Taxonomy

Component	Description
Reflex movements	Involuntary movements, exhibit at birth or with maturation. E.g.: Muscle contraction, Postural adjustments, etc.
Fundamental movements	Basic physical movements, consisted of reflex components and these movements are combined to construct complex skills. E.g.: Grasping, Walking, Running, etc.
Perceptual abilities	Ability to perform movements that make adjustments to the environment. React upon the received information from environment. E.g. Catching, punting, etc.
Physical abilities	Ability to carry out tasks that require efficiently functioning body, endurance, vigor, balance, strength. E.g. Cycling, Swimming, etc.
Skilled movements	Ability to perform complex procedures involves series of tasks. E.g. Sports, Dancing, Painting, etc.
Nondiscursive communication	Ability to communicate through bodily movements. E.g.: Acting, Mime, Ballet, etc.

2.1.3 Leaning styles

People around the world have different characteristics and traits identical to each individual, a thing that one person prefers might not be preferred by another person. Simply, people are different, and likewise learning styles are different.

2.1.3.1 Kolb's model

Kolb published his learning model in 1984 with his book *'Experiential Learning* [13]'. His theory proposed two major components, the cycle of experiential learning and four types of learning styles. His theory focuses on two approaches of experience gathering, Concrete experience / Abstract conceptualization and two forms of experience transforming, Active experimentation / Reflective observation, and he stated that the learning is a cyclic process from experiencing to reflecting to thinking to acting and back to experiencing and so on as depicted in Figure 2.1.

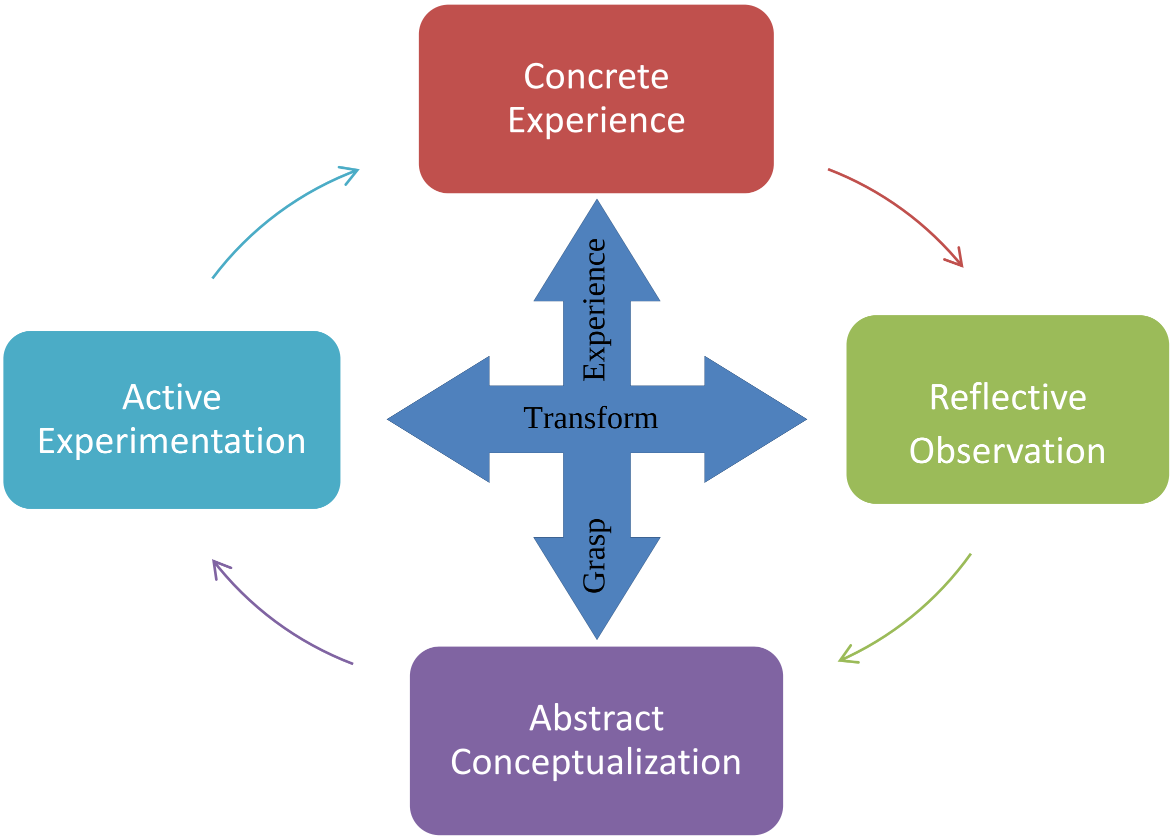


Figure 2.1- Kolb's Learning Style Model

In this cycle, the east-west axis is called the Processing Continuum which differentiates how we transform experiences, either by doing or by watching), and the north-south axis is called Perception Continuum which describes how we grasp experiences, either by feeling or thinking. Learning styles proposed by Kolb, are formed by the combination of parameters one from each axis and it is illustrated in Table 2.7 and Figure 2.2.

Table 2.7 - Types of Kolb's Leaning Styles

Learning Style	Combination
Diverging	Concrete Experience + Reflective Observation
Assimilating	Reflective Observation + Abstract Conceptualization
Converging	Abstract Conceptualization + Active Experiment
Accommodating	Active Experiment + Concrete Experience

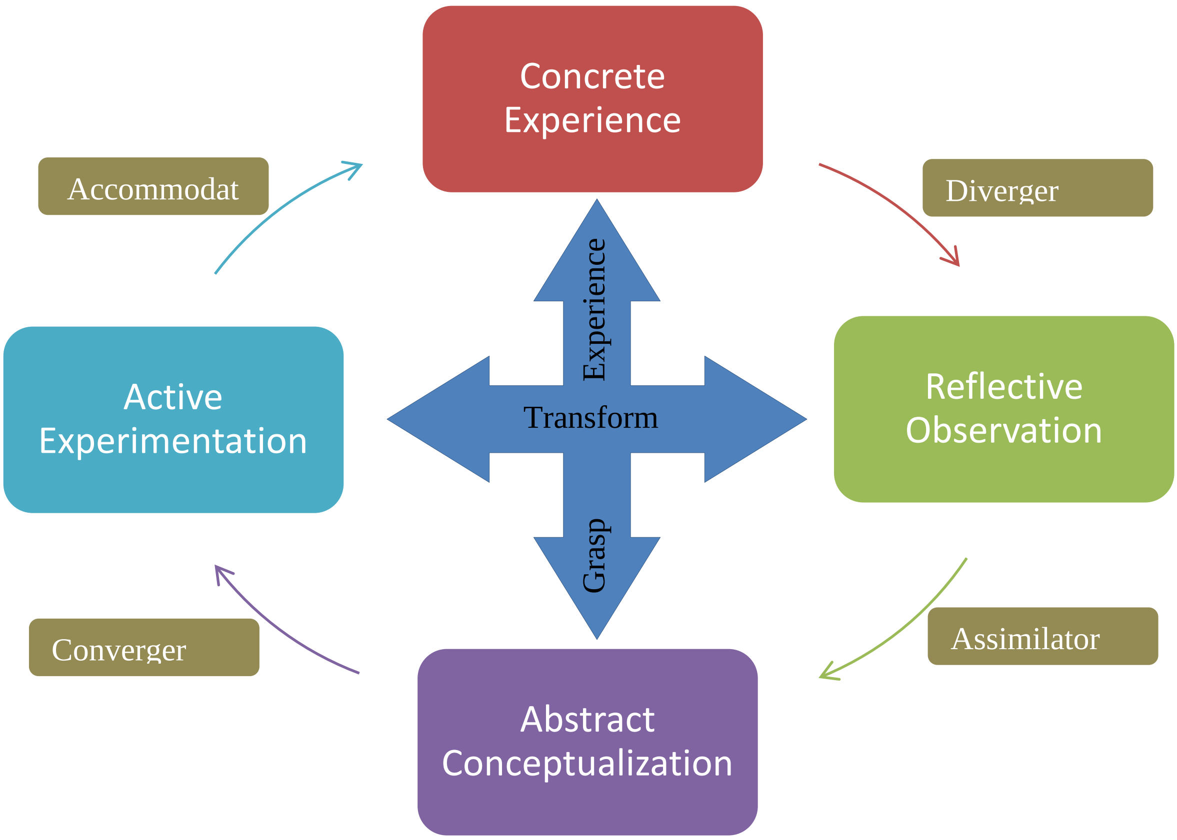


Figure 2.2 - Types of Learners with respect to Kolb's Learning Style Model

1) Diverging:

These people are good observers and sensitive, they like to watch than do, and possess good interpersonal skills. They are good at idea-generation, discussions, brainstorming and viewing a scenario in multiple viewpoints. People in this category are open to others ideas, feedbacks and they are open-minded. Social workers, Managers, Politicians and etc. are professions that require this behavior most.

2) **Assimilating:**

People with this learning preference value concepts and ideas than people. They are good at interpretation & theorizing, and they would like to have logical explanations rather than demonstrations. These people are usually good at science and mathematics, possess a sound logical reasoning ability, can organize knowledge in a logical & concise format. Students with this style prefer lectures, analytical models and they understand by thinking through. Philosophers, mathematicians, scientist and etc. are the professions that exhibit this behavior most.

3) **Converging:**

People with this learning style, prefer getting hands-on and they are talented at bringing ideas into practice and modifying theories so that they could be applied efficiently. They would love to experiment with ideas and theories. They are less concerned with people and they learn by doing experiments, simulations, practical, solving mathematical problems, etc. Engineers, Technicians, and etc. are examples of professions that require this learning style to excel in those respective professions.

4) **Accommodating**

Learners with this style trust intuition than logical reasoning, and they are good at practical doings and prefer to get hands-on experiences. They prefer to work in teams and they depend on other's analysis, and they learn more with more experiences. They are the first to take an action or initiatives. Students with this learning preference would like to attend lab sessions, watch demonstrations, group activities, etc. Professions like therapist, surgeon, artist and etc. which skills get shaped rapidly with experience require this behavior most.

2.1.3.2 Honey and Mumford's model

Based on the Kolb’s experiential learning inventory, Peter Honey and Alan Mumford identified four distinct learning styles and published a theory in their book ‘*The Manual of Learning Styles* [14]*’.*

They suggest that each individual naturally prefers a particular learning style and it is very important to understand learning style of each student and guide them through learning processes which their natural preferences are matched. Followings (in Table 2.8) are the four learning styles suggested by them.

Table 2.8 - Honey & Mumford’s Learning Style Model

Learning Style	Description
Activist	Like to get their hands dirty, learn by doing.
Reflector	Like to gather information and mull things over.
Pragmatists	Like to know how to put things they learn in to practice in real world.
Theorist	Like to learn theories, background information.

1) **Activist:**

This type of learners are active learners and they like to learn by engaging in activities. They do not hesitate to try out new experiences and they are open-minded, social and have good interpersonal skills.

Interests:

Group discussions, Competitions, Puzzles, Brainstorming sessions, Discovering solutions, Experiments, Take leadership.

2) **Reflector:**

These type of learners prefer to stand back, observe carefully and think thoroughly about what happened and understand. First, they collect information and then imagine a scenario in different perspectives, take their time and have an understanding.

Interests:

Small group or paired discussions, Watch experiments, Feedbacks, Interviews, Model answers.

3) Pragmatists:

These type of learners want to know how to apply a theory in actual usage in real life before they dive into the deeper level. Abstract concepts, theories, and hypothesis are off limits unless they can be converted into a usable real-world application.

Interests:

Case studies, Lab sessions, Discussions, Project implementations, Simulations, Prototyping, Designing.

4) Theorist:

This type of learners like to learn theories, background stories, and concepts. They possess a strong imagination, visualization, and logical reasoning capabilities. They are reluctant to learn without a prior knowledge of background stories, theorems or problem statements.

Interests:

Models, Background stories, Theorems, Proofs, Analysis, Statistics, Quotes, Debates.

2.1.3.2.1 **Honey and Mumford's learning styles questionnaire (LSQ)**

Peter Honey and Alan Mumford created a self-evaluative questionnaire [15] which contains a series of questions designed to identify learning style the student belongs to. Initially, a set of managers was asked to answer and without directly asking how they learn, this questionnaire tries to deduce their learning styles based on the given answers.

2.1.3.3 Barbe's VAK modalities

The learning modalities are the pathways or the channels an individual prefers in order to receive, deliver information or store acquired knowledge in mind. Perception is considered to be the most thoroughly investigated learning style. In 1979 W.B. Barbe and his colleagues published their findings of learning modalities through their book, 'Teaching through modality strengths: concepts practices [16]'. It has now become the most popular learning model due to its simplicity it is summarized in Table 2.9.

Table 2.9 - Walter Barbe's Learning Style Model

<table>
<tr><th colspan="2">Learning Modality</th><th>Description</th></tr>
<tr><td rowspan="2">Visual</td><td>Visual-linguistic</td><td>Learn by seeing text.</td></tr>
<tr><td>Visual-spatial</td><td>Learn by seeing graphical representations.</td></tr>
<tr><td colspan="2">Auditory</td><td>Learn by listening.</td></tr>
<tr><td colspan="2">Kinesthetic / Tactile</td><td>Learn by doing.</td></tr>
</table>

2.1.3.4 Fleming's VARK model

Neil Fleming proposed a learner model named 'VARK Model' [2] in 1992 which is an expansion upon Barbe's VAK model. They introduced another dimension to Barbe's model and change the definition for visual modality.

They identified that the way in which form the course materials are provided or the course itself is presented would not be preferred by every student, and students complain about it. Some students experience difficulties when the course materials are entirely written texts, some students find difficulties with graphical representations and some students don't understand when concrete examples are not provided, and etc.

Table 2.10 summarizes the proposed VARK model.

Table 2.10 - Neil Fleming's VARK Learning Style Model

Learning Modality	Description
Visual	Learn by seeing.
Auditory	Learn by listening.

Reading	Learn by reading.
Kinesthetic / Tactile	Learn by doing.

1) **Visual:**

This type of learners exhibit great ability for visual recall, they prefer to perceive, analyze, store information in visual format. They prefer learning with visual materials, such as charts, graphs, mind maps, animations, diagrams, posters, maps, displays. Students with this modality, learns well with diagrams and other visual materials, they draw diagrams to represent ideas and they store & recall those diagrams by visualizing.

2) **Auditory:**

This type of learners prefer to listen, or even they talk to themselves and listen. These students like to attend lectures and they prefer activities like group discussions, debating, Q & A sessions, also these learners perform well when they study with friends. They often record lectures and later on hear what was said.

3) **Reading:**

This is the preference for textual information. Most of the teachers and students use textual methods even if they are not best-suited method for some learners or teachers. This includes the preference for written assignments, reports, manuals, textbooks, articles, comments, essays and etc. This type of learners exhibit great skills in both writing and reading, they understand quickly when reading and can memorize phrases written on what they read and they possess great writing skills.

4) **Kinesthetic:**

People with this modality are connected to the application of knowledge, they prefer to see how theories are applied in real life, or they would like more to experience and engage in real life situations. Students who possess this modality prefer practical, lab sessions, field visits, demonstrations etc. They learn best with examples, model papers, quizzes, assignments and etc.

2.1.3.4.1 **VARK learning styles questionnaire**

This is a self-assessment questionnaire [17] developed to identify VARK learning styles prevailing in learners. This questionnaire contains 16 MCQ type questions where each question is a scenario and answers are related to every VARK dimensions, where user has to pick one or multiple answers for each, and then based on the behavior user have addressed those scenarios, the learner is assessed. As every question is weighed equally, the number of questions have been answered in a certain dimension is the measurement for this index, and the leaner is expected to possess the dimension in which dimension the learner has answered most of VARK questions, also multimodality is allowed in this model, where learners can exhibit more than one dominant VARK dimensions.

2.1.3.5 Grasha-Reichmann learning style scales (GRLSS)

In 1974 Grasha & Reichmann developed this behavioral model [18] to identify students’ participation in classroom activities. This model addresses individual student’s attitude towards learning, teachers, peers and classroom activities. The Table 2.11 summarizes this model.

Table 2.11 - Grasha-Reichmann Learning Style Model

Learning Style	Description
Competitive	Wants to win and earn recognition & rewards.
Collaborative	Enjoy doing classroom activities with peers.
Avoidant	Do not exhibit any interest in classroom activities.
Participant	Highly motivated & actively participate classroom activities.
Dependent	Wants support and guidelines.
Independent	Have good confident, guide themselves through leaning process.

We can clearly identify that counterpart of each parameter available in the above list, that is, competitive and collaborative, avoidant and participant, dependent and independent are mutually opposite pairs.

1) **Competitive:**

This style of learners compete with others to achieve to the top, they seek rewards & recognition. They like to take leadership, monopolize in group activities & discussions. They want to win attention from teachers and peers and want to be appreciated for doing good jobs.

Competitive type of learners prefer teacher-centric education systems, they perform well if the learning is arranged with quizzes, tests, spot tests and other opportunities for attaining accomplishments.

2) **Collaborative:**

This is the most common type of learners who believe that they can learn better by sharing knowledge with peers, they like to work with groups, prefer discussions with class. These type of learners are very cooperative with teachers & peers, and they like to share any learning material with others. They prefer small group discussions than large group lectures.

Collaborative learners perform well in group works like lab sessions conducted in small groups, group projects etc. Independent projects, quizzes, tests are not much appropriate for this type of students.

3) **Avoidant:**

Absentees in the classroom. This type of learners are not interested in classroom activities at all, they feel overwhelmed by learning tasks, they don't like to interact with teachers or peers, take no responsibilities in group activities and don't care whatever happens to their learning.

General this type of learners get very lower marks, poorly organize their academic career, avoid tests, exams and often fail to submit assignments properly. This type of learners may learn well in online courses, and self-guided programs where interactions with others minimal.

4) **Participant:**

This type of learners are enthusiastic about classroom activities, they take part in as many activities as they could, well related with peers and teachers, willing to accept responsibilities, highly motivated to learn and exhibit higher attendance rates. This type of learners willing to take extra steps, enroll optional subjects, explore knowledge that is not even taught in the classroom, read books and etc.

These learners perform well when they are given responsibilities within the group. When given group assignments, self-learning tasks and etc. (e.g. read a chapter and answer Comprehension question).

5) **Dependent:**

This type of learners seek A to Z guide from teachers, do only what is required, need clear deadlines and instructions, possess low intellectual curiosity, structure their work compared to peers. These type of learners get frustrated when they are presented with new challenges, when they are asked to find a solution for a scenario that is not taught in class, they don’t like to think out of the box.

Dependent learners perform well in the teacher-centric classroom, and when they are given well-structured tasks with clear deadlines and instructions, when given exams with predefined scopes and depths.

6) **Independent**:

This type of learners have a higher confidence in their learning procedure, they learn contents what they feel required, prefer independent tasks, willing to accept others’ opinions but take decisions independently. They are innovative and tends to think out of the box.

This type of students learn well in student-centric teaching, they perform well in problems that require creative solutions, when they are given maximum flexibility.

2.1.3.5.1 **Grasha-Reichmann learning styles questionnaire**

Along with their publication, Grasha and Reichmann proposed a self-evaluative questionnaire [4] to identify which dimension/dimensions a leaner belong to in Grasha-Reichmann model. This questionnaire has a total of randomly distributed 60 questions, 10 from every 6 dimensions of Grasha-Reichmann model. In this questionnaire, leaners have to rate themselves in a typical five-level Likert scale where points from 1 to 5 are assigned along its components, strongly disagree, moderately disagree, undecided, moderately agree and strongly agree. Total for each dimension is calculated and divide by 10 to average, as each question has been equally weighted. Then the highest mark above 3.0 will indicate the most relevant dimension for that particular learner.

2.1.3.6 Felder-Silverman learning and teaching styles model

In 1988 Richard Felder who was an engineering professor & Linda Silverman who was an educational psychologist published a paper published a paper [1] describing learning & teaching styles prevailing in engineering education, Although their study was focusing on engineering students, their invention can be applied to any group of students.

Their proposed framework describes students have preferences on how they receive information and on how they process information. They identified five dimensions each having two elements which are opposite of the other one, therefore by picking one from each dimension they suggested that a learner can be categorized into one of 32 (derived from 25) possible learning style combinations. Followings Table 2.12 summarizes the five dimensions of their proposed framework.

Table 2.12 - Felder-Silverman Learning Style Model

Learning Dimension	Description
Intuitive / Sensory	Two types of learners, characterized by what information they prefer.
Visual / Auditory	Two types of learners based on the preferred channel to receive information.

Inductive / Deductive	Two types of learners based on preferred way of information organization.
Active / Reflective	Two types of learners differentiated by how they prefer to process information.
Sequential / Global	Two types of learners, characterized by how they progress through learning.

1) Intuitive / Sensory:

Sensing learners prefer concrete data like facts, observable scenarios, data, and procedures while intuitive learners prefer abstract concepts like theories, mathematical models, and principles. Sensing learners solve problems by following standard procedures and they dislike innovations, in contrast, intuitive learners like experimenting and finding creative solutions as they hate repetition. Sensory learners are good observers, possess a good memory and they are attracted by real-world scenarios, while intuitive learners are good at conceptualizing and hypothetical thinking. Sensing learners are very careful and therefore they may be slow, while intuitive learners work fast and make more mistakes often.

2) Visual / Auditory:

Visual learners prefer the visual representation of information, like pictures, diagrams, charts, flow charts, demonstrations, video, symbols, timelines and etc., while auditory learners prefer written and spoken information, discussions, Q & A sessions, lectures, seminars, audio clips and etc. These two modalities are a subset of previously explained VARK learning styles.

3) Inductive / Deductive:

Inductive learners prefer inductive learning style, which is proceeding from observations, measurements or data to generality like a theory, law, rule or a fact. Deductive learning is the opposite process of inductive learning, this learning process begins with stating a theory or rule then justify these theories or rules by observable phenomena. Most of the students prefer inductive learning as it is said to be the natural learning method while most of the teachers carry out deductive teaching methods.

4) **Active / Reflective:**

Active learners are they type of learners who prefer to try things out, mostly they prefer to work with groups and they feel better involving in active experimentation. On the other hand, reflective learners prefer to examine and manipulate information introspectively, they are reflective observers and they require time to think about the information being presented, mostly they work alone or with one familiar partner. Active learners are said to be experimentalists while reflective learners are theoreticians.

5) **Sequential / Global:**

Sequential learners prefer learning in small incremental steps as taught in most schools, materials and lessons are presented in a logically ordered progression, first they master simple subject matters establish their experience in mind and then move on to the complex parts. Conversely, global learners want to see the big picture, they prefer holistic thinking and absorb knowledge almost randomly and try to connect pieces together.

Sequential learners think convergent and analyze while global learners think divergently and synthesis. When global learners learn a subject, initially nothing may make a sense to them and they may incapable of solving simple problems, however eventually at some point where they can connect key points into a big picture of their own, they can even fit newly learnt materials or even matters from other subjects into that big picture and gain a whole understanding which would never possibly achievable by a sequential learner.

2.1.3.6.1 **Index of learning styles (ILS) questionnaire**

This is a questionnaire [19] containing 44 questions to assess a learner's learning style with respect to the Felder-Silverman learning style model. This was developed by Felder himself and Barbara A. Soloman of North Carolina State University in 1999. Learners have to answer questionnaires using a five-level Likert scale where points from 1 to 5 are assigned. As 11 questions from each dimension of Felder-Silverman model are included, learner assessor has to divide by 11 and take the average. A higher average beyond 3.0 indicates a tendency towards that particular dimension.

2.1.3.7 Dunn and Dunn learning style model

In 1985 professors Rita Dunn and Kenneth Dunn published [5] a model as an outcome of their researches carried out in the 1970s. They raised the awareness that different students learn in different ways and multiple strategies should be incorporated into the education system to cater all the learning styles.

They spread their model in five key dimensions to comprehensively identify learning styles prevailed with learners and the Table 2.13 illustrates them.

Table 2.13 - Dunn & Dunn Learning Style Model

Dimension	Sub Category	Description
Environmental	Sound	Where do learners willing to take their learning experience?
	Light	
	Temperature	
	Design	
Emotional	Motivational support	Do the learners need motivational support?
	Persistence	
	Individual Responsibility	
	Structure	
Sociological	Individual	What is the sociological state in which the learner learn best?
	Pairs or Teams	
	Adult	
	Varied	
Physiological	Perceptual	How does a learner physically engage when learning better?
	Intake	

	Time	
	Mobility	
Psychological	Global	The way a learner process information & ideas.
	Analytical	
	Impulsive	
	Reflective	

1) **Environmental:**

This addresses the environmental conditions of an ideal place to learn. Some prefer a place where warm, bright and with many peoples around, with much verbal interaction while other groups of learners need a quiet, cool environment. Some prefer bright light and some prefer low light. Some prefer an informal arrangement of desks and others hate such environment and need formal environment.

2) **Emotional:**

Some students are self-motivated while others need a lot of support and guidance from instructors, some students are highly persistent while others are low persistence and ignorant. Some students responsibly carry out their study works while others feel less responsible, and some students prefer structured work while others not.

3) **Sociological:**

Learners are different in the way they interact with other students. Some students like to work with peers while others prefer to work alone, some seek authority from the experienced individual while others seek freedom.

4) **Physiological:**

This includes all physiological preferences by learners. Learning modalities belong to physiological dimension, some students like to learn visually, while another group like to learn auditory and so on. There are students who need to move around periodically, and some students prefer to learn in the morning while another group of students likes to learn in the evening.

5) Psychological:

In the above Felder-Silverman model we discussed several psychological factors, such as some students prefer global learning and they want to see the big picture, while others prefer sequential and they prefer learning in logically progressing stepwise manner. Some students prefer actively experiment while others observe carefully and want much time to introspect.

2.1.3.7.1 **Dunn and Dunn learning styles questionnaires**

There are four online assessments [20] based on the age group to model learners with respect to Dunn & Dunn model. The four assessments according to the target age group are summarized in Table 2.14.

Table 2.14 - Dunn & Dunn Learning Style Questionnaires

Assessment	Description	Authors	Year	Age (years)
ELSA	Elementary Learning Style Assessment	Burke, K. & Dunn, R.	2007	7 - 9
LSCY	Learning Style: The Clue to You!	Burke, K. & Dunn, R.	1988	10 - 13
LIVES	Learning in Vogue: Elements of Style	Missere, N. & Dunn, R.	2007	14 - 18
BE	Building Excellence (BE) Survey	Rundle, S. & Dunn, R.	1996-2007	17+

After taking the questionnaire, they provide an analysis report of the learner with respect to Dunn and Dunn model.

2.2 The Myth of Learning Styles

There are counter-arguments which challenge the existence of these learning style theories. In [21] & [22] Daniel T. Willingham et al challenged the existence of learning styles.

However, they suggest that they are agreed to four areas that matter for learning. First, they accept that people possess a different level of competencies in different areas of content, simply they call it ability, talent or intelligence. Secondly, they suggest that learning is influenced by interests. If a student has a passion for something (e.g. Aeronautics, Robotics, Football, Math, etc.) He/she will learn that subject matter faster irrespective of its presented format. Third, they suggest that learning is influenced by background knowledge, as an example, if a student has done commerce in ordinary level classes, he/she has an advantage in learning commerce in advanced level. Finally, they suggest that students having disabilities in certain areas that affect learning show lower performances. As an example students with Dyslexia may exhibit difficulties in knowledge acquisition with books, students with Autism Spectrum Disorder (ASD) may experience difficulties with group works.

2.3 Context Awareness

The term ‘context’ is defined as ‘The circumstances that form the setting for an event, statement, or idea, and in terms of which it can be fully understood’ in Oxford dictionary [23]. In contrast, computer science defines ‘context’ as the mandatory or optional factors that a software component taken as inputs for its operation. The term ‘context’ was originated from ubiquitous computing which in turn is defined as computing appears in anytime anywhere apart from the conventional use of desktop computers for computing tasks. With the advancement of mobile devices and smartphones, context-aware computing became more usable and popular and people began to develop billions of software components that sense the environment and response based on the circumstances.

The term ‘Context Awareness’ was first introduced by Schilit et al. [24] with their publication in 1994. They identified important aspects of contexts as, where you are, who you are with, and what resources are nearby. Even though initially, researchers identified ‘context’ as location, Anind K. Dey [25] identified context is more than just location related information, they defined context as ‘any information that can be used to characterize the situation of an entity’. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves’. He defined any information which characterizes the situation of user interaction with the system as context.

Context is classified into two categories:

- Atomic context
- Composite context

Atomic context is the usable context that associated with raw data which is sensed from the environment or profiled by a user. On the other hand, composite context is derived context from atomic context by means of inferring or learning techniques.

Contextual information is obtained both by explicitly and implicitly. When explicitly gathering contextual information, the user is provided with options to fill out contextual information or the user is prompted with dialogs to provide relevant information. When implicitly obtaining contextual information, the system actively monitors the context of the running environment using sensors or by inferring using statistical or data mining methods [26].

Generally, available context information is uncountable as various applications are using different contextual information.

2.4 Related Work

Over the past two decades, many researchers have been developing learning related systems to enhance the effectiveness of learning by incorporating personalized learning experience into the education system, among them adaptive learning material recommenders and learning style detectors were popular.

2.4.1 Learning recommender by Carver et al.

In 1999 Carver et al. [27] proposed a system to enhance student learning by providing hypermedia according to their learning styles.

This system consists of lists of learning materials for each dimension according to a ranking based on Felder-Silverman learning styles. Each learning hypermedia course materials are given a score ranging from 0 to 100 for each dimension in Felder-Silverman model. In this study, first, the students were presented with a questionnaire consisting 28 questions in order to determine student's learning styles according to Felder-Silverman model. Based on their answers a model is built for each individual and once a learner first logins to the system the leaner is given an option to explore course materials according to their learning style. If the student chose to proceed with their learning styles, the student is presented with an ordered list of learning materials prepared according to mentioned raking of each learning material and student have to sequentially click on links to learn the course in a way that matching to their learning styles.

2.4.2 Learner evaluator by Bajraktarevic et al.

Bajraktarevic et al. [28] developed a system in 2003 using the same learning style as in above to evaluate the impact of using learning styles in the learning process.

First, they provided students the Felder-Silverman Index of Learning Styles Questionnaire (ILSQ) to evaluate their learning styles. Then they presented two sessions, one with the learning materials that matched their learning styles and the other one with the materials that did not match. In the first session, students are presented with a pre-test, then learning materials that matched their learning styles, and then a recalling type post-test. The questions in post-test are tied to levels of Bloom's taxonomy and learning objectives of that course. In the second session, another subject is selected and first provide a pre-test, then learning materials that do not match their learning styles and then a post-test as in the previous session. Then by comparing achievement scores for two post-tests are evaluated using hypothesis testing.

2.4.3 iWeaver by Wolf

iWeaver [29] is another learning recommender system developed by Wolf, C. in 2003. This system teaches Java programming language providing a dynamically adapting personalized environment.

When a student first logs into the system, it prompts 118 multiple choice questions of 'Building Excellence Inventory' introduced with Dunn and Dunn learning styles model. Then it generates a learning style profile and an analysis. Then the learners are presented with two sets of learning contents based on the generated learning profile. There are 4 content sets and they termed them as 'media experiences'.

Each learning content has modules (i.e. for separate subjects) and each module is divided into units. After completion of each unit, the learner can repeat with the other media experience or can navigate to the next unit. However, before commencing the next unit, the user has to rate the encountered media experience, impression on the current learning progress and overall satisfaction. Once the learner completes a module, a test with multiple choice questions is presented to evaluate the learning progress. Followings are the four types of media experiences.

- Visual texts.
- Visual pictures.
- Tactile-kinesthetic.
- Auditory.

Visual text type of media experience is preferred by learners who remember materials best by reading them, here it contains textual content, highlighted key concepts, annotations and etc. Visual picture media experience helps learners who remember pictorial information best, like diagrams, mind maps, flow charts, animations, charts and etc. Tactile-kinesthetic learners prefer media experiences like interactive animations, drag and drop puzzles, computer-based interactions. And finally, the auditory type of learners learn best with media experiences that contain speeches, such as lecture videos, audible tutorials, audible powerpoint presentations and etc.

In addition to the described media experiences, iWeaver provides learning tools to identify different learning styles belong to the psychological domain in Dunn and Dunn model. iWeaver offers a tool for taking notes which helps reflective learners where they can sketch information and think about. For impulsive learners who prefer to straightly jump into and try out, they provided a link to online java compiler where the learners can try out learned concepts right away. They have provided a mind map for global learners, where they can view the current progress of the learning process, what did they learn at which point of the tutorial they are in and what comes next within the content structure. There is an option to view relevant information around the topic being currently learning as internal kinesthetic learners try to make connections between concepts

By adding 'activity context' into the three context dimensions which are in turn 'computing context', 'user context', and 'physical context' identified by Schilit [24], Benlamri et al. obtained context in four dimensions and developed a context-aware recommender for mobile learners [30].

3 METHODOLOGY

In previous chapters we discussed learning styles, context-awareness and current context-aware learning systems. In this section, we propose the methodology we used to implement a context-aware mobile system to identify learning styles of students. Section 3.1 gives details about LMSs selection of a proper LMS for this research. Section 3.2 discusses mobile contextual information useful for this research and in Section 3.3 the development of learner modeling is discussed. Finally, in Section 3.4, the learner classification with respect to selected four learning style models is discussed.

We can observe some drawbacks in current mobile learning services, they lack context-awareness and most of them just provide learning materials without proper personalization, even if they provide personalized materials they lack doing reasoning and learner modeling mechanisms to identify best-suited learning materials for particular learners.

Major objectives of this research are to:

1) Identify contextual information to serve as input for the proposed learner modeling system.
2) Build a learner model.
3) Classify learners using the developed model.

However, the 3rd stage (i.e. classifying learners) is reserved to be optimized later on, focusing on context identification and model building as priority objectives. A simple classification method based on mock data is used in this research to demonstrate the functionality of learner modeling.

3.1 Selection of a Learning Management System (LMS)

In this section we discuss the criteria for selecting a suitable Learning Management System (LMS) for this study, the prospective LMS should possess some features as we are developing a prototype system for learner modeling based on mobile context.

3.1.1 What is an LMS?

An LMS is a software application which helps to make lives of learners, tutors, and administrators easy in many ways. Typically an LMS help administrators to, register students and teachers, enroll students into courses, publish news and notifications, reporting services and to do other management tasks, and for teachers to provide course materials, track performance of students, collect assignments, grading, provide examinations, manage classes, communicating with students and etc. while students to collect learning materials, review their progress, manage course enrollments, communicating with teachers & peers and etc.

Application of computers for learning has a long history. LMSs have a progressive journey since the invention of the first teaching machine in 1924 to today's sophisticated online systems. In past 10 years, LMSs became a mainstream in educational sectors and is widely used across many universities around the globe. With the invention of TCP/IP in 1982, Tim Berners Lee and Robert Cailliau could invent World Wide Web (WWW) which made a revolutionary change in computer science, then in 1990 the first LMS called 'FirstClass' [31] [32] was launched by 'SoftArc' and it was used by The United Kingdom's Open University to deliver online learning.

3.1.2 Features analysis and selection of an LMS

There are lots of LMSs with different functionalities and features available in the market, commercial products, and open source ones. When we selecting an LMS for this research, it is essential it to be easily extensible and customizable and should be supported in mobile platforms, therefore we set the followings as the selection criteria.

1) Open-source.
2) Mobile support.
3) Web-based.
4) Stable version.
5) Documentation.
6) Customizable / Plugin-support.
7) Community support.

A web-based system is an indirect indication of popularity as the ease of access by many users. Next generation Learning Management Systems (LMS), Content Management Systems (CMS), Enterprise Management Systems (EMS), Hospital Management Systems (HMS) and etc. are web-based systems. As we are going to customize the LMS in order to integrate learner modeling modules, a good documentation is essential for development. Also, it's beneficial to select one with an active community like forums, discussions, blogs and etc. where developers can get ideas and support from other developers, it also indicates that the developing product would be well supported and can be of interest of many people for further enhancements. A stable development status indicates a reliable and error-free product, which is widely deployed among a variety of environments. If the product supports plugins, we don't have to change the core sections of the LMS source code, and only have to develop a compatible plugin to extend the LMS to support learner modeling, then interested users can just install the plugin and have the learner modeling support.

In addition to the above basic criteria, the selected LMS should cater features that required for learner modeling. These functionalities can be categorized as in Table 3.1.

Table 3.1 - Required Functionalities of an LMS for Learner Modeling

Category	Description
Administration Tasks	Register users. Create courses. Enroll learners. Authorization.
Content Management	Creating, storing, sharing, learning objects. Import / export learning materials.

	Create and manage tests, quizzes, examinations.
Learner Management	User profiles. Grading. Performance tracking. Attendance and other involvements tracking.
Teacher Management	Create and manage courses. Create and manage schedules. Managing associated learners. Reporting.
Communication	Notifications and announcements. Inbuilt mailing, forums, discussions, blogs & chat. Video / audio conferencing.
Technology	Installation, customization, deployment. System architecture, programming languages and used frameworks. Running environment. Dependencies. Mobile support. Security. Stability. Load balancing.
Extensibility	Open-source. Plugins. Documentation. System architecture and coding standards. Support.
Usability	UI / UX. Customization / Personalization. Multi-lingual

Administrative features are essential for an LMS and can be observed in almost all LMSs, and these features are not much important for learner modeling.

Content management related features are also very important in all LMSs and almost all LMSs possess these features in different levels. Learning contents in LMSs are called learning objects and ability to create and manage learning materials, conduct tests, import and export learning objects from other LMSs etc. We need to save meta-data related to learner modeling along with learning objects themselves to be used in learner modeling. As the leaners behaviors vary with different fields of study, the ability track course level user activities is very important for learner modeling.

Learner management features are the information that the system can identify and prompt in user level granularity. These are essential features for this research we focusing on modeling learners according to their learning styles, and finally, output a model personalized to each user. User activities should be tracked and those logs would be used in calculations of learner modeling algorithms.

Teacher management is a basic feature in any LMS and courses and students management have a cross-reference to teacher management. In this research, teacher management components should support allowing learner modeling controlled by teachers, such as they get to decide which courses, which set of students need to be modeled using learner modeling modules and etc.

Communication-related features can be used to communicate with the users of the system as well as the users outside the system. Communication is also an important parameter for learner modeling, therefore the selecting LMS should possess communication features like forums, discussions, chats or other communication-related features as communication is a part of learning styles discussed in previous chapters.

Technology is one of the most important factors with respect to this research as the selected LMS should technically support embedding a learner modeling model. Most importantly it should support mobile access, and it should allow installing with fewer troubles.

Extensibility is another most important factor concerning this research, as the selected LMS should be open-source, should support plugins and properly documented. Support from a developer community is beneficial for prototype development.

3.1.3 Moodle

Moodle [33] (an acronym for **M**odular **O**bject-**O**riented **D**ynamic **L**earning **E**nvironment) was first developed by ‘Martin Dougiamas’ and released in 2002. Now the development of Moodle is majorly done by an Australian company called Moodle HQ and also it is assisted by open source programmers. Table 3.2 summarizes the features available in Moodle.

Table 3.2 - Summary of Functionalities of MOODLE

Feature	Description
Technology	PHP, MariaDB / MySQL
Communication	Whiteboard, Messaging, Chat, Forum,
Mobile support	Yes
Extensibility	Plugin support (1400 plugins available as of 2017), Web services, Documentation, Community support.

We selected Moodle due to its excellent mobile support, strong extensibility, comprehensive documentation and large community support.

3.2 Identifying Mobile Contextual Information with respect to Learning Style Models.

As mentioned in chapter one many different learning style models exist in literature and they have been using in the learning process. In this research, we focus on embedding a module within an LMS to passively identify the learning styles preferred by students using the mobile context of investigated students.

The following learning styles are to be incorporated into Moodle.

- VARK Model by Neil Fleming.
- Grasha-Reichmann Learning Style Scales.
- Felder-Silverman Learning and Teaching Styles Model.

- Dunn and Dunn Learning Style Model.

All the above learning style models are developed based on traditional learning methods rather than LMSs or mobile devices, therefore some sort of mapping between the behavior of students in traditional environment and LMS / mobile environment is required.

3.2.1 Evaluation of VARK model for learner modeling in LMS / mobile context

In VARK model [2], learning styles are assessed with respect to visual, auditory, reading and kinesthetic dimensions. To evaluate the VARK tendencies observed in learners, several features in LMS and mobile context can be considered. Followings are some possible user behaviors for identifying VARK learning styles within the LMS/mobile context.

1) Content Objects in Moodle

In addition to information from mobile devices, we can always examine user interaction with Moodle servers and monitor activities related to learning styles irrespective of whether the user accessed Moodle with a desktop computer or a mobile device.

Content objects are the components that compose a course in Moodle, these content objects belong to any of VARK category, for instances, a pdf file with diagrams belongs to visual category, a video of an experiment is kinesthetic, a tutorial containing theories belongs to reading category and an interview with a professional belongs to auditory category. These content objects are tagged when they are included in Moodle and we record the parameters in Table 3.3 for each content object.

Table 3.3 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_visual_content_visits*	*Visual*
2	*no_of_auditory_content_visits*	*Auditory*
3	*no_of_reading_content_visits*	*Reading*
4	*no_of_kinesthetic_content_visits*	*Kinesthetic*
5	*visual_content_stay_time*	*Visual*
6	*auditory_content_stay_time*	*Auditory*
7	*reading_content_stay_time*	*Reading*
8	*kinesthetic_content_stay_time*	*Kinesthetic*
9	*no_of_visual_content_downloads*	*Visual*
10	*no_of_auditory_content_downloads*	*Auditory*
11	*no_of_reading_content_downloads*	*Reading*
12	*no_of_kinesthetic_content_downloads*	*Kinesthetic*

Also, there are questionnaires and tests which have questions belong to certain dimensions of VARK theory, for these types of content objects, we record the student performance for each dimension. Thus, as examples, the number of correctly answered visual questions and respectively for other dimensions as in Table 3.4.

Table 3.4 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_correct_visual_questions*	*Visual*
2	*no_of_correct_auditory_questions*	*Auditory*
3	*no_of_correct_reading_questions*	*Reading*
4	*no_of_correct_kinesthetic_questions*	*Kinesthetic*

2) Files in Mobile Device

Sometimes learners used to download content objects from Moodle and view them in mobile devices (or in a desktop computer), also they download learning materials from referenced links for a particular course module, and also sometimes they find and download learning materials of their own interest.

Metadata of a file is the basic information about the file. Almost every file formats contain metadata. We use this metadata to store information about VARK modality of the file, each file related to academic is tagged according to the VARK modality. Such as a learning material for 'Computer Networking' would be tagged as *"Subject* = Computer Networking", *"VARK Dimension = V"*. Then the parameters in Table 3.5 are recorded to be used in learner modeling.

Table 3.5 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_visual_file_open*	*Visual*
2	*no_of_auditory_file_open*	*Auditory*
3	*no_of_reading_file_open*	*Reading*
4	*no_of_kinesthetic_file_open*	*Kinesthetic*
5	*visual_file_stay_time*	*Visual*
6	*auditory _file_stay_time*	*Auditory*
7	*reading _file_stay_time*	*Reading*
8	*kinesthetic _file_stay_time*	*Kinesthetic*

Some learners having reading orientation usually tends to highlight text in PDFs and slides, therefore if the file is modified that information are stored with a parameter. Some learners having kinesthetic orientation used to read test answers, examples and do assignments over and over again, therefore these modifications are also tracked as in Table 3.6.

Table 3.6 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_visual_file_modification*	*Visual*
2	*no_of_auditory_file_modification*	*Auditory*
3	*no_of_reading_file_modification*	*Reading*
4	*no_of_kinesthetic_file_modificatio n*	*Kinesthetic*

3) Web search / Web visit / Bookmark

Web searching, web visiting and bookmarking are another important activities characterizes a learner. Students search the web for learning materials, hence by monitoring the search keywords, visited sites, ignored sites, site visitation durations and bookmarked sites we can determine the VARK orientation of a particular person. Therefore we obtain parameters in Table 3.7 by examining the internet usage of a mobile device as follows.

Table 3.7 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_ visual_web_searches*	*Visual*
2	*no_of_auditory_ web_searches*	*Auditory*
3	*no_of_reading_ web_searches*	*Reading*
4	*no_of_kinesthetic_web_searches*	*Kinesthetic*
5	*no_of_visual_web_visits*	*Visual*
6	*no_of_auditory_web_visits*	*Auditory*
7	*no_of_reading_web_visits*	*Reading*
8	*no_of_kinesthetic_web_visits*	*Kinesthetic*
9	*visual_web_stay_time*	*Visual*
10	*auditory_web_stay_time*	*Auditory*
11	*reading_web_stay_time*	*Reading*
12	*kinesthetic_web_stay_time*	*Kinesthetic*
13	*no_of_visual_web_bookmarks*	*Visual*
14	*no_of_auditory_web_bookmarks*	*Auditory*
15	*no_of_reading_web_bookmarks*	*Reading*
16	*no_of_kinesthetic_web_bookmarks*	*Kinesthetic*
17	*no_of_visual_web_ignores*	*Visual*
18	*no_of_auditory_web_ignores*	*Auditory*
19	*no_of_reading_web_ignores*	*Reading*

20	*no_of_kinesthetic_web_ignores*	*Kinesthetic*

4) Location

Location is another factor that should be analyzed as it provides some important indications about the VARK tendencies present in a learner.

Attending to lectures can be a compulsory task in a course module and in some course modules attendance is optional. In this research, we assume that lectures are optional as we observe the learners behavior and try to obtain a model. In VARK model it is stated that lectures generally belong to the auditory category, however, it depends on the instructor, some instructors conduct lectures in a visually oriented way, they explain using slides full of diagrams, animations, graphs,, charts, and some instructors provide notes and students have to read them, these type of lectures are reading oriented, some instructors conduct their classes like discussion sessions with students, ask more questions, get ideas from students, present ideas of professionals, etc. these lectures are auditory oriented and some instructors carry out lectures in a more interactive way, do more exercises, give more activities and conduct in class practicals, these kind of lectures are kinesthetic oriented.

Moodle has a great calendar feature and we obtain lecture schedule using it and we introduce another parameter, *'teaching_vark_orientation'* for each instructor based on the way they conduct lectures. Then using GPS of the mobile device or by using attendance records, we can obtain student pattern of attending lectures and parameterize them as in Table 3.8.

Table 3.8 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_visual_lecture_attends*	*Visual*
2	*no_of_auditory_lecture_attends*	*Auditory*
3	*no_of_reading_lecture_attends*	*Reading*
4	*no_of_kinesthetic_lecture_attends*	*Kinesthetic*

5	*no_of_visual_lecture_ignores*	*Visual*
6	*no_of_auditory_lecture_ignores*	*Auditory*
7	*no_of_reading_lecture_ignores*	*Reading*
8	*no_of_kinesthetic_lecture_ignores*	*Kinesthetic*

5) Meetings / Conversations

By using phone's microphone with the aid of speech diarization and word recognition techniques, we identify that if a learner is in a meeting where certain subject matters are discussed, also alternatively we ask learners to verify gathering up with colleagues for studying which indicates auditory learning style. Additionally, we identify meetings with instructors, by using information from the task scheduler of the phone together with its location sensors (e.g. GPS or WiFi network identification) and the meetings count & duration is recorded as in Table 3.9.

Table 3.9 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*auditory_study_count_with_colleagues*	*Auditory*
2	*auditory_study_time_with_colleagues*	*Auditory*
3	*auditory_discussions_count_with_instructors*	*Auditory*
4	*auditory_discussions_time_with_instructors.*	*Auditory*

6) Library Usage

A book usually belongs to reading modality in VARK model and most of the books are written in VARK reading style, however in certain situations books may belong to other categories, as instances, a Q & A book belongs to auditory type, a book full of charts, diagrams or pictures belongs to visual category while a book containing discussions, or stories belongs to kinesthetic dimension. It is possible to feed information from library system to Moodle about borrowed books and then we record the parameters in Table 3.10 to be used in learner modeling.

Table 3.10 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*no_of_visual_book_borrowings*	*Visual*
2	*no_of_auditory_book_borrowings*	*Auditory*
3	*no_of_reading_book_borrowings*	*Reading*
4	*no_of_kinesthetic_book_borrowings*	*Kinesthetic*

If the user not using university/college library and go to public libraries, we have to assume the student exhibits reading modality and record the parameters listed in 3.11.

Table 3.11 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*reading_no_of_library_visits*	*Reading*

7) Lecture Recording

Another strong indication of the auditory model is learners recording lectures for further reference, therefore we obtain the parameters listed in Table 3.12.

Table 3.12 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*auditory_lecture_recordins_count*	*Auditory*
2	*auditory_lecture_recordins_duration*	*Auditory*

8) Textual Communication using Moodle and Phone

Textual communication related to a certain course module is another strong indication of learner's orientation towards VARK auditory style, these text messages can be Moodle chat, Moodle messages, Moodle 'quickmail', phone SMS, chats in social networks and emails.

We can track these messages shared between colleagues and lectures to get a measure on how much the learner engaged in textual communication related to subject matters. We predefine a certain set of keywords related to every course module the user has enrolled and then search for those technical words inside above mentioned textual messages. Hence we can obtain required parameters as in Table 3.13.

Table 3.13 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*auditory_moodle_messages_sent_count_with_colleagues*	*Auditory*
2	*auditory_moodle_messages _sent_count_with_instructors*	*Auditory*
3	*auditory_moodle_chat_sent_count_with_colleagues*	*Auditory*
4	*auditory_moodle_chat_sent_count_with_colleagues*	*Auditory*
5	*auditory_moodle_quickmails_sent_count_with_colleagues*	*Auditory*
6	*auditory_moodle_quickmails_sent_count_with_colleagues*	*Auditory*
7	*auditory_sms_sent_count_with_colleagues*	*Auditory*
8	*auditory_sms _sent_count_with_instructors*	*Auditory*
9	*auditory_social_media_chat_sent_count_with_colleagues*	*Auditory*
10	*auditory_social_media _chat_sent_count_with_colleagues*	*Auditory*
11	*auditory _emails_sent_count_with_colleagues*	*Auditory*
12	*auditory _emails_sent_count_with_colleagues*	*Auditory*

9) Verbal Communication over Phone

Calls are another important parameter for identifying learners' tendency towards auditory dimension of the VARK model. To incorporate this dimension we need to identify whether a call with colleague or teacher is regarding a certain subject matter or not, for this we select a passive approach, using speech diarization and word recognition techniques, or alternatively we can use an active approach by prompting the user a dialog box to confirm whether the discussion was about a subject matter or not, after a phone call with a colleague or a lecturer. Thus we can obtain the parameters in Table 3.14.

Table 3.14 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*auditory_call_count _with_colleagues*	*Auditory*
2	*auditory_call_count_with_instructors*	*Auditory*
3	*auditory_call_duration_with_colleagues*	*Auditory*
4	*auditory_call_duration_with_instructors*	*Auditory*
5	*auditory_call_person_count_instructors*	*Auditory*
6	*auditory_call_person_count_colleagues*	*Auditory*

10) Mobile App Usage

There are certain applications belongs to particular VARK dimensions, as examples, a puzzle game would belong to VARK kinesthetic dimension, a reading app would belong to the reading category, an online training app would belong to auditory dimension, the user might use a mind map tool to generate mind maps which indicate visual dimension. Therefore we record app usage patterns as in Table 3.15.

Table 3.15 - Indicators for VARK Modeling

	Parameters	Assumed Indication
1	*visual_app_count*	*Visual*
2	*auditory_app_count*	*Auditory*
3	*reading_app_count*	*Reading*
4	*kinesthetic_app_count*	*Kinesthetic*
5	*visual_app_usage_time*	*Visual*
6	*auditory_app_usage_time*	*Auditory*
7	*reading_app_usage _time*	*Reading*
8	*kinesthetic_app_usage_time*	*Kinesthetic*

3.2.2 Evaluation of Felder-Silverman model for learner modeling in LMS / mobile context

Basically, in Felder-Silverman Learning and Teaching Styles Model (FSLTSM) [1], learner behaviors are evaluated along five dimensions where each dimension have two different extensions. Those are, Intuitive/Sensory, Visual/Auditory, Inductive/ Deductive, Active/Reflective and Sequential/Global. Among these dimensions, modeling Inductive/Deductive dimension is exempted as it is difficult to detect it in LMS/Mobile context, and as the Visual/Auditory dimension has already been taken into account in Neil Fleming's VARK model. Therefore, we consider only the other three dimensions,

1) Intuitive/Sensory
2) Active/Reflective
3) Sequential/Global

Following describes what information is taken from LMS/Mobile context to identify the above three dimensions.

1) Content Objects

As in VARK model, content objects provide an immense of information to model Felder-Silverman model as well.

A leaner with Intuitive dimension would exhibit a more frequent interaction with the intuitive type of contents, such as documents containing theoretical content, documents describing hypothetical models, eBooks and etc. In contrast, a learner with sensory dimension would exhibit an interest in documents containing case studies, lab practical, documentary videos, statistical reports and etc.

Active learners prefer trying things out, they are interested in resources like, documents containing exercises, past papers, model papers, on the other hand, reflective learners prefer resources like, documents containing Q & A, model answers, examples etc.

Sequential learners are the type of learners who take information in a stepwise manner, therefore they prefer resources like tutorials, eBooks while global learners prefer documents containing extra reading, summaries, what ifs, overall big picture.

By correctly categorizing resources provided for learners, we can observe their interaction with those content objects, then their interactions are tracked as in Table 3.16.

Table 3.16 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*no_of_intuitive_content_visits*	*Intuitive*
2	*no_of_sensory_content_visits*	*Sensory*
3	*no_of_active_content_visits*	*Active*
4	*no_of_reflective_content_visits*	*Reflective*
5	*no_of_sequential_content_visits*	*Sequential*
6	*no_of_global_content_visits*	*Global*
7	*intuitive_content_stay_time*	*Intuitive*
8	*sensory_content_stay_time*	*Sensory*
9	*active_content_stay_time*	*Active*
10	*reflective_content_stay_time*	*Reflective*
11	*sequential_content_stay_time*	*Sequential*
12	*global_content_stay_time*	*Global*
13	*no_of_intuitive_content_downloads*	*Intuitive*
14	*no_of_sensory_content_downloads*	*Sensory*
15	*no_of_active_content_downloads*	*Active*
16	*no_of_reflective_content_downloads*	*Reflective*
17	*no_of_sequential_content_downloads*	*Sequential*
18	*no_of_global_content_downloads*	*Global*

2) Files in Mobile Device

As in VARK modeling, we introduce a file metadata tag for the Felder-Silverman method as well, for example, a tag for an intuitive oriented file would be as *"FSLSM Dimension = Intuitive"*. Learners may obtain files from anywhere, such as from resources in Moodle, from references of course modules or by simply surfing the internet, however, even if files in course references or internet cannot be tagged we can tag resource files before publishing in Moodle. Then the parameters in Table 3.17 are recorded to be used in learner modeling.

Table 3.17 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*no_of_intuitive_file_open*	*Intuitive*
2	*no_of_sensory_file_open*	*Sensory*
3	*no_of_active_file_open*	*Active*
4	*no_of_reflective_file_open*	*Reflective*
5	*no_of_sequential_file_open*	*Sequential*
6	*no_of_global_file_open*	*Global*
7	*intuitive_file_stay_time*	*Intuitive*
8	*sensory_file_stay_time*	*Sensory*
9	*active_file_stay_time*	*Active*
10	*reflective_file_stay_time*	*Reflective*
11	*sequential_file_stay_time*	*Sequential*
12	*global_file_stay_time*	*Global*
13	*no_of_intuitive_file_modifications*	*Intuitive*
14	*no_of_sensory_file_modifications*	*Sensory*
15	*no_of_active_file_modifications*	*Active*
16	*no_of_reflective_file_modifications*	*Reflective*
17	*no_of_sequential_file_modifications*	*Sequential*
18	*no_of_global_file_modifications*	*Global*

3) Web search / Web visit / Bookmark

As in VARK modeling, we can monitor learners' internet surfing for obtaining parameters related to Felder-Silverman modeling.

Intuitive learners surf the web for theoretical resources while sensory learners search for real-life examples. Active learners search for exercises, question papers, interactive activities, quizzes, online exams and etc. while reflective learners search for model answers, example calculations, Q & A, eBook answers and etc. Sequential learners would search for online courses, tutorials, eBooks while a global learners search for summarizations, concepts and etc. Therefore by examining their behaviors, we can obtain the parameters in Table 3.18 which are related to internet usage.

Table 3.18 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*no_of_intuitive_web_searches*	*Intuitive*

2	*no_of_sensory_web_searches*	*Sensory*
3	*no_of_active_web_searches*	*Active*
4	*no_of_reflective_web_searches*	*Reflective*
5	*no_of_sequential_web_searches*	*Sequential*
6	*no_of_global_web_searches*	*Global*
7	*no_of_intuitive_web_visits*	*Intuitive*
8	*no_of_sensory_web_visits*	*Sensory*
9	*no_of_active_web_visits*	*Active*
10	*no_of_reflective_web_visits*	*Reflective*
11	*no_of_sequential_web_visits*	*Sequential*
12	*no_of_global_web_visits*	*Global*
13	*intuitive_web_stay_time*	*Intuitive*
14	*sensory_web_stay_time*	*Sensory*
15	*active_web_stay_time*	*Active*
16	*reflective_web_stay_time*	*Reflective*
17	*sequential_web_stay_time*	*Sequential*
18	*global_web_stay_time*	*Global*
19	*no_of_intuitive_web_bookmarks*	*Intuitive*
20	*no_of_sensory_web_bookmarks*	*Sensory*
21	*no_of_active_web_bookmarks*	*Active*
22	*no_of_reflective_web_bookmarks*	*Reflective*
23	*no_of_sequential_web_bookmarks*	*Sequential*
24	*no_of_global_web_bookmarks*	*Global*
25	*no_of_intuitive_web_ignores*	*Intuitive*
26	*no_of_sensory_web_ignores*	*Sensory*
27	*no_of_active_web_ignores*	*Active*
28	*no_of_reflective_web_ignores*	*Reflective*
29	*no_of_sequential_web_ignores*	*Sequential*
30	*no_of_global_web_ignores*	*Global*

4) Library Usage

Types of books a learner reads are an important parameter for leaner modeling in Felder-Silverman model as in VARK model. By linking Moodle and library system we can investigate the learner behavior of borrowing books.

Intuitive learners typically borrow books written in a manner that explains pure of theories, concepts, and models, while a sensory learner would borrow books full of application of theories and case studies, books about lab sessions and practical and etc.

An active learners are interested in borrowing books containing exercises, model questions, past paper books and etc. while reflective learners borrow items like answer books and etc.

Sequential learners favor to borrow books that explain a certain a subject in stepwise increasing manner, reference books for certain course modules, while global learners are interested in books that are strangely related to subjects, or books that interconnect two study areas, or books with advanced concepts beyond the scope they are asked to learn and articles, DVDs, interviews, magazines containing new trends and discussions with experts.

The parameters in Table 3.19 are to be recorded regarding library usage.

Table 3.19 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*no_of_intuitive_book_borrowings*	*Intuitive*
2	*no_of_sensory_book_borrowings*	*Sensory*
3	*no_of_active_book_borrowings*	*Active*
4	*no_of_reflective_book_borrowings*	*Reflective*
5	*no_of_sequential_book_borrowings*	*Sequential*
6	*no_of_global_book_borrowings*	*Global*

5) Forum Discussions

Moodle has discussion forums where learners can discuss their subject matters, ask questions from colleagues or from instructors, post their opinions and etc. Active learners are expected to convey an active contribution towards these forums, while reflective learners are expected to observe them while standing back posting their ideas. The parameters in Table 3.20 are obtained regarding forum discussions.

Table 3.20 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*active_reflective_forum_post_count*	*Active / Reflective*
2	*active_reflective_forum_visit_count*	*Active / Reflective*
3	*active_reflective_forum_stay_time*	*Active / Reflective*

6) Assignment Submissions

As active learners are motivated to do exercises than reflective learners, and reflective learners used to observe others first and then do their works, active learners tend to submit assignments earlier than reflective learners and they rarely miss deadlines. Therefore the parameters in Table 3.21 are recorded for learner modeling.

Table 3.21 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*active_reflective_no_of_assignemts_submission_on_time*	*Active / Reflective*
2	*active_reflective_no_of_deadline_missings*	*Active / Reflective*

7) Mobile Apps Usage

Educational mobile apps can be categorized based on Felder-Silverman modalities. For example, there are apps that provide information about core subject matters like theories, models these apps belong to Felder-Silverman intuitive category, while there are another set of apps that explain the application of theories, these apps belong to the sensory category.

There are apps that users can interactively learn with, these apps belong to the active category. Information providing apps in forms of articles belong to the reflective category. Also, there are educational apps that provide students learning experience in a stepwise manner, these apps belong to the sequential category. Therefore the parameters in Table 3.22 are recorded to be used in leaner modeling with Felder-Silverman model.

Table 3.22 - Indicators for Felder-Silverman Modeling

	Parameters	Assumed Indication
1	*no_of_intuitive_apps*	*Intuitive*
2	*no_of_sensory_apps*	*Sensory*
3	*no_of_active_apps*	*Active*
4	*no_of_reflective_apps*	*Reflective*
5	*no_of_sequential_apps*	*Sequential*
6	*intuitive_app_usage_time*	*Intuitive*
7	*sensory_app_usage_time*	*Sensory*
8	*active_app_usage_time*	*Active*
9	*reflective_app_usage_time*	*Reflective*
10	*sequential_app_usage_time*	*Sequential*

3.2.3 Evaluation of Grasha-Reichmann model for learner modeling in LMS / mobile context

In this model, the learners are categorized into the following dimension.

1. Competitive
2. Collaborative
3. Avoidant
4. Participant
5. Dependent
6. Independent

1) Forum Discussions / Moodle Blog / Wiki

If we consider about dependent learners, they are expected to ask more questions on forums, while competitive, collaborative and participant learners are expected to answer them. Also, competitive learners and participant learners are expected to write opinions in those forums while competitive learners avoid asking many questions. Competitive learners and participant learners are expected to write in Moodle blogs and Wikis. An avoidant learner expected to contribute very less amount or no participation at all for these LMS activities. Therefore the parameters in Table3.23 are recorded.

Table 3.23 - Indicators for Grasha-Reichmann Modeling

	Parameters	Assumed Indication
1	*dependent_no_of_forum_question_askings*	*Dependent*
2	*competitive_collaborative_participant_no_of_forum_answerings*	*Competitive / Participant / Collaborative*
3	*competitive_participant_no_of_forum_opinion_writings*	*Competitive / Participant*
4	*competitive_participant_no_of_blog_posts*	*Competitive / Participant*
5	*competitive_participant_no_of_wiki_pages*	*Competitive / Participant*
6	*competitive_participant_no_of_wiki_updates*	*Competitive / Participant*

2) Location

Participant learners are expected to attend almost every lecture while avoidant learners expected to absent. Collaborative learners and dependent learners are expected to spend more time with peers when studying, while independent learners study alone. By using speech diarization and word recognition techniques collaboratively with location information, it is possible to identify group studying activities.

Independent learners are expected to study along, therefore they are expected to study in studying areas of a university, study area in libraries etc., by using GPS, Wi-Fi network locating or access cards we obtain their study time information as well. Therefore the parameters in Table 3.24 are considered.

Table 3.24 - Indicators for Grasha-Reichmann Modeling

	Parameters	Assumed Indication
1	*participant_no_of_lecture_attendings.*	*Participant*
2	*collaborative_dependent_study_time_with_peers.*	*Collaborative*
3	*independent_study_time*	*Independent*

3.2.4 Evaluation of Dunn and Dunn's model for learner modeling in LMS / mobile context

In this model, the following areas are used to model learners. This model characterizes learners along five dimensions and following is a concise illustration of the model.

1) Environmental
    - Sound
    - Light
    - Temperature
    - Design

2) Emotional
    - Motivational support
    - Persistence
    - Individual Responsibility
    - Structure

3) Sociological
    - Individual
    - Pairs or Teams
    - Adult
    - Varied

4) Physiological
    - Perpetual
    - Intake
    - Time
    - Mobility

5) Psychological
    - Global

- Analytical
- Impulsive
- Reflective

We only focus on parameters that are feasible and additional to this model, as emotional factors are difficult to capture by LMS/Mobile context, we exempt this dimension. Sociological factors and psychological factors have been discussed and parameterized in previous sections. Therefore, we do not consider them in this section.

Environmental parameters can be easily obtained by mobile devices. The only problem is we want to identify whether a learner is engaged in self-driven studying activity in particular conditions, for this purpose we prompt the learner to confirm by asking. Sound levels can be obtained by the microphone, hence we can obtain the parameter *noise_level*, lighting levels are from photometer hence the parameter *light_level*, temperature by thermometers hence the parameter *temperature*, humidity by sensors hence *humidity_level.* The Table 3.25 summarized those parameters.

Table 3.25 - Indicators for Dunn & Dunn Modeling

	Parameters
1	*environmental_self_study_noise_level*
2	*environmental_self_study_light_level*
3	*environmental_self_study_temperature_level*
4	*environmental_self_study_humidity_level*

Physiological factor time can be obtained by prompting the user to confirm whether he is studying early morning or night. Hence we can obtain parameters *morning_study_count, morning_study_duration, night_study_count, night_study_duration.* Regarding mobility, usually students do not keep the phone with them when they are studying, therefore it is difficult to use any sensor to detect this activity, and hence we prompt the user to confirm whether he did studying with mobility or not. The Table 3.26 summarized those parameters.

Table 3.26 - Indicators for Dunn & Dunn Modeling

	Parameters
1	physiological_*morning_study_count*
2	physiological_*morning_study_duration*
3	physiological_*night_study_count*
4	physiological_*night_study_duration*
5	physiological_m*obile_study_count*
6	physiological_*mobile_study_duration*

3.3 Building the Models for Learning Style Detection

In this section, we discuss how to develop models for automatic learning style detection. The proposed approach describes the development of four models.

1) Model for VARK learning styles
2) Model for Felder-Silverman learning styles
3) Model for Grasha-Reichmann learning styles
4) Model for Dunn and Dunn learning styles

After these models are built we use these models to the automatic detection of learning styles, and information from newly detected learners are fed back to the model to optimize the model into a solid one.

As previously described in section 2.1.3, there are some approaches for the manual detection of learning styles, one popular one is, learners are asked to fill out a questionnaire and based on their answers learning styles are inferred. In this case, every time a learner is modeled, the learner has to fill out a form and modeling is done afterward.

3.3.1 Use of learning style questionnaires in the initial phase

In our approach, first we have to train the system with some available data, therefore in the initial phase we have to ask a selected set of learners to verify their learning styles with the old-fashioned questionnaire-based approach, and then assuming the questionnaire based approach correctly identified learning styles, we can move on to development of the automatic detection phase.

As we model VARK learning styles, Felder-Silverman learning styles, Grasha-Reichmann learning styles and Dunn and Dunn learning styles, we use their respective learning style questionnaires to obtain data for the initial phase. Each student selected for learner modeling are given with the following 4 questionnaires,

- VARK learning styles questionnaire
- Felder-Silverman index of learning styles questionnaire
- Grasha-Reichmann learning styles questionnaire
- Dunn and Dunn learning styles questionnaire

Based on their answers to each questionnaire, we determine the learners' perceptive learning styles. However, in this study, we set a threshold of at least 75% of total questions from a particular questionnaire to be answered in a certain dimension to the learner is considered to belong to that particular dimension.

3.3.1.1 Possible drawbacks of collaborative learner modeling

These questionnaire results are crucial and therefore should be done carefully as this model is going to be used in later stages of detection of learning styles. It is common this collaborative learner modeling is ineffective due to several reasons, such as,

- Lack of self-awareness.
- Reluctant to fill out questionnaires.
- Influences from other people.
- Emotional state when they filling the questionnaire.

Therefore it is very important to provide these questionnaires avoiding above situations as much as possible by giving enough time, asking students to fill-out carefully when they are not stressed, individually without taking help from friends and recalling past learning experiences when they are answering the questionnaire.

3.3.2 Parameterizing indicators

In previous sections, we discussed how to identify relevant parameters for learner modeling in each selected learning style models. In this section, we discuss parameterizing selected parameters.

3.3.2.1 Parameterizing VARK indicators

After identifying indicators for each dimension, these indicators need to be parameterized to be used in learning styles detection phase, thus we need mean(μ) and standard deviation(σ) values for the each and every indicator we selected in the previous section.

We identified a set of qualified parameters with the aid of a selected group for VARK modeling and providing them with the VARK questionnaire, however, learners do not usually answer all the questionnaire indicating a certain VARK dimension. Therefore again by applying the 75% rule on leaners, we select learners to be used in learner modeling. Thus the learners who have answered more than 12 questions (i.e. = 16 * 75%) indicating a certain dimension are eligible for learner modeling. The secondly selected samples are to be used to parameterize indicators pertaining to that particular dimension. Then we compute mean and standard deviation values of each indicator using those learners as in Table 3.27.

Table 3.27 - Parameterized VARK Indicators

	VARK Dimensions	VARK Indicators	Mean	Standard Deviation
1	Visual	$VP_{v,1}$,	$\mu_{VP_{v,1}}$	$\sigma_{VP_{v,1}}$
		…	…	…
		$VP_{v,p}$	$\mu_{VP_{v,p}}$	$\sigma_{VP_{v,p}}$
2	Auditory	$VP_{a,1}$,	$\mu_{VP_{a,1}}$	$\sigma_{VP_{a,1}}$
		…	…	…
		$VP_{a,q}$	$\mu_{VP_{a,q}}$	$\sigma_{VP_{a,q}}$
3	Reading	$VP_{r,1}$,	$\mu_{VP_{r,1}}$	$\sigma_{VP_{r,1}}$
		…	…	…
		$VP_{r,r}$	$\mu_{VP_{r,r}}$	$\sigma_{VP_{r,r}}$
4	Kinesthetic	$VP_{k,1}$,	$\mu_{VP_{k,1}}$	$\sigma_{VP_{k,1}}$
		…	…	…

		$VP_{k,s}$	$\mu_{VP_{k,s}}$	$\sigma_{VP_{k,s}}$

3.3.2.2 Parameterizing Felder-Silverman indicators

Following the same procedure as in above section, we compute and obtain probability density functions of Felder-Silverman parameters of selected learners as in Table 3.28.

Table 3.28 - Parameterized Felder-Silverman Indicators

	Felder-Silverman Dimensions	Felder-Silverman Indicators	Mean	Standard Deviation
1	Intuitive	$FS_{int,1}$	$\mu_{FS_{int,1}}$	$\sigma_{FS_{int,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{int,p}$	$\mu_{FS_{int,p}}$	$\sigma_{FS_{int,p}}$
2	Sensory	$FS_{sen,1}$	$\mu_{FS_{sen,1}}$	$\sigma_{FS_{sen,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{sen,q}$	$\mu_{FS_{sen,q}}$	$\sigma_{FS_{sen,q}}$
3	Active	$FS_{act,1}$	$\mu_{FS_{act,1}}$	$\sigma_{FS_{act,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{act,r}$	$\mu_{FS_{act,r}}$	$\sigma_{FS_{act,r}}$
4	Reflective	$FS_{ref,1}$	$\mu_{FS_{ref,1}}$	$\sigma_{FS_{ref,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{ref,s}$	$\mu_{FS_{ref,s}}$	$\sigma_{FS_{ref,s}}$
5	Sequential	$FS_{seq,1}$	$\mu_{FS_{seq,1}}$	$\sigma_{FS_{seq,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{seq,t}$	$\mu_{FS_{seq,t}}$	$\sigma_{FS_{seq,t}}$
6	Global	$FS_{glo,1}$	$\mu_{FS_{glo,1}}$	$\sigma_{FS_{glo,1}}$
		$\ldots$	$\ldots$	$\ldots$
		$FS_{glo,u}$	$\mu_{FS_{glo,u}}$	$\mu_{FS_{glo,u}}$

3.3.2.3 Parameterizing Grasha-Reichmann indicators

We follow the same procedure as in parameterizing VARK modeling and Felder-Silverman modeling to obtain probability distribution functions (i.e. mean and standard deviation values) of selected learners for modeling Grasha-Reichmann learning styles as in Table 3.29.

Table 3.29 - Parameterized Grasha-Reichmann Indicators

	Grasha-Reichmann Dimensions	Grasha-Reichmann Indicators	Mean	Standard Deviation
1	Competitive	$GR_{com,1}$	$\mu_{GR\ com,1}$	$\sigma_{GR\ com,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{com,p}$	$\mu_{GR\ com,p}$	$\sigma_{GR\ com,p}$
2	Collaborative	$GR_{col,1}$	$\mu_{GR\ col,1}$	$\sigma_{GR\ col,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{col,q}$	$\mu_{GR\ col,q}$	$\sigma_{GR\ col,q}$
3	Avoidant	$GR_{avo,1}$	$\mu_{GR\ avo,1}$	$\sigma_{GR\ avo,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{avo,r}$	$\mu_{GR\ avo,r}$	$\sigma_{GR\ avo,r}$
4	Participant	$GR_{par,1}$	$\mu_{GR\ par,1}$	$\sigma_{GR\ par,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{par,s}$	$\mu_{GR\ par,s}$	$\sigma_{GR\ par,s}$
5	Dependent	$GR_{dep,1}$	$\mu_{GR\ dep,1}$	$\sigma_{GR\ dep,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{dep,t}$	$\mu_{GR\ dep,t}$	$\sigma_{GR\ dep,t}$
6	Independent	$GR_{ind,1}$	$\mu_{GR\ ind,1}$	$\sigma_{GR\ ind,1}$
		$\dots$	$\dots$	$\dots$
		$GR_{ind,u}$	$\mu_{GR\ ind,u}$	$\mu_{GR\ ind,u}$

3.3.2.4 Parameterizing Dunn and Dunn indicators

Using the same procedure as in previous three sections, we obtain mean and standard deviation values for the learners elected for modeling Dunn and Dunn learning styles as in Table 3.30.

Table 3.30 - Parameterized VARK Indicators

	Dunn & Dunn Dimensions	Dunn & Dunn Indicators	Mean	Standard Deviation
1	Environmental Sound	$DD_{env\_s,1}$	$\mu_{DD\ env\_s,1}$	$\sigma_{DD\ env\_s,1}$
		$\dots$	$\dots$	$\dots$
		$DD_{env\_s,p}$	$\mu_{DD\ env\_s,p}$	$\sigma_{DD\ env\_s,p}$
2	Environmental Light	$DD_{env\_l,1}$	$\mu_{DD\ env\_l,1}$	$\sigma_{DD\ env\_l,1}$
		$\dots$	$\dots$	$\dots$
		$DD_{env\_l,u}$	$\mu_{DD_{env\_l,u}}$	$\sigma_{DD_{env\_l,u}}$
3	Environmental Temperature	$DD_{env\_t,1}$	$\mu_{DD_{env\_t,1}}$	$\sigma_{DD_{env\_t,1}}$
		$\dots$	$\dots$	$\dots$

		$DD_{env\_t,u}$	$\mu_{DD_{env\_t,u}}$	$\sigma_{DD_{env\_t,u}}$
4	Environmental Design	$DD_{env\_d,1}$	$\mu_{DD_{env\_d,1}}$	$\sigma_{DD_{env\_d,1}}$
		…	…	…
		$DD_{env\_d,d}$	$\mu_{DD_{env\_d,d}}$	$\sigma_{DD_{env\_d,d}}$
5	Emotional Motivational Support	$DD_{emo\_m,1}$	$\mu_{DD_{emo\_m,1}}$	$\sigma_{DD_{emo\_m,1}}$
		…	…	…
		$DD_{emo\_m,e}$	$\mu_{DD_{emo\_m,e}}$	$\sigma_{DD_{emo\_m,e}}$
6	Emotional Persistence	$DD_{emo\_p,1}$	$\mu_{DD_{emo\_p,1}}$	$\sigma_{DD_{emo\_p,1}}$
		…	…	…
		$DD_{emo\_p,f}$	$\mu_{DD_{emo\_p,f}}$	$\sigma_{DD_{emo\_p,f}}$
7	Emotional Individual Responsibility	$DD_{emo\_i,1}$	$\mu_{DD_{emo\_i,1}}$	$\sigma_{DD_{emo\_i,1}}$
		…	…	…
		$DD_{emo\_i,g}$	$\mu_{DD_{emo\_i,g}}$	$\sigma_{DD_{emo\_i,g}}$
8	Emotional Structure Indicators	$DD_{emo\_s,1}$	$\mu_{DD_{emo\_s,1}}$	$\sigma_{DD_{emo\_s,1}}$
		…	…	…
		$DD_{emo\_s,h}$	$\mu_{DD_{emo\_s,h}}$	$\sigma_{DD_{emo\_s,h}}$
9	Sociological Individual	$DD_{soc\_i,1}$	$\mu_{DD_{soc\_i,1}}$	$\sigma_{DD_{soc\_i,1}}$
		…	…	…
		$DD_{soc\_i,i}$	$\mu_{DD_{soc\_i,i}}$	$\sigma_{DD_{soc\_i,i}}$
10	Sociological Pairs or Teams	$DD_{soc\_p,1}$	$\mu_{DD_{soc\_p,1}}$	$\sigma_{DD_{soc\_p,1}}$
		…	…	…
		$DD_{soc\_p,j}$	$\mu_{DD_{soc\_p,j}}$	$\sigma_{DD_{soc\_p,j}}$
11	Sociological Adult	$DD_{soc\_a,1}$	$\mu_{DD_{soc\_a,1}}$	$\sigma_{DD_{soc\_a,1}}$
		…	…	…
		$DD_{soc\_a,k}$	$\mu_{DD_{soc\_a,k}}$	$\sigma_{DD_{soc\_a,k}}$
12	Sociological Varied	$DD_{soc\_v,1}$	$\mu_{DD_{soc\_v,1}}$	$\sigma_{DD_{soc\_v,1}}$
		…	…	…
		$DD_{soc\_v,l}$	$\mu_{DD_{soc\_v,l}}$	$\sigma_{DD_{soc\_v,l}}$
13	Physiological Perpetual	$DD_{phy\_p,1}$	$\mu_{DD_{phy\_p,1}}$	$\sigma_{DD_{phy\_p,1}}$
		…	…	…
		$DD_{phy\_p,m}$	$\mu_{DD_{phy\_p,m}}$	$\sigma_{DD_{phy\_p,m}}$
14	Physiological Intake	$DD_{phy\_i,1}$	$\mu_{DD_{phy\_i,1}}$	$\sigma_{DD_{phy\_i,1}}$
		…	…	…
		$DD_{phy\_i,n}$	$\mu_{DD_{phy\_i,n}}$	$\sigma_{DD_{phy\_i,n}}$
15	Physiological Time	$DD_{phy\_t,1}$	$\mu_{DD_{phy\_t,1}}$	$\sigma_{DD_{phy\_t,1}}$
		…	…	…

		$DD_{phy\_t,o}$	$\mu_{DD_{phy\_t,o}}$	$\sigma_{DD_{phy\_t,o}}$
16	Physiological Mobility	$DD_{phy\_m,1}$	$\mu_{DD_{phy\_m,1}}$	$\sigma_{DD_{phy\_m,1}}$
		…	…	…
		$DD_{phy\_m,p}$	$\mu_{DD_{phy\_m,p}}$	$\sigma_{DD_{phy\_m,p}}$
17	Psychological Global	$DD_{psy\_g,1}$	$\mu_{DD_{psy\_g,1}}$	$\sigma_{DD_{psy\_g,1}}$
		…	…	…
		$DD_{psy\_g,q}$	$\mu_{DD_{psy\_g,q}}$	$\sigma_{DD_{psy\_g,q}}$
18	Psychological Analytical	$DD_{psy\_a,1}$	$\mu_{DD_{psy\_a,1}}$	$\sigma_{DD_{psy\_a,1}}$
		…	…	…
		$DD_{psy\_a,r}$	$\mu_{DD_{psy\_a,r}}$	$\sigma_{DD_{psy\_a,r}}$
19	Psychological Impulsive	$DD_{psy\_i,1}$	$\mu_{DD_{psy\_i,1}}$	$\sigma_{DD_{psy\_i,1}}$
		…	…	…
		$DD_{psy\_i,s}$	$\mu_{DD_{psy\_i,s}}$	$\sigma_{DD_{psy\_i,s}}$
20	Psychological Reflective	$DD_{psy\_r,1}$	$\mu_{DD_{psy\_r,1}}$	$\sigma_{DD_{psy\_r,1}}$
		…	…	…
		$DD_{psy\_r,t}$	$\mu_{DD_{psy\_r,t}}$	$\sigma_{DD_{psy\_r,t}}$

Collaborative student modeling will be error-prone and it will provide students learning style at a specific point in time. Therefore Automatic detection of learning styles is necessary. It is possible to optimize the model on the run using the feedbacks from automatically detected learner profiles (refer Figure 3.1).

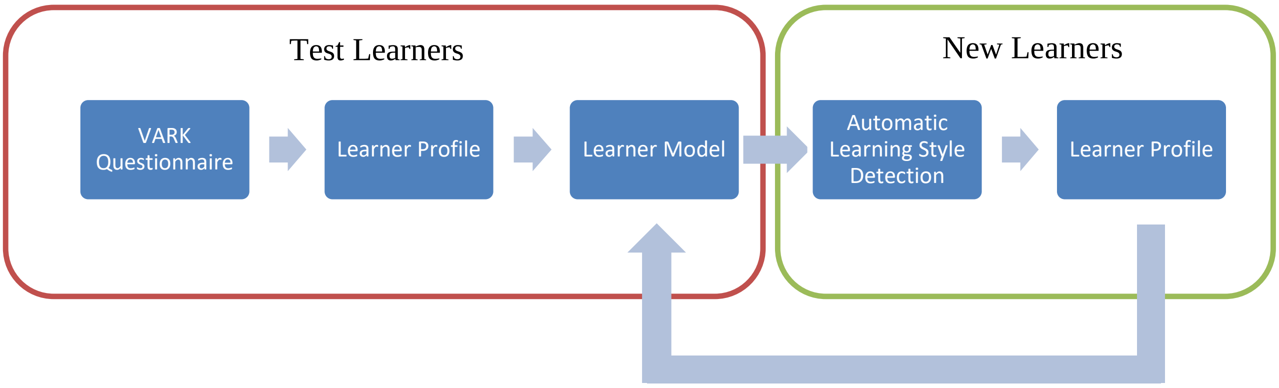


Figure 3.1 - Optimizing Model Using Feedbacks

3.4 Automatic Detection of Learning Styles using the Developed Model

After obtaining the probability distribution functions for each indicator, it becomes a data mining classification problem to identify learning styles. For this classification task we can use a number of classifiers like Support Vector Machine (SVM) classifier, Linear Discriminant Analysis (LDA) based classifier, Bayes Theorem based classifier, Random Forest classifier etc. in this study we will use Bayes classification for identifying learning styles.

3.4.1 Bayes' classification

Bayes classification is a type of probabilistic classifier based on Bayes' theorem [34]. This classifier is suited when the input dimensionality is high as its high accuracy and performance in large inputs. Bayes' classifier assumes the class conditional independence, in other words, input parameters are independent of each other.

The number of data points we used in training set is low (i.e. 20 data points) therefore we assume the class conditional independency & we assume that each indicator has no correlation with any other indicator. In Bayes' classification, probabilities for belonging to each predefined classes are calculated and then accept the class with the maximum-likelihood.

Let's X be an observed data sample where the class label is unknown, H_k is a hypothesis that X belongs to class C_k. Then $P(H_k|X)$ is the probability that X holds the hypothesis H_k, thus classifier calculates $P(H_i|X)$ for all classes and accept H_i with highest $P(H_i|X)$ value.

Given training data X, the posteriori probability of a hypothesis H_i, $P(H_i|X)$ follows the Bayes theorem

$$P(H_i|X) = \frac{P(X|H_i) \times P(H_i)}{P(X)}$$

$P(H_i) : \ prior\ probability\ (the\ initial\ probability)$

$P(X) : \ probability\ that\ sample\ data\ is\ observed.$

$P(X|H_i): posteriori\ probability\ (the\ probability\ of\ observing\ the\ sample\ X, given\ that\ the$

Classification is to derive the maximum posterior, i.e., the maximal $P(H_i|X)$. Suppose there are m classes then X belongs to class C_i if and only if the following condition is satisfied.

$$P(H_i|X) > \ P(H_j|X) \quad ; for\ 1 \leq j \leq m, j \neq i$$

Since $P(X)$ is constant for all classes, only $P(X|H_i) \times P(H_i)$ needs to be maximized.

Assuming attributes are conditionally independent,

$$P(X|H_i) = \prod_{k=1}^{n} P(X_k|H_i)$$

$$= P(X_1|H_i) \times P(X_2|H_i) \ldots \ldots \times P(X_n|H_i)$$

If X_k is categorical, $P(X_k|H_i)$ is the number of tuples in C_i having values X_k, divided by the total of tuples in C_i. If the distribution of X is continuous, use Gaussian distribution function for X to calculate the probability $P(X_k|H_i)$.

$$P(X_k|H_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \times e^{-\frac{(x_k-\mu_i)^2}{2\sigma^2}}$$

Where,

$$\mu_i = \frac{\sum_{k=1}^{N} x_k}{N}$$

$$\sigma_i = \sqrt{\frac{1}{N} \times \sum_{k=1}^{N} (x_k - \mu)^2}$$

Consider D is the set of training tuples from all classes and then, class prior probabilities $P(H_i)$ are estimated as follows,

$$P(H_i) = \frac{|C_i, D|}{|D|}$$

$|C_i, D| = number\ of\ class\ i\ tupples\ in\ training\ set$

$|D| = number\ of\ total\ tupples\ in\ training\ set$

3.4.2 Applying Bayes' classification

In this scenario X_k is continuous, therefore the probability of X_k in C_i is calculated assuming the standard normal distribution for X_k (Gaussian distribution of X_k). We have calculated mean values and standard deviations for each indicator parameter for all dimensions. Therefore by probability density function for a normal distribution,

$$P(X_k|H_i) = \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(x_k-\mu)^2}{2\sigma^2}}$$

$\mu = mean\ of\ X_k$

$\sigma = standard\ deviation\ of\ X_k$

Therefore,

$$P(X|H_i) = \prod_{k=1}^{n} \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(x_k-\mu)^2}{2\sigma^2}}$$

And as obtained in previous section,

$$P(H_i) = \frac{|C_i, D|}{|D|}$$

Therefore,

$$P(X|H_i) \times P(H_i) = \left(\prod_{k=1}^{n} \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(x_k-\mu)^2}{2\sigma^2}}\right) \times \frac{|C_i, D|}{|D|}$$

For automatic learning style detection we find, classes with maximum $P(X|H_i) \times P(H_i)$ which gives the maximum posterior probability $P(H_i|X)$ with respect to indicators of each learning style.

3.4.2.1 Applying automatic learning style detection for VARK model

In section 3.3.1 we selected a sample most suited for VARK modeling, we use 90% of data from this sample as training data and the rest 10% to be test data. By using Bayes' classification on different data samples, and using 90% for training and 10% as test data, we verify the validity of the classifier.

In VARK model, there are four classes,

$$C_1 = \{visual\}$$

$$C_2 = \{auditory\}$$

$$C_3 = \{reading\}$$

$$C_4 = \{kinesthetic\}$$

Then $\mu_1, \mu_2, \mu_3, \mu_4$ and $\sigma_1, \sigma_2, \sigma_3, \sigma_4$ values are calculated for each indicator for visual, auditory, reading and kinesthetic dimensions respectively using the training set.

Then we consider how to verify one test data learner belongs to a certain dimension using Bayes' classifier. First, we obtain conditional probabilities for each indicator values of the selected test data learner,

$$P(X_k|H_1) = \frac{1}{\sigma_1 \sqrt{2\pi}} \times e^{-\frac{(x_k-\mu_1)^2}{2\sigma^2}}$$

$$P(X_k|H_2) = \frac{1}{\sigma_2 \sqrt{2\pi}} \times e^{-\frac{(x_k-\mu_2)^2}{2\sigma^2}}$$

$$P(X_k|H_3) = \frac{1}{\sigma_3 \sqrt{2\pi}} \times e^{-\frac{(x_k-\mu_3)^2}{2\sigma^2}}$$

$$P(X_k|H_4) = \frac{1}{\sigma_4 \sqrt{2\pi}} \times e^{-\frac{(x_k-\mu_4)^2}{2\sigma^2}}$$

By substituting above conditional probability values of each indicator, we obtain posterior probabilities for each VARK dimension using the following equations.

$$P(X|H_1) = P(X_1|H_1) \times P(X_2|H_1) \ldots\ldots \times P(X_n|H_1)$$

$$P(X|H_2) = P(X_1|H_2) \times P(X_2|H_2) \ldots\ldots \times P(X_n|H_2)$$

$$P(X|H_3) = P(X_1|H_3) \times P(X_2|H_3) \ldots\ldots \times P(X_n|H_3)$$

$$P(X|H_4) = P(X_1|H_4) \times P(X_2|H_4) \ldots\ldots \times P(X_n|H_4)$$

Then we obtain prior probabilities by dividing the number of learners from each class by total number of learners in training set as follows,

$$P(H_1) = \frac{|C_1, D|}{|D|}$$

$$P(H_2) = \frac{|C_2, D|}{|D|}$$

$$P(H_3) = \frac{|C_3, D|}{|D|}$$

$$P(H_4) = \frac{|C_4, D|}{|D|}$$

Then we calculate $P(X|H_i) \times P(H_i)$ for each class which are proportional to $P(H_i|X)$ as $P(X)$ is constant over each class as $P(X)$ is independent of class,

$$P(H_1|X) \sim P(X|H_1) \times P(H_1)$$

$$P(H_2|X) \sim P(X|H_2) \times P(H_2)$$

$$P(H_3|X) \sim P(X|H_3) \times P(H_3)$$

$$P(H_4|X) \sim P(X|H_4) \times P(H_4)$$

Then the highest value among above four values should belong to the same class as the class of the test data learner in order to verify the model. Likewise, we verify all the test data to verify this model. Then once the data of a new learner whose class is unknown, fed into the model we can classify the learner into one of VARK classes.

3.4.2.1.1 **Multimodality in VARK learning styles**

Even though the study is carried out so far for single-modality, learners may exhibit multiple learning style orientations in VARK model, if a student exhibit higher probabilities in Bayes' classification for multiple classes, we can conclude that the learner has multimodality orientation, for this a threshold is introduced for probability to be elected for a certain class. On the other hand, if any of indicator did not reach the threshold value, the student is said to exhibit no particular learning style.

3.4.2.2 Applying automatic learning style detection for Felder-Silverman model

In Felder-Silverman model there are 3 groups of classes and therefore we have to run the described procedure in section 2.3.2.1 three times. Each group contains two classes.

$$Category\ 1\ , class\ C_1 = \{Intuitive\}$$

$$Category\ 1\ , class\ C_2 = \{Sensory\}$$

$$Category\ 2\ , class\ C_3 = \{Active\}$$

$$Category\ 2\ , class\ C_4 = \{Reflective\}$$

$$Category\ 3\ , class\ C_5 = \{Sequential\}$$

$$Category\ 3\ , class\ C_6 = \{Global\}$$

3.4.2.3 Applying automatic learning style detection for Grasha-Reichmann model

In Grasha-Reichmann model we have 6 learning styles and therefore we execute the described procedure in section 2.4.2.1 for six classes.

$$C_1 = \{Competitive\}$$

$$C_2 = \{Collaborative\}$$

$$C_3 = \{Avoidant\}$$

$$C_4 = \{Participant\}$$

$$C_5 = \{Dependent\}$$

$C_6 = \{Independent\}$

3.4.2.4 Applying automatic learning style detection for Dunn & Dunn model

As explained in section 2.2.4, we have exempted 'Emotional' factors and as we have already considered 'Sociological' and 'Psychological' factors in Felder-Silverman modeling we don't classify those classes in this section.

We evaluated Dunn & Dunn model's applicability to this study in section 2.2.4. In there we concluded that, as environmental parameters, 'noise level', 'light level', 'temperature level' and 'humidity level' are obtainable in Mobile/LMS context, and as physiological parameters 'time' and 'mobility' is possible to parameterize. Therefore we identified classes as follows.

$$Envirometal\ Category\ 1, Noise\ Level\ Parameter\ \rightarrow class\ C_1 = \{low\ noise\ level\}$$

$$Envirometal\ Category\ 1, Noise\ Level\ Parameter\ \rightarrow class\ C_2 = \{moderate\ noise\ level\}$$

$$Envirometal\ Category\ 1, Noise\ Level\ Parameter\ \rightarrow class\ C_3 = \{high\ noise\ level\}$$

$$Envirometal\ Category\ 2, Light\ Level\ Parameter\ \rightarrow class\ C_4 = \{low\ temperature\ level\}$$

$$Envirometal\ Category\ 2, Light\ Level\ Parameter\ \rightarrow class\ C_5 = \{moderate\ temperature\ level\}$$

$$Envirometal\ Category\ 2, Light\ Level\ Parameter\ \rightarrow class\ C_6 = \{high\ temperature\ level\}$$

$$Envirometal\ Category\ 3, Temperature\ Level\ Parameter\ \rightarrow class\ C_7 = \{low\ temperature\ level\}$$

$$Envirometal\ Category\ 3, Temperature\ Level\ Parameter\ \rightarrow class\ C_8 = \{moderate\ temperature\ level\}$$

$$Envirometal\ Category\ 3, Temperature\ Level\ Parameter\ \rightarrow class\ C_9 = \{high\ temperature\ level\}$$

$$Envirometal\ Category\ 4, Humidity\ Level\ Parameter\ \rightarrow class\ C_{10} = \{low\ humidity\ level\}$$

$$Envirometal\ Category\ 4, Humidity\ Level\ Parameter\ \rightarrow class\ C_{11} = \{moderate\ humidity\ level\}$$

$$Envirometal\ Category\ 4, Humidity\ Level\ Parameter\ \rightarrow class\ C_{12} = \{high\ humidity\ level\}$$

$$Physiological\ Category\ 1, Time\ Parameter\ \rightarrow class\ C_{13} = \{morning\ study\}$$

$$Physiological\ Category\ 1, Time\ Parameter\ \rightarrow class\ C_{14} = \{night\ study\}$$

$$Physiological\ Category\ 2, Mobility\ Parameter\ \rightarrow class\ C_{15} = \{mobility\ required\}$$

$$Physiological\ Category\ 2, Mobility\ Parameter\ \rightarrow class\ C_{16} = \{stationary\ required\}$$

Now we carry out a similar procedure as described in section 2.4.2.1 to classify learners according to the identified parameters of Dunn & Dunn model.

3.4.3 Identifying relevant parameters for learner modeling

In this section, we focus to address "would students with different learning styles, exhibit different behaviors in LMS / Mobile context during their learning process". As we discussed earlier, we take samples from each group of students who claim to possess certain learning styles from each learning styles models, and check whether those students from respective samples behave differently to the subject population.

Furthermore, it is important to identify which behaviors are relevant to learning style detection. Therefore, we need to filter parameters obtained in section 3.2 and obtain input parameters for the learning style detection process. For this purpose, we use hypothesis testing statistical analysis method to check whether is there any relation between students selecting a particular answer in each questionnaire and their behavior in LMS / Mobile context.

In the following subsections we discuss how to identify relevant parameters to be used in the development of the selected 4 learner models.

3.4.3.1 Identify relevant VARK modeling parameters

As discussed above, initially we present VARK questionnaire to the selected sample of students and ask them to answer carefully depending on their preferences. Each question in VARK questionnaire belongs to one dimension of VARK model, therefore students are divided into 4 groups according to their answers to each question. Thus we have 64 (i.e. = 4*16) groups as for each question there are 4 groups. Note that one learner may belong to multiple groups as multimodality is allowed.

Following is an example how we carry out hypothesis testing for a parameter obtained in section 3.2.1. We have to proceed the below calculations for each and every parameter to check whether the assumed parameter is relevant for model building.

Example:

For example calculation, we consider the parameter: "*no_of_visual_web_searches*" with the learners who have answered visually in each VARK question against the learners who have answered in other dimensions for each VARK questions respectively.

Assumptions:

1) VARK questionnaire can be used to model learners, even though it contains some questions entirely irrelevant to educational field.
2) Learners PC's browser and Mobile device's browsers are sync and so that the web searches and bookmark information reside in PC also can be fetched by reading Mobile device.
3) 'Visual web searches count' follows a normal distribution.
4) Significance level (α), below which the null hypothesis is rejected is 5%.

Then the mean value and the standard deviation of "no_of_visual_web_searches" are calculated as follows.

$$\mu_0 = \frac{\sum_{i=0}^{n} x_i}{n}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(x - \mu_0)^2}$$

Then we have to carry out hypotheses testing iteratively for all 16 questions in VARK questionnaire for the parameter "no_of_visual_web_searches". As an example, below describes how do we carry out hypotheses testing for question number 1,

State the hypotheses statements,

The null hypothesis, H_0: There is no difference in *"no_of_visual_web_searches"* between those who claimed to be visual learners in VARK question 1 and others.

$$H_0: \mu = \mu_0$$

The alternative hypothesis, H_α: number of *"visual_web_searches"* are different between those who claimed to be visual learners in VARK question 1 and others.

$$H_\alpha\colon\ \mu \neq \mu_0$$

Then we formulate an analysis plan for this analysis. The significance level is 0.05 (i.e. 5%). The test method is two-tailed z-test. Calculate the z value as follows.

$$z = \frac{\mu - \mu_0}{\sigma/\sqrt{n}}$$

$z = z - score$

$\mu\ = mean\ no_of_$visual_web_searches $of\ those\ who\ claimed\ to$
$be\ visual\ learners\ in\ VARK\ question\ 1.$

$\mu_0 = mean\ no_of_$visual_web_searches $of\ entire\ population$

$\sigma = standard\ deviation\ of\ no_of_$visual_web_searches $of\ entire\ population$

n
$= number\ of\ students\ who\ claimed\ to\ be\ visual\ learners\ in\ VARK\ question\ 1.$

In standard normal distribution, the critical values for the two-tailed t-test with the significance level of 0.05 (5%) are $P(z \leq -1.96\ )$ and $P(z \geq 1.96\ )$. Those ranges are depicted in Figure 3.2.

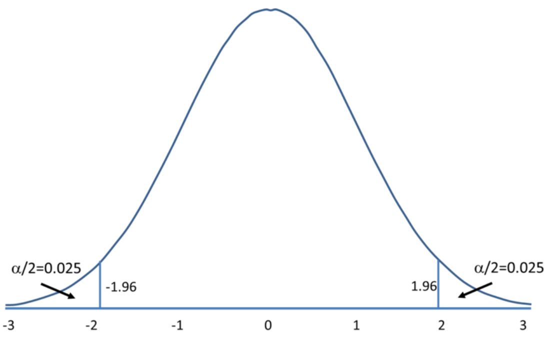


Figure 3.2 - Critical Values for Two Tailed T-Test with Significance Level 5%.

Therefore if the above calculate z-score is greater than 1.96 or lesser than -1.96 we can reject the null hypothesis which earns enough evidence to conclude that there is a difference in no_of_visual_web_searches of those who claimed to be visual learners in VARK question 1 and others. Likewise, we proceed hypotheses testing for all 16 questions and obtain a list of questions which have enough evidence to reject null hypotheses and claim that we can use parameter no_of_visual_web_searches as a relevant parameter for learner modeling. In ideal case, all the 16 questions should accept null hypothesis or all the questions should reject the null hypothesis. But it would not happen due to the following possible reasons,

1) The parameter is not a strong indication of VARK visual dimension.
2) All questions are not equally strong enough or relevant enough to identify the VARK orientation in learners.
3) Lack of self-awareness of learners answering the VARK questions.

Therefore we assume that if the parameter 'no_of_visual_web_searches' get qualified in more than 75% of VARK questions, the parameter is elected as a relevant parameter.

$$Number\ of\ questions\ rejected\ the\ null\ hypothesis > 75\%\ of\ total\ number\ of\ quesions$$

In this case, the parameter 'no_of_visual_web_searches' should reject the null hypothesis in more than 12 questions (i.e. = 16 * 75%) to get qualified as a reliable and relevant parameter for learner modeling.

Likewise, we analyze every parameter assumed to be relevant in section 3.2.1 and filter reliable and relevant parameters only. By doing this, we identify parameters with enough evidence in hypothesis testing to be relevant reliable, thus we obtain lists of parameters from each dimension of VARK learning style. Parameters which produced good evidence with best significant levels are called indicators and questions which filter most of those parameters are best questions for identifying VARK orientations, following Table 3.31 is an example set of visual, auditory, reading and kinesthetic indicators.

Table 3.31 - Example set of parameters

	VARK Indicator	Parameters
1	Visual Indicators	$VP_{v,1}, VP_{v,2}, \dots \dots \dots. \quad VP_{v,p-1}, VP_{v,p}$
2	Auditory Indicators	$VP_{a,1}, VP_{a,2}, \dots \dots \dots. \quad VP_{a,q-1}, VP_{a,q}$
3	Reading Indicators	$VP_{r,1}, VP_{r,2}, \dots \dots \dots. \quad VP_{r,r-1}, VP_{r,r}$
4	Kinesthetic Indicators	$VP_{k,1}, VP_{k,2}, \dots \dots \dots. \quad VP_{k,s-1}, VP_{k,s}$

VARK modeling is now independent of the VARK questionnaire and we no longer require asking students to fill out questionnaires to identify VARK orientations prevailing in them, instead, we monitor these qualified parameters.

This procedure for identifying relevant parameters is a generic process where it can be applied to other models as well. Therefore in the proceeding sections, we do not discuss in details how we filter parameters for modeling the other three learning styles.

3.4.3.2 Identify relevant Felder-Silverman modeling parameters

In the previous section, we discussed how we obtain VARK indicators for VARK learner modeling. As the previous procedure is a generic one, we apply the exact same steps to filter Felder-Silverman parameters as well. In section 3.2.2, we obtained a set of parameters that are assumed to be Felder-Silverman related parameters, However after filtering, as for instance, we consider the parameters in Table 3.32 are indicators of Felder-Silverman modeling,

Table 3.32 - Example set of parameters

	Felder-Silverman Indicators	Parameters
1	Intuitive Indicators	$FS_{int,1}, FS_{int,2}, \dots \dots \dots. \quad FS_{int,p-1}, FS_{int,p}$
2	Sensory Indicators	$FS_{sen,1}, FS_{sen,2}, \dots \dots \dots. \quad FS_{sen,q-1}, FS_{sen,}$
3	Active Indicators	$FS_{act,1}, FS_{act,2}, \dots \dots \dots. \quad FS_{act,r-1}, FS_{act,r}$
4	Reflective Indicators	$FS_{ref,1}, FS_{ref,2}, \dots \dots \dots. \quad FS_{ref,s-1}, FS_{ref,}$
5	Sequential Indicators	$FS_{seq,1}, FS_{seq,2}, \dots \dots \dots. \quad FS_{seq,t-1}, FS_{seq,t}$
6	Global Indicators	$FS_{glo,1}, FS_{glo,2}, \dots \dots \dots. \quad FS_{glo,u-1}, FS_{glo,u}$

3.4.3.3 Identify relevant Grasha-Reichmann modeling parameters

In the previous section, we discussed about obtaining Felder-Silverman modeling parameters. By following the same procedure as in obtaining VARK modeling parameters and Felder-Silverman modeling parameters, we obtain reliable and related parameters from the assumed list stated in section 3.2.3 as follows (refer Table 3.33).

Table 3.33 - Example set of parameters

	Grasha-Reichmann Indicators	Parameters
1	Competitive Indicators	$GR_{com,1},\ GR_{com,2},\dots\dots\dots.\quad GR_{com,p-1},\ GR_{com,p}$
2	Collaborative Indicators	$GR_{col,1},\ GR_{col,2},\dots\dots\dots.\quad GR_{col,q-1},\ GR_{col,q}$
3	Avoidant Indicators	$GR_{avo,1},\ GR_{avo,2},\dots\dots\dots.\quad GR_{avo,r-1},\ GR_{avo,r}$
4	Participant Indicators	$GR_{par,1},\ GR_{par,2},\dots\dots\dots.\quad GR_{par,s-1},\ GR_{par,s}$
5	Dependent Indicators	$GR_{dep,1},\ GR_{dep,2},\dots\dots\dots.\quad GR_{dep,t-1},\ GR_{dep,t}$
6	Independent Indicators	$GR_{ind,1},\ GR_{ind,2},\dots\dots\dots.\quad GR_{ind,u-1},\ GR_{ind,u}$

3.4.3.4 Identify relevant Dunn and Dunn modeling parameters

In the previous section, we identified relevant parameters for modeling Grasha-Reichmann learning style model, here we follow the same procedure as in previous sections to obtain indicators among the listed parameters in section 3.2.4 for modeling Dunn and Dunn learning style. These indicators are illustrated in Table 3.34.

Table 3.34 - Example set of parameters

	Dunn and Dunn Indicators	Parameters
1	Environmental Sound Indicators	$DD_{env\_s,1},\ DD_{env\_s,2},\dots\dots\dots.DD_{env\_s,a-1},\ DD_{env\_s,a}$
2	Environmental Light Indicators	$DD_{env\_l,1},\ DD_{env\_l,2},\dots\dots\dots.\ DD_{env\_l,b-1},\ DD_{env\_l,b}$
3	Environmental Temperature Indicators	$DD_{env\_t,1},\ DD_{env\_t,2},\dots\dots\dots.\ DD_{env\_t,c-1},\ DD_{env\_t,c}$
4	Environmental Design Indicators	$DD_{env\_d,1},\ DD_{env\_d,2},\dots\dots\dots.DD_{env\_d,d-1},\ DD_{env\_d,d}$
5	Emotional Motivational Support Indicators	$DD_{emo\_m,1},\ DD_{emo\_m,2},\dots\dots\dots.DD_{emo\_m,e-1},\ DD_{emo\_m,e}$

6	Emotional Persistence Indicators	$DD_{emo\_p,1}$, $DD_{emo\_p,2}$, … … … . $DD_{emo\_p,f-1}$, $DD_{emo\_p,f}$
7	Emotional Individual Responsibility Indicators	$DD_{emo\_i,1}$, $DD_{emo\_i,2}$, … … … . $DD_{emo\_i,g-1}$, $DD_{emo\_i,g}$
8	Emotional Structure Indicators	$DD_{emo\_s,1}$, $DD_{emo\_s,2}$, … … … . $DD_{emo\_s,h-1}$, $DD_{emo\_s,h}$
9	Sociological Individual Indicators	$DD_{soc\_i,1}$, $DD_{soc\_i,2}$, … … … . . $DD_{soc\_i,i-1}$, $DD_{soc\_i,i}$
10	Sociological Pairs or Teams Indicators	$DD_{soc\_p,1}$, $DD_{soc\_p,2}$, … … … . $DD_{soc\_p,j-1}$, $DD_{soc\_p,j}$
11	Sociological Adult Indicators	$DD_{soc\_a,1}$, $DD_{soc\_a,2}$, … … … . $DD_{soc\_a,k-1}$, $DD_{soc\_a,k}$
12	Sociological Varied Indicators	$DD_{soc\_v,1}$, $DD_{soc\_v,2}$, … … … . $DD_{soc\_v,l-1}$, $DD_{soc\_v,l}$
13	Physiological Perpetual Indicators	$DD_{phy\_p,1}$, $DD_{phy\_p,2}$, … … … . $DD_{phy\_p,m-1}$, $DD_{phy\_p,m}$
14	Physiological Intake Indicators	$DD_{phy\_i,1}$, $DD_{phy\_i,2}$, … … … . $DD_{phy\_i,n-1}$, $DD_{phy\_i,n}$
15	Physiological Time Indicators	$DD_{phy\_t,1}$, $DD_{phy\_t,2}$, … … … . $DD_{phy\_t,o-1}$, $DD_{phy\_t,o}$
16	Physiological Mobility Indicators	$DD_{phy\_m,1}$, $DD_{phy\_m,2}$, … … … . $DD_{phy\_m,p-1}$, $DD_{phy\_m,p}$
17	Psychological Global Indicators	$DD_{psy\_g,1}$, $DD_{psy\_g,2}$, … … … . $DD_{psy\_g,q-1}$, $DD_{psy\_g,q}$
18	Psychological Analytical Indicators	$DD_{psy\_a,1}$, $DD_{psy\_a,2}$, … … … . $DD_{psy\_a,r-1}$, $DD_{psy\_a,r}$
19	Psychological Impulsive Indicators	$DD_{psy\_i,1}$, $DD_{psy\_i,2}$, … … …. $DD_{psy\_i,s-1}$, $DD_{psy\_i,s}$
20	Psychological Reflective Indicators	$DD_{psy\_r,1}$, $DD_{psy\_r,2}$, … … …. $DD_{psy\_r,t-1}$, $DD_{psy\_r,t}$

4 IMPLEMENTATION

In this chapter, we discuss what implementations have been carried out in order to develop a learner modeling system runs in LMS / Mobile context. The implementation consists of two major divisions and, Section 4.1 discusses the extension of Moodle LMS and Section 4.2 discusses the development of the mobile app.

In order to comprehensively identify all the learning styles selected in this study, we need to incorporate necessary changes described in above sections for selected four learning styles. However due to the development complexity, we implemented only VARK modeling limited to the following user behavior areas,

1) File accesses in the mobile device.
2) Web searches.
3) Web visits.
4) Bookmarks.
5) Textual messaging.

4.1 Extensions in Moodle LMS

Moodle [33] is a free and open-source web application written in PHP, and its name is an acronym for **M**odular **O**bject-**O**riented **D**ynamic **L**earning **E**nvironment. To install Moodle, it is required to have configured a web server (e.g. Apache), a database (e.g. MySQL, MariaDB or PostgreSQL) and PHP. Moodle server is downloaded from https://download.moodle.org/. Table 4.1 summarizes the server specifications used in this research.

Table 4.1 - Moodle Server Specification Used in this Research

Specification	Value
Moodle Server Version	2.9.9
MariaDB Version	10.2
PHP Version	5.6

4.1.1 Introduction to Moodle architecture

As **<u>M</u>** in its name suggests, it has a modular architecture. It is structured with a core level and a number of plugins around it. These plugins follow a set of common interfaces and the standard Moodle distribution consists of Moodle core and a set of necessary plugins to make immediately usable as an LMS. The followings are the components that constitute the Moodle core.

- Courses
- Activities
- Users
- Enrolments
- Navigation
- Settings and configurations
- JavaScript libraries.
- Upgrading
- Logs and statistics

Due to its modular architecture, Moodle is highly extensible and customizable. In the following sections, we discuss how we developed a module to embed learner modeling functionalities into Moodle.

4.1.2 Development of VARK plugin

As stated in the previous section, Moodle follows a modular architecture, therefore the proper way of extending Moodle is through the development of a plugin. This plugin should be capable of doing two tasks,

1) Generate VARK learner model.
2) Classify learners within VARK learning style.

Developers can develop a variety of plugin types using Moodle's framework, such as 'Activity' modules, 'Block' modules, 'Reporting' modules, 'Themes' and etc. The scope of each plugin type differs according to their usage, as an instance 'Activity' modules are added in course scope, ‘Block’ modules are added in site scope, ‘Theme’ modules effects on site scope and etc. However, learner modeling modules have to be inserted into Moodle in site scope and therefore we decided to develop a ‘Block’ module for development.

Only the administrators can execute model building and user classification functionalities, while both administrators and learners are allowed to answer VARK questionnaire. As discussed in section 2.3.1, it is necessary to use VARK questionnaire for the initial phase of this model building task. Followings are the screenshots (Figure 4.1 & 4.2) of the created learner modeling blocks customized for administrators and learners respectively.

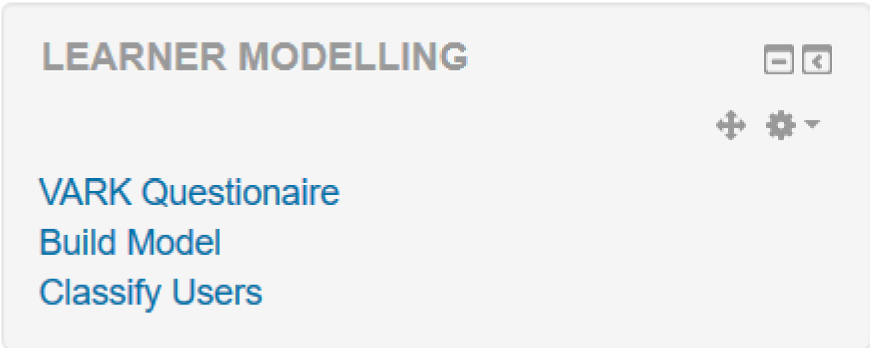


Figure 4.1 - Administrator’s View of Learner Modeling Block

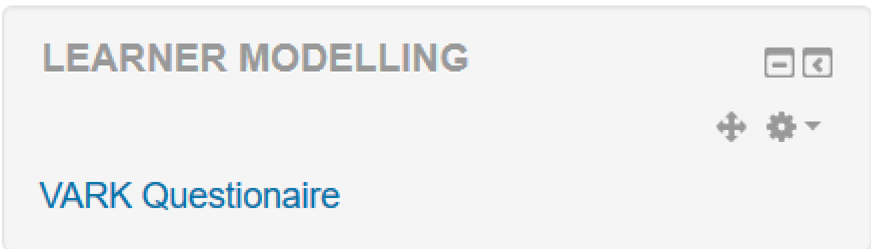


Figure 4.2 - Learner’s View of Learner Modeling Block

Adding this block is limited and it can be added only to the user dashboard as learner modeling is a user-wise process. Following steps are followed to add this block to Moodle.

Go to user dashboard → in 'ADD A BLOCK' block select 'Learner Modeling' block (refer Figure 4.3 & Figure 4.4).

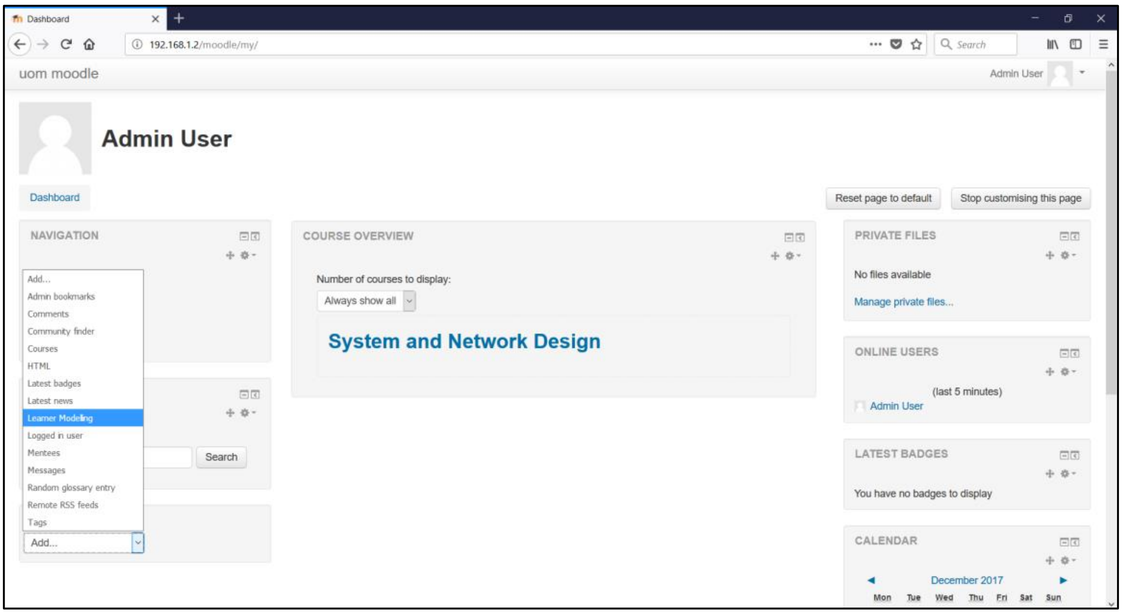


Figure 4.3 - Adding Learner Modeling Block to Moodle

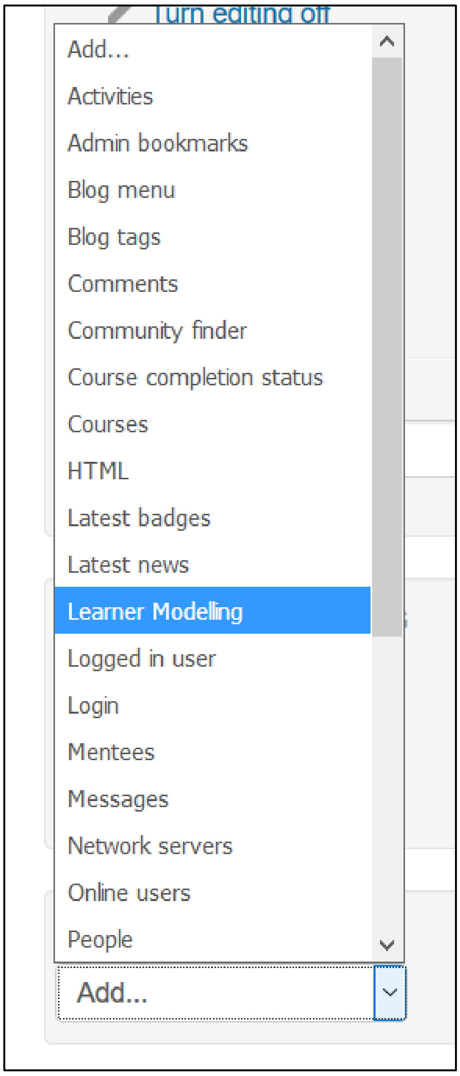


Figure 4.4 - Adding Learner Modeling Block to Moodle

4.1.2.1 VARK questionnaire in learner modeling Moodle block

When the user clicks on 'VARK Questionnaire' link in the above block, the user is navigated to a page where he/she can answer the VARK questionnaire composed by Neil Fleming. Then the user has to submit their answers. In this way, we obtained sample sets for Visual, Auditory, Reading and Kinesthetic learners. The Figure 4.5 & Figure 4.6 depict the UI of VARK questionnaire in MOODLE.

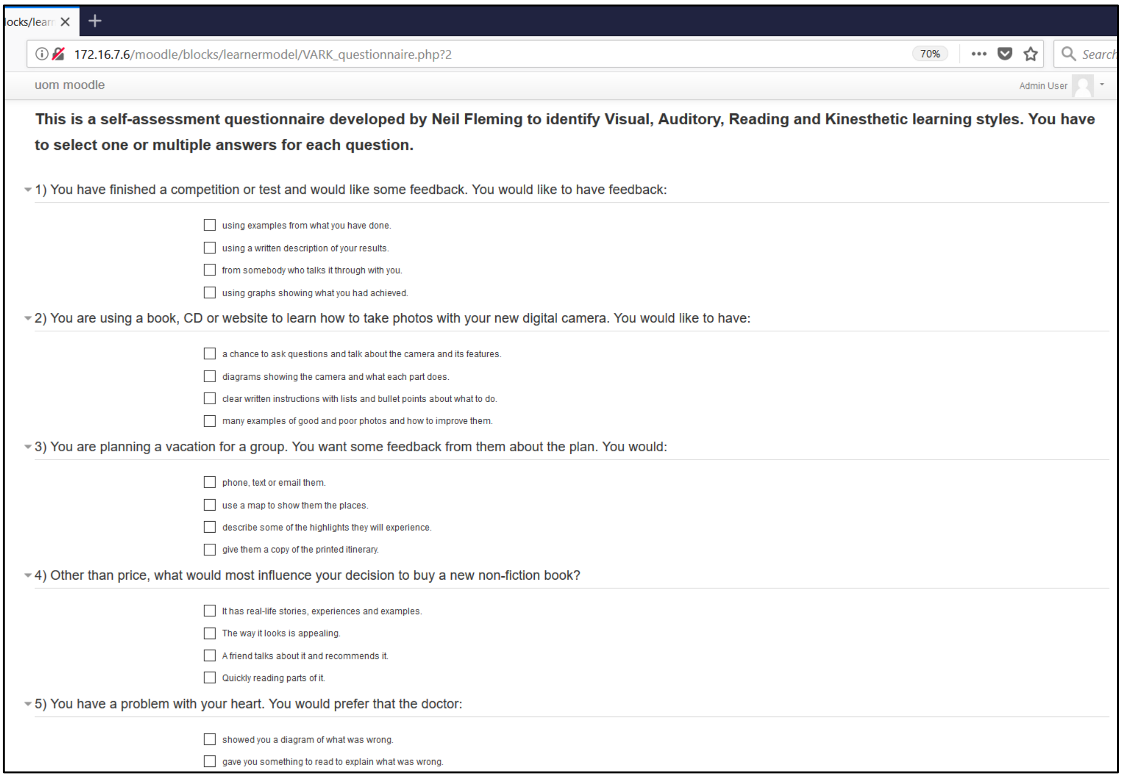


Figure 4.5 - VARK Questionnaire of Learner Modeling Block

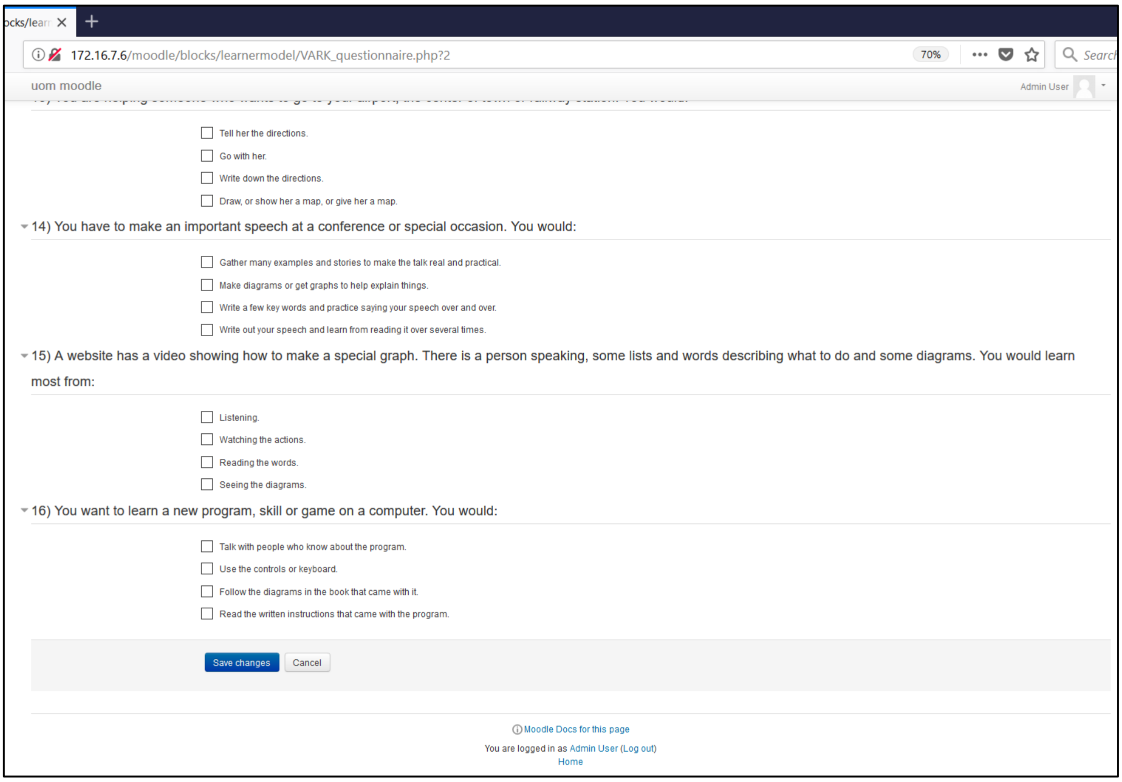


Figure 4.6 - VARK Questionnaire of Learner Modeling Block

For displaying VARK questionnaire and record answers of each leaner, we created the database tables in Table 4.2 in Moodle database.

Table 4.2 - Database Tables Added for VARK Questionnaire

	Database Table Name	Columns
1	mdl_vark_question	id
		question_text
2	mdl_vark_answer	id
		questionid
		v_val
		a_val
		r_val
		k_val
3	mdl_vark_answer_check	id
		userid
		timestamp
		ans_0
		ans_1
		..
		..
		ans_62
		ans_63

4.1.2.2 Web service support in Moodle modules

It is required to collect information from mobile devices of learners in order to build learner model and later to classify learners. For this purposes, we need to have a method for communicating the developed mobile application with Moodle server. Thus we implement web service functionalities into the developed 'Learner Modeling' plugin. Moodle supports various protocols like AMF, REST, SOAP and XML-RPC. In this research, we exposed web services of 'Learner Modeling' block using SOAP protocol.

4.1.2.3 Model building of learner modeling Moodle block

In section 2.3, we discussed in details, about how we carry out learner modeling with respect to selected learning styles. However, as we focus on only VARK learning style in implementation, here we discuss how we perform VARK modeling in the LMS/mobile context.

In our approach, there are two stages of building the model,

1) 1st stage: Identifying the relevant VARK indicators
2) 2nd stage: Parameterizing the identified VARK indicators.

For identifying VARK indicators, we need to have two data,

1) Answers to VARK questionnaire from each sample which has learners from respective VARK dimensions.
2) Values for their VARK parameters in mobile context.

In section 3.1.2.1 we obtained answers for VARK questionnaire from each sample, and by using web services described in the above section, we obtained values for VARK parameters. For the demonstrational purpose, we selected 20 learners, divided them according to their claimed VARK dimension and obtained 4 groups containing 5 members each. Then we set up Moodle accounts for them and activated Learner Model plugin for each of them and ask them to install Learner Model mobile app which is going to be discussed in the next subsection. Then we asked them to answer the VARK questionnaire using either the described Learner Model plugin or using the Learner Model mobile app. After using the mobile app for some time, they sent relevant data using the application itself. Thus we obtained values for the parameters in Table 4.3.

Table 4.3 - Obtained Parameters from Learner Model Mobile App

	Parameters	Assumed Indication
1	*no_of_visual_file_open*	*Visual*
2	*no_of_auditory_file_open*	*Auditory*
3	*no_of_reading_file_open*	*Reading*
4	*no_of_kinesthetic_file_open*	*Kinesthetic*

5	*visual_file_stay_time*	*Visual*
6	*auditory _file_stay_time*	*Auditory*
7	*reading _file_stay_time*	*Reading*
8	*kinesthetic _file_stay_time*	*Kinesthetic*
9	*no_of_ visual_web_searches*	*Visual*
10	*no_of_auditory_ web_searches*	*Auditory*
11	*no_of_reading_ web_searches*	*Reading*
12	*no_of_kinesthetic_web_searches*	*Kinesthetic*
13	*no_of_visual_web_visits*	*Visual*
14	*no_of_auditory_web_visits*	*Auditory*
15	*no_of_reading_web_visits*	*Reading*
16	*no_of_kinesthetic_web_visits*	*Kinesthetic*
17	*no_of_visual_web_bookmarks*	*Visual*
18	*no_of_auditory_web_bookmarks*	*Auditory*
19	*no_of_reading_web_bookmarks*	*Reading*
20	*no_of_kinesthetic_web_bookmarks*	*Kinesthetic*
21	*auditory_sms_sent_count_with_colleagues*	*Auditory*
22	*auditory_sms _sent_count_with_instructors*	*Auditory*

The database tables (refer Table 4.4) are created in order to record these parameters.

Table 4.4 - Database Tables Added for Recording Contextual Information from Mobile App

	Database Table Name	Columns
1	mdl_lm_websearch	id
		recorded_timestamp
		occured_timestamp
		userid
		text
		type
2	mdl_lm_webvisit	id
		recorded_timestamp
		occured_timestamp
		userid
		url
		type

3	mdl_lm_bookmark	id
		recorded_timestamp
		occured_timestamp
		userid
		url
		type
4	mdl_lm_fileaccess	id
		recorded_timestamp
		occured_timestamp
		userid
		file_name
		type
		duration
5	mdl_lm_sms	id
		recorded_timestamp
		occured_timestamp
		userid
		phone_no
		message_text
		type

As discussed in section 2.3.1.1, there is a possible drawback in using VARK questionnaire if the users are lack of self-awareness. Therefore to mitigate the effect of lacking self-awareness, we assume that, for a learner to be chosen to build the model, he/she should have answered VARK questionnaire exhibiting a certain dimension in more than 75% of questions (i.e. more than 12 questions). To record this information in Moodle database the database table illustrated in Table 4.5 is created.

Table 4.5 - Database Tables Added for Recording Contextual Information from Mobile App

	Database Table Name	Columns
1	mdl_lm_sample_users_analysis_result	id
		userid
		is_qualified
		type

Then we calculated the populate mean and standard deviation values of the parameters using the learners from all four samples and record it in the database as in Table 4.6.

Table 4.6 - Database Tables Added for Recording Population Parameters

	Database Table Name	Columns
1	mdl_lm_population_analysis_result	id
		parameter
		type
		value
		mean
		standard_deviation

Then we followed the procedure described in section 2.3.2.1 to identify qualified parameters for VARK learner modeling using null hypothesis rejection (i.e. hypothesis testing) and parameterize the identified qualified parameters. Then record the results in database tables as in Table 4.7 & Table 4.8.

Table 4.7 - Database Tables Added for Recording Analysis of User Answers for the VARK Questionnaire

	Database Table Name	Columns
1	mdl_lm_question_analysis_result	id
		parameter
		type
		questionid
		value
		user_count
		mean
		z

Table 4.8 - Database Tables Added for Recording Parameter Analysis

	Database Table Name	Columns
1	mdl_lm_parameter_analysis_result	id
		parameter
		type
		is_qualified
		number_of_questions
		mean
		standard_deviation

Now we have obtained a set of qualified parameters (i.e. a set of indicators) and probability distribution functions to be used in VARK classification.

4.1.2.4 Classifying learners using learner modeling Moodle plugin

The final stage of this research is classifying learners according to the VARK learning style model. In the previous section, we described how we implemented model building part of the research. In this section, we focus on implemented VARK learning style detection utilizing the obtained model. We implemented VARK learning style detection using Bay's classification as discussed in section 2.4.

There are two methods of invoking the classification functionality.

1) Using the Moodle website.
2) Using the mobile app.

When using the Moodle site, administrators can select any user and proceed for classification using the developed Learner Modeling block as in Figure 4.7.

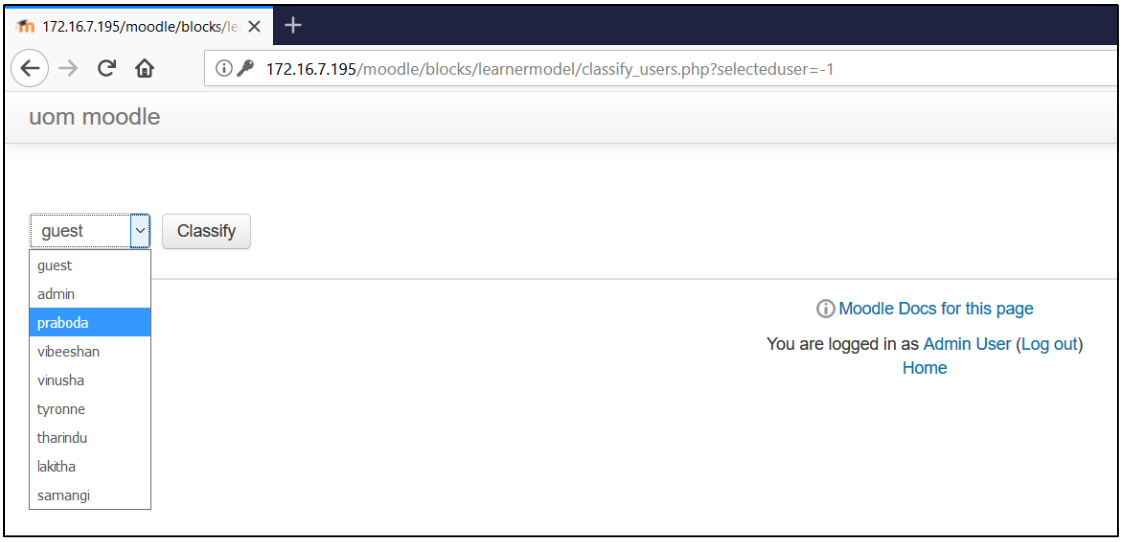


Figure 4.7 - Selecting User for VARK Learner Classification using Moodle

And when administrator clicks on 'Classify' button, Bay's classifier will be executed and the user's tendency is displayed along with the conditional probabilities as in Figure 4.8.

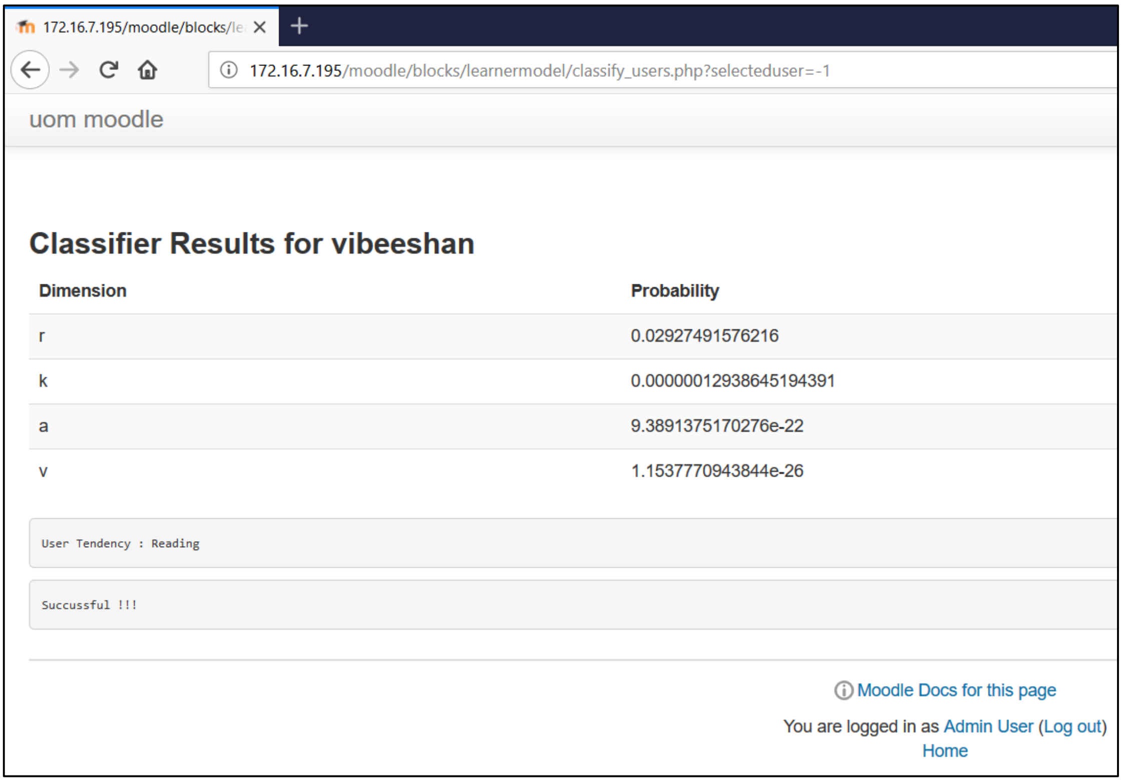


Figure 4.8 - Example VARK Learner Classification Result obtained using Moodle Site

The Mobile application allows only to run classification for the logged in user. Following screenshot (Figure 4.9) depicts the result for the same user when we run classification using the mobile app.

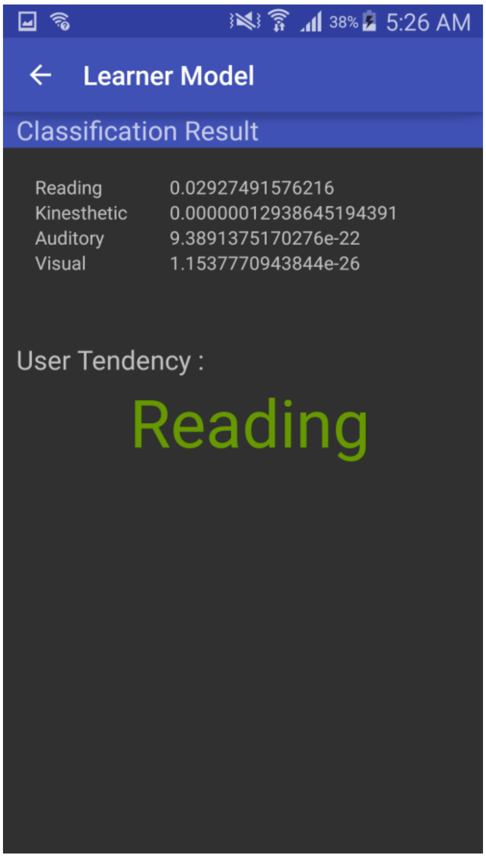


Figure 4.9 - Example VARK Learner Classification Result obtained using Mobile App

For recording classification results we inserted a database table into Moodle as in Table 4.9. However, the algorithm is executed every time users query for classification.

Table 4.9 - Database Tables Added for Recording Classification Result

	Database Table Name	Columns
1	mdl_lm_classifier_analysis_result	id
		userid
		dimension
		probability

4.2 Development of Mobile Application

In order to capture learner’s mobile context and send the necessary contextual information to the Moodle server, we developed a mobile app called ‘Learner Modeling’. This application is a native android app and development carried out using the android studio.

This learner modeling mobile app can carry out the following tasks required for this study.

1) Collect contextual information and filter required information for VARK modeling.
2) Learners can answer VARK questionnaire and submit answers to the Moodle server.
3) Push collected necessary contextual information.
4) Execute VARK classification and view result.

The Figure 4.10 is a screenshot of the home page of the app.

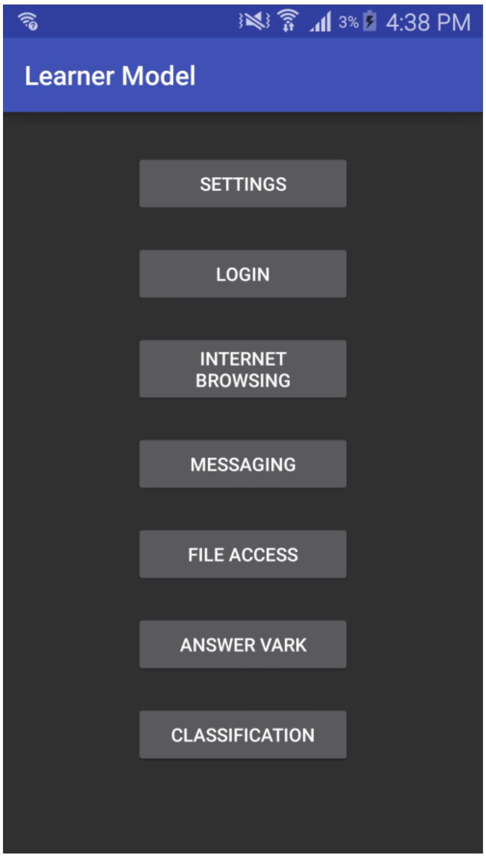


Figure 4.10 - Home page of Learner Modeling Mobile App

The user has to first configure the mobile app with the IP address of the Moodle server and provide username of the Moodle login. Once this configuration is set, it will get saved and the next time user will be prompted directly with the login screen.

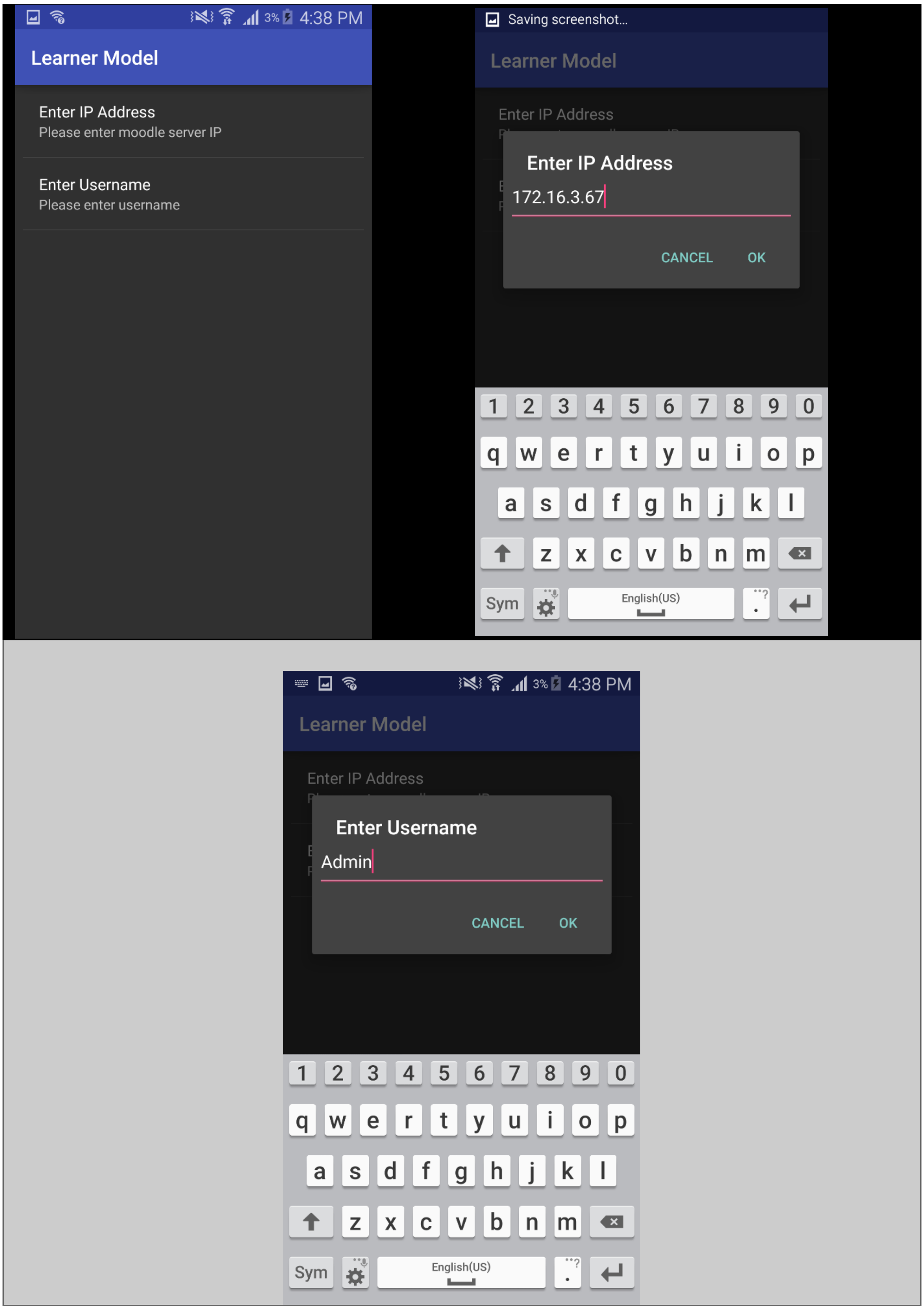


Figure 4.11 - Settings Page of the Learner Modeling Mobile App

Then, the learner has to login to Moodle to use web services and the following is the login page (refer Figure 4.12).

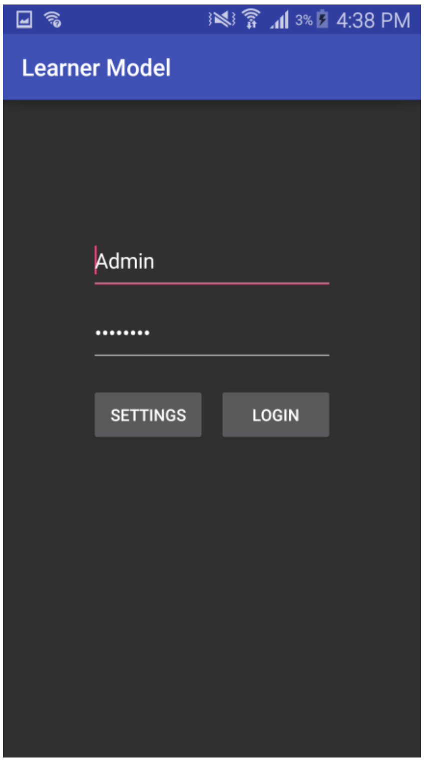


Figure 4.12 - Login Page of the Learner Modeling Mobile App

Learners can answer the VARK questionnaire and submit using the mobile app and the following (refer Figure 4.13) is a screenshot of the VARK questionnaire page.

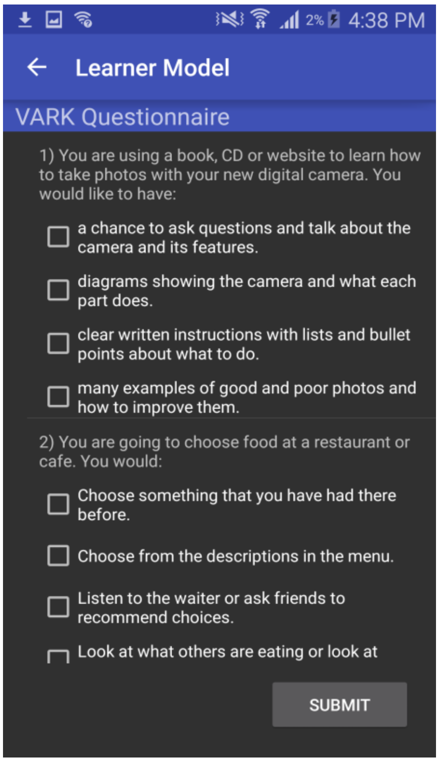


Figure 4.13 - VARK Questionnaire Page of the Learner Modeling Mobile App

Users can view and submit relevant contextual information to the Moodle server, such as, web searches, web visits, bookmarks, file access information and messaging information. The followings (refer Figure 4.14) are some screenshots of these functionalities.

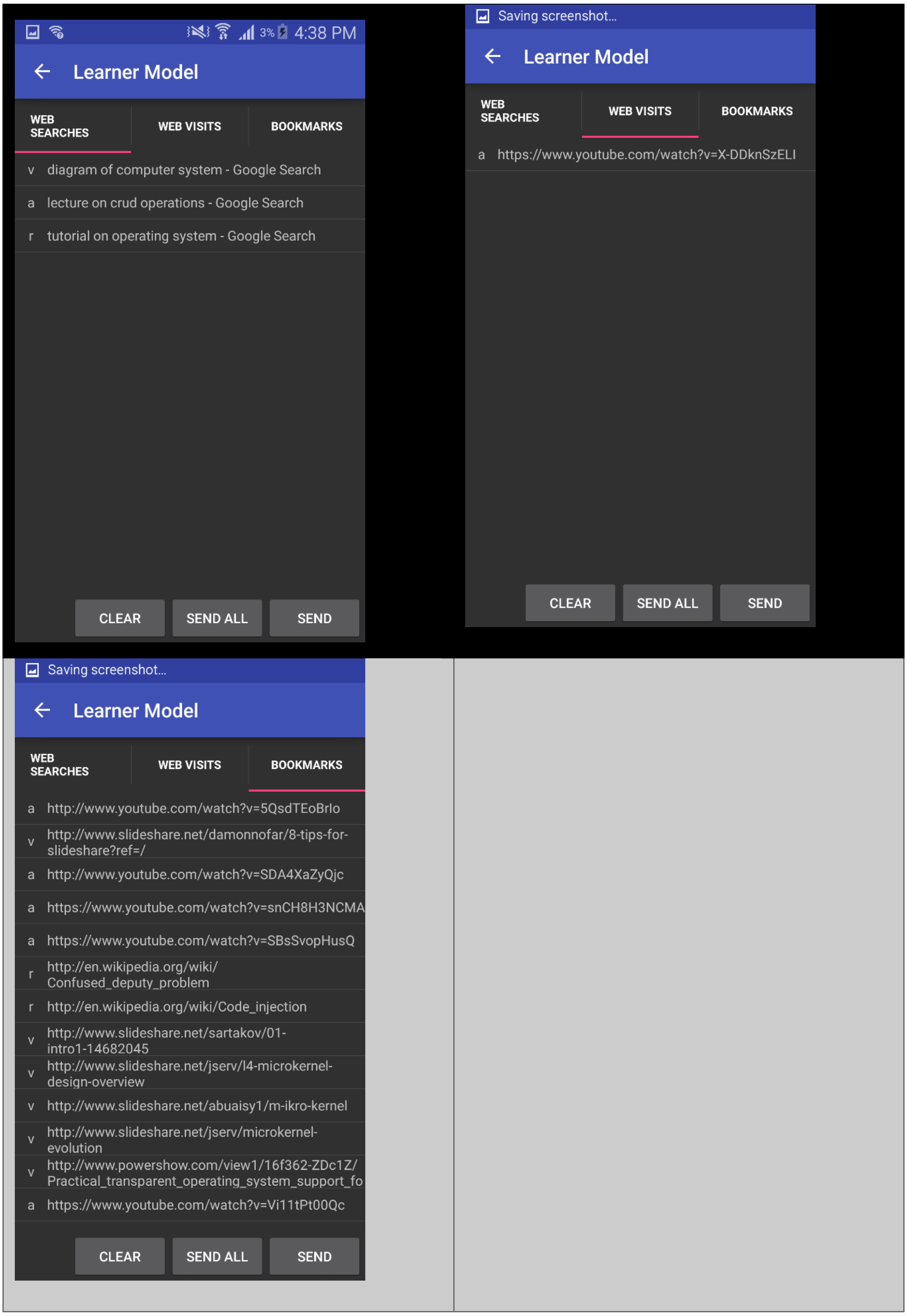


Figure 4.14 - Context Acquiring and Feeding Pages of the Learner Modeling Mobile App

This mobile app can execute learner classification function of developed Moodle plugin through web services and, this will send a request to classify the current logged in user. The Figure 4.15 is an example classification result.

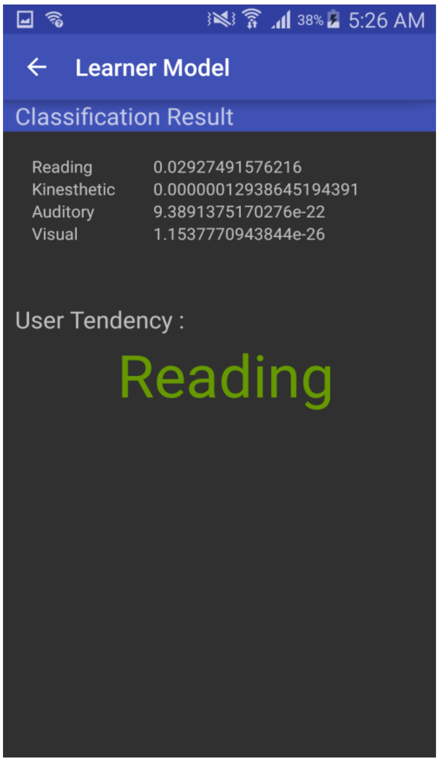


Figure 4.15 - VARK Classification Result Page of the Learner Modeling Mobile App

5 RESULTS

In this section, we discuss a sample result obtained using the developed system. Section 5.1 provides details of contextual information collection and section 5.2 discusses results of model development and parameters of the developed VARK model. In section 5.3 a sample classification using the VARK model is discussed.

Deploying the learner modeling plugin into a live Moodle system in a university is a tedious task, therefore a Moodle LMS is installed on a local server and added the developed Moodle plugin into it. A set of 20 colleagues are selected and divided them into 4 groups such that each group consisting individuals who claim to have a certain VARK dimension, 3 members from each group are selected for the model building part and the rest 2 members from each group are used to verify the model.

5.1 Information Gathering for Model Building

In the first stage, the VARK questionnaire is provided for all of them and recorded their answers. Table 5.1 is the summary of answers of learners for VARK questionnaire.

Table 5.1 - Summary of VARK Questionnaire Answers of Selected Sample

Category	Leaner	No. of Visual Answers	No. of Auditory Answers	No. of Reading Answers	No. of Kinesthetic Answers
Visual	Learner_1	16	4	6	0
	Learner_2	13	8	3	9
	Learner_3	12	3	8	4
	Learner_4	11	7	6	9
	Learner_5	14	1	5	8
Auditory	Learner_6	9	15	8	7
	Learner_7	8	14	2	6
	Learner_8	4	13	7	4
	Learner_9	6	15	0	8

	Learner_10	7	12	6	9
Reading	Learner_11	5	8	16	1
	Learner_12	6	7	12	6
	Learner_13	8	4	12	8
	Learner_14	7	1	11	9
	Learner_15	9	0	14	2
Kinesthetic	Learner_16	6	8	5	15
	Learner_17	7	6	0	12
	Learner_18	2	9	6	14
	Learner_19	8	5	8	13
	Learner_20	1	4	6	16

As stated above, first three learners from each class are selected to be used as training tuples and last two learners of each class are selected as test tuples.

Then the developed mobile app is installed on their mobile phones. Due to the limitations, we faced when testing this system in an actual environment, we had to carry out the testing in an alternative way. As the developed mobile app support to fetch five contextual information and feed them to the Moodle server, an alternative approach is taken as described below in order to test the validity of the system.

1) Obtaining Web Search, Web Visit and Bookmark Information.

First, they were provided some educational topics and asked them to surf the internet to search more details about the topics, and they were instructed to bookmark websites that they find useful to learn about those topics while they surfing. After they used the application for a week, data is fed to Moodle using the mobile app and accounted for learner modeling.

The followings (refer Figure 5.1, Figure 5.2 and Figure 5.3) are screenshots of part of obtained web search, web visit and bookmark data.

+ Options

	id	recorded_timestamp	occured_timestamp	userid	text	type
Edit Copy Delete	171	1500337358	1500163203	5	network topologies diagram	v
Edit Copy Delete	172	1500412105	1500166356	5	chart of hierarchical database model	v
Edit Copy Delete	173	1504965268	1504429976	5	diagram of translation lookaside buffer	v
Edit Copy Delete	174	1507973265	1507777879	5	network topologies illustration	v
Edit Copy Delete	175	1506497298	1506386966	5	hierarchical database model posters	v
Edit Copy Delete	176	1508029377	1507767260	5	translation lookaside buffer slide show	v
Edit Copy Delete	177	1497237709	1496927213	5	fibonacci heaps slides	v
Edit Copy Delete	178	1499598152	1499316191	5	osi seven-layer diagram	v
Edit Copy Delete	179	1509114441	1508940483	5	database transaction concepts mind map	v
Edit Copy Delete	180	1503209048	1502847490	5	slide show of sql operations	v
Edit Copy Delete	181	1508332827	1508193600	5	flow chart of phases of a compiler	v
Edit Copy Delete	182	1504342468	1504327232	5	chart of computer vision edge detection	v
Edit Copy Delete	183	1491626146	1491279365	5	hierarchical database model efficiency charts	v
Edit Copy Delete	184	1511969270	1511483945	5	routing algorithms slides	v
Edit Copy Delete	185	1499507104	1499196348	5	slides on hidden terminal problem	v
Edit Copy Delete	186	1493771988	1493157691	5	cpu scheduling algorithms steps flow chart	v
Edit Copy Delete	187	1508748448	1508322158	5	dynamic programming steps diagram	v
Edit Copy Delete	188	1499414906	1498944380	5	multiple division techniques mind map	v
Edit Copy Delete	189	1492893893	1492415365	5	olap operations slides	v
Edit Copy Delete	190	1506738918	1506405725	5	illustration on network topologies	v
Edit Copy Delete	191	1496565190	1496311793	5	shortes path algorithm slides	v
Edit Copy Delete	192	1498524108	1497953625	5	context aware applications slides	v
Edit Copy Delete	193	1512217596	1511840405	5	slides for architectural model for the management ...	v

Figure 5.1 - Part of Web Search Data of the Selected Sample

+ Options

	id	recorded_timestamp	occured_timestamp	userid	url	type
Edit Copy Delete	287	1508170945	1507708115	5	www.pics4learning.com	v
Edit Copy Delete	288	1508296369	1507962798	5	www.thinkature.com	v
Edit Copy Delete	289	1499928248	1499709937	5	www.mindmeister.com	v
Edit Copy Delete	290	1508342751	1508212239	5	www.thinkature.com	v
Edit Copy Delete	291	1508443969	1508285105	5	www.powershow.com	v
Edit Copy Delete	292	1508943802	1508676551	5	www.powershow.com	v
Edit Copy Delete	293	1496494486	1496363274	5	www.wiziq.com	v
Edit Copy Delete	294	1494552944	1494068144	5	www.thinkature.com	v
Edit Copy Delete	295	1496694968	1496693790	5	www.powershow.com	v
Edit Copy Delete	296	1504837584	1504317194	5	www.scooch.gr0w.com	v
Edit Copy Delete	297	1508519705	1508128860	5	www.mindmeister.com	v
Edit Copy Delete	298	1493303153	1493185258	5	www.scooch.gr0w.com	v
Edit Copy Delete	299	1496106662	1495996701	5	www.kartoo.com	v
Edit Copy Delete	300	1498720676	1498129660	5	www.scooch.gr0w.com	v
Edit Copy Delete	301	1505849942	1505279768	5	www.wiziq.com	v
Edit Copy Delete	302	1504227060	1503584260	5	www.scooch.gr0w.com	v
Edit Copy Delete	303	1503749584	1503518766	5	www.powershow.com	v
Edit Copy Delete	304	1494182136	1493633107	5	www.thinkature.com	v
Edit Copy Delete	305	1498510309	1498228703	5	www.scooch.gr0w.com	v
Edit Copy Delete	306	1511116348	1510511059	5	www.pics4learning.com	v
Edit Copy Delete	307	1501024319	1500712849	5	www.kartoo.com	v
Edit Copy Delete	308	1494662472	1494207990	5	www.visuwords.com	v
Edit Copy Delete	309	1494454497	1493993413	5	www.slideshare.net	v
Console t Copy Delete	310	1495499816	1495093329	5	www.scooch.gr0w.com	v

Figure 5.2 - Part of Web Visit Data of the Selected Sample

+ Options

←T→	id	recorded_timestamp	occured_timestamp	userid	url	type
Edit Copy Delete	2	1505134426	1504695005	5	www.wiziq.com	v
Edit Copy Delete	3	1495226130	1495022226	5	www.slideshare.net	v
Edit Copy Delete	4	1507605454	1507055596	5	www.powershow.com	v
Edit Copy Delete	5	1498860473	1498439429	5	www.mindmeister.com	v
Edit Copy Delete	6	1512390527	1511805261	5	www.bubbl.us	v
Edit Copy Delete	7	1497345520	1496729993	5	www.thinkature.com	v
Edit Copy Delete	8	1494187846	1493933257	5	www.visuwords.com	v
Edit Copy Delete	9	1501790891	1501638569	5	www.pics4learning.com	v
Edit Copy Delete	10	1501512681	1500990884	10	www.wiziq.com	v
Edit Copy Delete	11	1492598321	1492258889	10	www.slideshare.net	v
Edit Copy Delete	12	1496131082	1495818079	10	www.powershow.com	v
Edit Copy Delete	13	1496342022	1496302782	10	www.mindmeister.com	v
Edit Copy Delete	14	1508525427	1508061913	10	www.bubbl.us	v
Edit Copy Delete	15	1501834919	1501682632	10	www.thinkature.com	v
Edit Copy Delete	16	1509359595	1509255950	11	www.wiziq.com	v
Edit Copy Delete	17	1508922483	1508480813	11	www.slideshare.net	v
Edit Copy Delete	18	1495926201	1495586788	11	www.powershow.com	v
Edit Copy Delete	19	1510473318	1509990510	11	www.mindmeister.com	v
Edit Copy Delete	20	1512482008	1511976144	11	www.bubbl.us	v
Edit Copy Delete	21	1492500419	1492204247	11	www.thinkature.com	v
Edit Copy Delete	22	1509899032	1509536477	11	www.visuwords.com	v
Edit Copy Delete	23	1507227229	1506655928	11	www.pics4learning.com	v
Edit Copy Delete	24	1501566126	1500974240	11	www.scooch.gr0w.com	v
Console t Copy Delete	25	1511509328	1511342404	11	www.kartoo.com	v

Figure 5.3 - Part of Bookmark Data of the Selected Sample

2) Obtaining File Access Information.

Also, the selected learners are provided with some educational materials on those topics and asked to rate them in a Likert Scale from 1 to 10 according to their perspective in which they find those materials useful for mastering those topics. Assuming these rates are directly proportional to the file access time, these values are also fed into Moodle for learner modeling calculations. The Figure 5.4 depicts a part of data set.

+ Options

	id	recorded_timestamp	occured_timestamp	userid	file_name	type	duration
Edit Copy Delete	1	0	0	5	Operating Systems Concepts_Slides	v	6
Edit Copy Delete	2	0	0	5	Data Mining Concepts and Techniques_Slides	v	7
Edit Copy Delete	3	0	0	5	Distributed Systems Concepts and Design_Slides	v	9
Edit Copy Delete	4	0	0	5	Database System Concepts_Slides	v	6
Edit Copy Delete	5	0	0	5	Exploring Enterprise, System of Systems, and Syste...	v	10
Edit Copy Delete	6	0	0	10	Operating Systems Concepts_Slides	v	8
Edit Copy Delete	7	0	0	10	Data Mining Concepts and Techniques_Slides	v	10
Edit Copy Delete	8	0	0	10	Distributed Systems Concepts and Design_Slides	v	9
Edit Copy Delete	9	0	0	10	Database System Concepts_Slides	v	10
Edit Copy Delete	10	0	0	10	Exploring Enterprise, System of Systems, and Syste...	v	8
Edit Copy Delete	11	0	0	11	Operating Systems Concepts_Slides	v	7
Edit Copy Delete	12	0	0	11	Data Mining Concepts and Techniques_Slides	v	7
Edit Copy Delete	13	0	0	11	Distributed Systems Concepts and Design_Slides	v	7
Edit Copy Delete	14	0	0	11	Database System Concepts_Slides	v	9
Edit Copy Delete	15	0	0	11	Exploring Enterprise, System of Systems, and Syste...	v	10
Edit Copy Delete	16	0	0	12	Operating Systems Concepts_Slides	v	7
Edit Copy Delete	17	0	0	12	Data Mining Concepts and Techniques_Slides	v	7
Edit Copy Delete	18	0	0	12	Distributed Systems Concepts and Design_Slides	v	9
Edit Copy Delete	19	0	0	12	Database System Concepts_Slides	v	8
Edit Copy Delete	20	0	0	12	Exploring Enterprise, System of Systems, and Syste...	v	7
Edit Copy Delete	21	0	0	13	Operating Systems Concepts_Slides	v	6
Edit Copy Delete	22	0	0	13	Data Mining Concepts and Techniques_Slides	v	9
Edit Copy Delete	23	0	0	13	Distributed Systems Concepts and Design_Slides	v	7
Console Copy Delete	24	0	0	13	Database System Concepts_Slides	v	10

Figure 5.4 - Part of File Access Data of the Selected Sample

3) Obtaining Phone Call & SMS Information.

Each learner is asked to mention the average number of calls they take a week with colleagues and instructors for learning purposes, also they were asked to indicate the average number of SMSs as well. These data also fed into Moodle and accounted for learner modeling calculations.

5.2 VARK Model Building Results

When administrator select ‘Build Model’ from the plugin, first it calculates the mean and standard deviation values for the entire population. Figure 5.5 is a summary of gathered web search, web visit, bookmark and file access information.

Population Parameters

Parameter	Type	Value	Mean	Standard Deviation
websearch	v	68	5.6666666666667	9.9610351983226
websearch	a	60	5	8.746427842268
websearch	r	44	3.6666666666667	6.3813965730256
websearch	k	68	5.6666666666667	9.8516778040878
webvisit	v	180	15	26.060826285186
webvisit	a	178	14.833333333333	25.777358713069
webvisit	r	123	10.25	17.814437029181
webvisit	k	104	8.6666666666667	15.07941938169
bookmark	v	24	2	3.5590260840104
bookmark	a	39	3.25	5.6880723155272
bookmark	r	16	1.3333333333333	2.3213980461974
bookmark	k	16	1.3333333333333	2.3213980461974
fileaccess	v	269	22.416666666667	10.973136389484
fileaccess	a	679	56.583333333333	28.111262076889
fileaccess	r	447	37.25	18.244291344601
fileaccess	k	1140	95	48.863756166167

Figure 5.5 - Population Mean & Standard Deviation Values of Training Sample

In the next stage, plugin elects a set of parameters as indicators for VARK modeling following the methodology described in section 2.3.2, and then parameterize those indicators for elected learners. Figure 5.6 is the result of indicator parameterizing stage.

Parameters Analysis Result

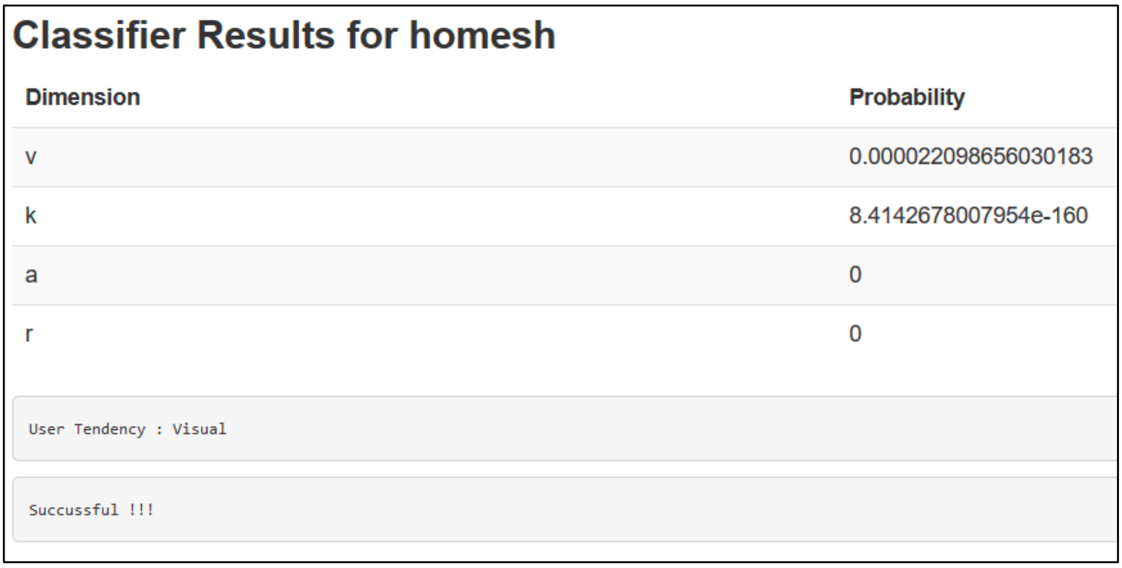
Parameter	Type	Is Qualified	Number of Questions	Mean	Standard Deviation
websearch	v	1	16	22.666666666667	3.3993463423952
websearch	a	1	16	20	2.4494897427832
websearch	r	1	16	14.666666666667	1.2472191289246
websearch	k	1	16	22.666666666667	1.6996731711976
webvisit	v	1	16	60	4.0824829046386
webvisit	a	1	16	59.333333333333	4.1899350299922
webvisit	r	1	16	41	2.9439202887759
webvisit	k	1	16	34.666666666667	2.8674417556809
bookmark	v	1	16	8	1.6329931618555
bookmark	a	1	16	13	1.6329931618555
bookmark	r	1	16	5.3333333333333	0.47140452079103
bookmark	k	1	16	5.3333333333333	0.47140452079103
fileaccess	v	1	16	41	2.9439202887759
fileaccess	a	1	16	104.66666666667	1.6996731711976
fileaccess	r	1	16	68.333333333333	0.47140452079103
fileaccess	k	1	16	178.66666666667	6.1824123303305

Figure 5.6 - Mean & Standard Deviation Values of Obtained Indicators

5.3 User Classification Results

By utilizing the above indicator values, learners can be classified accordingly into one of Visual, Auditory, Reading and Kinesthetic dimensions. The major objective is of this research is up to the described model building part and this classification process is reserved for further optimization in future, however for demonstration purpose, Bayes' classifier is used and it is comprehensively described in section 2.4.

Following (refer Figure 5.7, Figure 5.8, Figure 5.9 and Figure 5.10) are some screenshots of classification results obtained to verify the model by classifying test data samples.

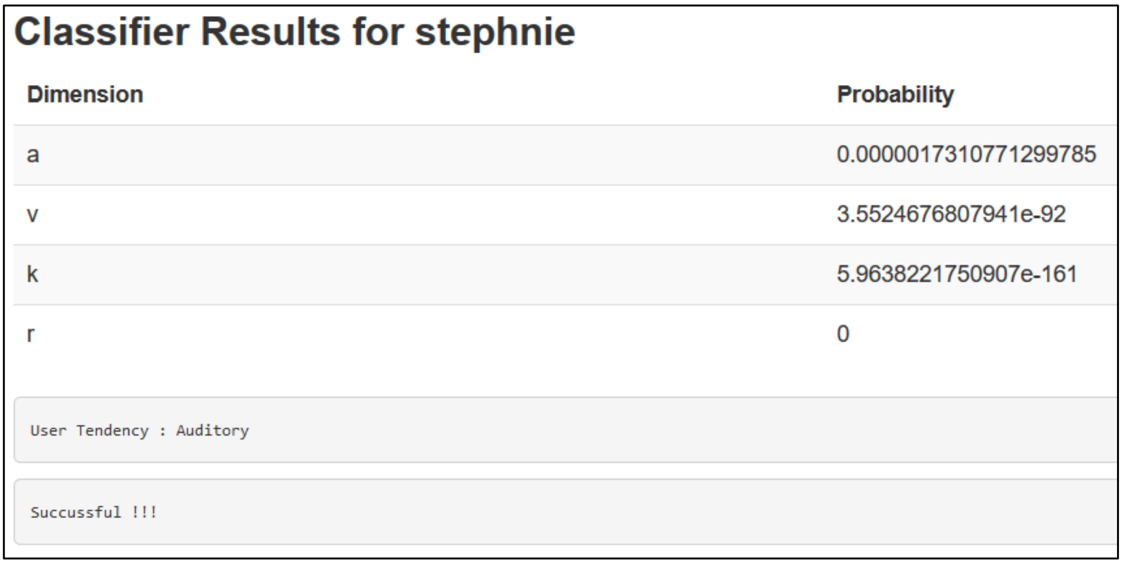

Classifier Results for homesh

Dimension	Probability
v	0.000022098656030183
k	8.4142678007954e-160
a	0
r	0

User Tendency : Visual

Succussful !!!

Figure 5.7 - Classification Result for Learner_4 of Visual Test Sample



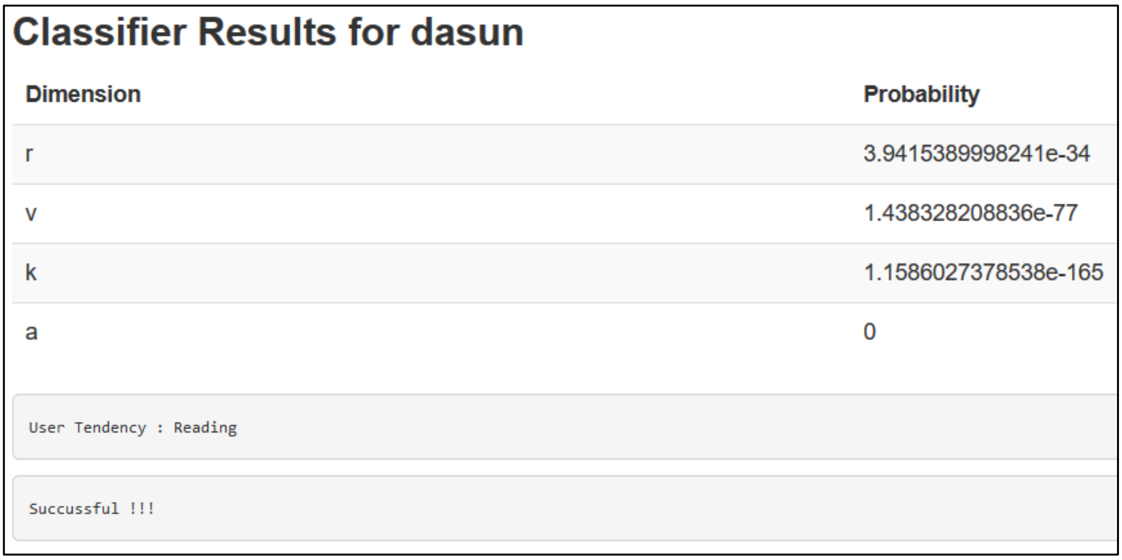
Classifier Results for stephnie

Dimension	Probability
a	0.0000017310771299785
v	3.5524676807941e-92
k	5.9638221750907e-161
r	0

User Tendency : Auditory

Successful !!!

Figure 5.8 - Classification Result for Learner_9 of Auditory Test Sample



Classifier Results for dasun

Dimension	Probability
r	3.9415389998241e-34
v	1.438328208836e-77
k	1.1586027378538e-165
a	0

User Tendency : Reading

Successful !!!

Figure 5.9 - Classification Result for Learner_14 of Reading Test Sample

Classifier Results for chathura

Dimension	Probability
k	0.0000068971669557481
v	1.3667140102319e-87
a	0
r	0

```
User Tendency : Kinesthetic
```

```
Succussful !!!
```

Figure 5.10 - Classification Result for Learner_19 of Kinesthetic Test Sample

As can be observed the probabilities of even the highest probability dimension is very low in Bayes' Classification results. This happens due to that the probability is not the real exact probability and it is a score within the considered other classes and the probability derived from multiplication of all probabilities of observed indicators to be in the considered class. Consider the calculation of posterior probability of observed data set with respect to a certain VARK dimension, as stated in section 2.4.1 it is obtained by,

$$P(X|H_i) \times= P(X_1|H_i) \times P(X_2|H_i) \dots\dots \times P(X_n|H_i)$$

Here, $n = 16$ (as there are 16 indicators) and any $P(X_k|H_i)$ is lower than 1 as it is a probability, therefore multiplication of 16 numbers which are lower than 1 is definitely a very small number. But in this research, we define a threshold value 10^{-6} for being classified to exhibit a visual, auditory, reading or kinesthetic learner. If the highest posterior probability is lower than 10^{-6} the learner considered to exhibit none of the VARK learning dimensions.

The same results can be obtained through the mobile app as well. Followings (refer Figure 5.11, Figure 5.12, Figure 5.13 and Figure 5.14) are the screenshots of obtained classification results using the developed mobile app.

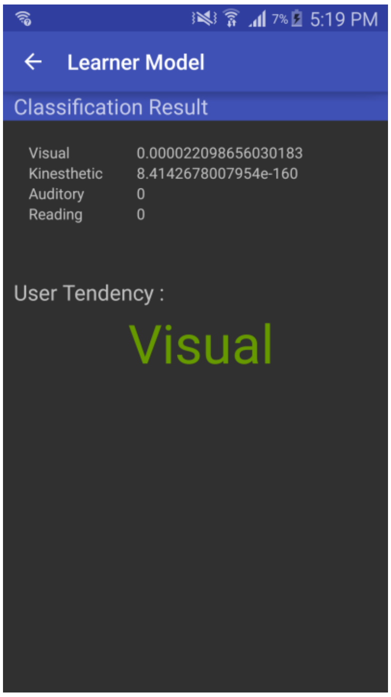


Figure 5.11 - Classification Result from Mobile App of Learner_4 of Visual Test Sample

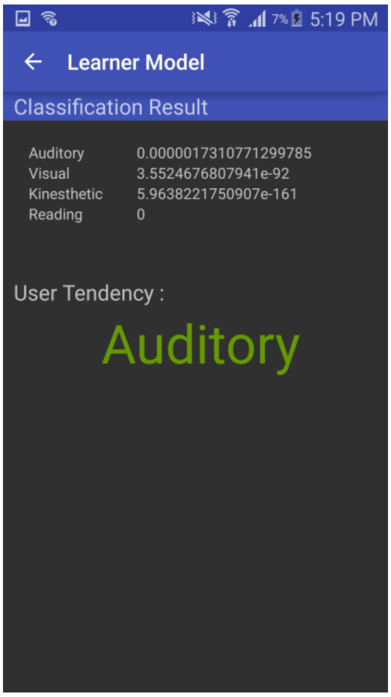


Figure 5.12 - Classification Result from Mobile App of Learner_9 of Auditory Test Sample

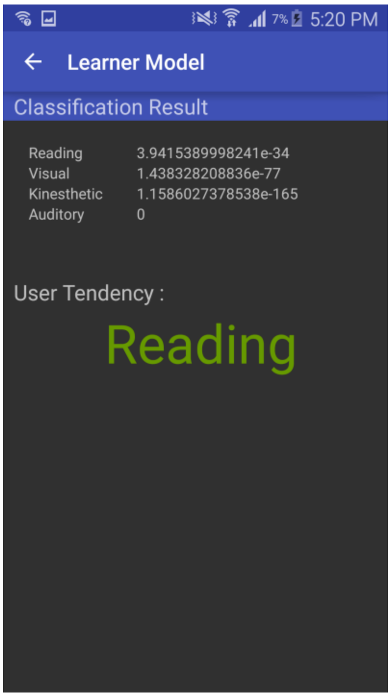


Figure 5.13 - Classification Result from Mobile App of Learner_14 of Reading Test Sample

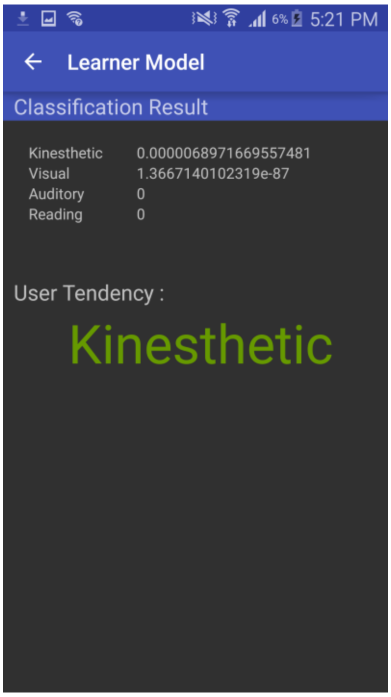


Figure 5.14 - Classification Result from Mobile App of Learner_19 of Kinesthetic Test Sample

From the results obtained above for the test data samples, we can conclude that the model is verified and can be used for VARK learner modeling with respect to LMS/Mobile context.

6 CONCLUSION AND FUTURE WORK

With the advancement of mobile technology, ubiquitous and pervasive computing has become increasingly popular and useful in many areas, e-learning is one such field that has attracted an extensive attention over last decade. Due to the differences in individuals, each learner prefers various methods of learning and also the effectiveness of such methods differ from learner to learner. Therefore, it is important to personalize learning methods in such a way that suits individual learners. However, the learning process can be further optimized by considering the current situation of the learner. In other words, context-aware personalized learning recommenders would be more promising. Context information is diverse and lack of better representing methods is a problem in the field of Technology Enhanced Learning.

In summary, this work is focused on identifying and obtaining the necessary context of a learner and then utilize them to build a model of the learner to be used in future learner recommender systems. We have analyzed the feasibility of using mobile contextual information for learner classification and conclude that the classification of learners through mobile contextual information is effective. Specifically, we have identified several learning styles that are suitable for categorizing the learners using contextual information and the appropriate contextual information and the models for categorization. The implementation is limited to the VARK model classification on LMS. However, can be easily extended to include other models and support other LMSs. Moreover, extending the context capturing mechanism to the incorporate context within the LMS can further improve the performance and the usability of the proposed solution. This system can be further improved by incorporating all the identified LMS/Mobile contextual information into the calculations and broadening the system to identify learning styles with respect to Felder-Silverman model, Grasha-Reichman model, and Dunn & Dunn model.

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