Enhancing Learning Management Systems by using Learning Styles

By

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A dissertation submitted in partial fulfillment
of the requirements for the
Degree of Doctor of Engineering

In the
Interdisciplinary Graduate School of Science
and Engineering
of
Shimane University
Japan

January 2016

Declaration

I hereby certify that this dissertation entitled "Enhancing Learning Management Systems by using Learning Styles" is entirely my own work. Wherever other sources of information have been used, they have been acknowledged.

This dissertation has not been accepted for any degree and is not being submitted for any other degree.

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Acknowledgements

I dedicate my first sentence to offer my sincere gratitude to my supervisor, Professor Masahito Hirakawa for accepting me as a student in Shimane University. His accepting me as a student in his laboratory was a clear pathway to progress on my research work. Sensei's direct supervision, encouragement assisted me to continue my research work and reach the necessary competent level of research. His research outlook attributions were a generous mentoring to me. His guiding the research process gave me sufficient encouragement to achieve the desired objectives.

As my first child was born while I was progressing on my research study, balancing research with child care was itself a challenge. This challenge was met by my own imitativeness with the confidence gained by Sensei's support and My family supportive roles to keep me focused and motivated.

The academic staff members of the Department of Mathematics and Computer Science at Shimane University deserve recognition for their advice. Especially Prof. Yamada's advice on Data Mining was helpful to structure the research at its initial stage. My lab members at Hirakawa Lab should receive special thanks for their friendship and assistance for research work. The staff of the International Student Section of Shimane University assisted me in numerous occasions, and I am indebted to them.

As I was a privately funded student, the generous scholarships I received from the Kunibiki Foundation in 2013/14 and Japan Student Services Organization (JASSO) in 2014/15 helped me immensely. I pay very special gratitude for these two organizations for selecting me and granting me the scholarship funding.

The pilot dataset used in this research was obtained with permission from a Learning Management System installed at Siksil Institute of Business and Technology, Sri Lanka. I thank the Chairman and the staff for this assistance. The main datasets used in this research were obtained with permission from a Learning Management System used at the Department of Information Technology, University of Sri Jayewardenepura, Sri Lanka. I extend my sincere thanks to the Academic Staff of the Department of Information Technology and Staff of the Information Technology Resource Centre for their assistance.

For evaluating the content recommendation module, I utilized a course conducted by My Sensei, Professor Masahito Hirakawa. My thanks again for Sensei and the students of the course for their cooperation and assistance.

At present, I am on leave from my workplace, University of Sri Jayewardenepura, Sri Lanka to pursue my doctoral studies. I wish to acknowledge the assistance provided by the Vice Chancellor, Dean of the Faculty of Management Studies & Commerce, and Coordinator, Information Technology Resource Centre (ITRC) in granting me leave, as well as my colleagues at the ITRC for covering up my duties during my absence gratefully.

I am indeed indebted to my family for the continuous support provided through my entire life. Both my parents dedicated themselves to put me onto a firm education foundation as a dream of their own. I bow my head in deep respect for them in my own Buddhist way. I'm indeed fortunate to be with my loving husband – Lasith, who has been truly a limelight. He guided me through multiple roles to enhance my quality of education and life while taking care of our loving daughter Senuli, in the midst of his research work as well.

Abstract

This thesis investigates how Learning Management Systems (LMSs) can be enhanced by using learning styles of learners. The cost of computing devices and connectivity to the Internet has seen a gradual fall throughout the years. This cost decline has resulted in increase in the number of individuals who own computing devices including smartphones. Ubiquitous computing is a term that can be applied to the present day. Educational establishments around the world are realizing the need to extend learning beyond the classroom using technology. LMSs are often the choice of e-learning systems in the endeavor to create virtual classrooms.

It has been nearly 15 years since the first LMSs appeared on the market. While the number of LMS implementations and their users are on the rise, they have not been universally accepted as providing ultimate solutions to educational needs. Some researchers attribute this reason to the approach of presenting the same educational content for all learners of a course irrespective of learner differences as an unresolved limitation of LMSs. Among learner differences, learning styles have been researched extensively. Educational theorists have forwarded a number of models to explain the learning preferences of learners. Recently research investigating the applicability of learning styles to computer-based learning environments has been trending.

The literature survey attempted to review the research and techniques to evaluate the current state, limitations and trends in LMS. One observation from the existing research is the popularity of Moodle – an open source LMS. In the investigation of learning style models, similarities between them, as well as common criticisms are found. The Felder-Silverman Learning Style Model (FSLSM) is one of the most cited models with respect to e-learning and is the chosen learning style model for this research. Several researchers have investigated how to identify learning styles of learners in an LMS and provide a mapping between learner activity in an LMS and learning styles. The methods adopted include questionnaire type instruments as well as automatic detection of learning styles. Automatic detection of learning styles requires close monitoring of the student activities. Analyzing student activities using the database log is one of the most frequently used methods. A data mining software tool can help to extract user patterns from log data.

A significant contribution of this research is to present a framework for a learning management system that provides personalized learning material recommendations using the automatically detected learner's learning styles. The framework contains modules for automatically detecting learners learning styles, storing individual profiles and

recommending content based on their learning styles. Recommendations are provided initially using a mapping we introduce between different types of content and learning styles to avoid the “cold start” problem. Later the collaborative filtering technique using the k-nearest neighbor algorithm is used for recommendations.

Little study on the awareness of learners to the concept of learning styles, and a relationship of a learner’s learning style to others has been done in existing research. The learning style visualization introduced in this research is aimed at filling this void. A learning style map is developed which vizualizes eight learning preference characteristics corresponding to eight preferences of the FSLSM. This visualization is a unique and valuable contribution to this research, and can even be used by instructors in their aim to understand learners better, as well as structure their content according to the learners.

The research contributions do not limit to theory. The proposed framework can be seamlessly integrated into the Moodle LMS. This research will benefit future researchers who wish to conduct further research on learning style integration into an LMS. Technical implementation details, including database modifications, software development, and API configuration for data mining are further mentioned. The open source software Weka is chosen as a data mining tool.

The performance of the framework is explained where three datasets are used for the comparison. The results reveal that the J48 Decision Tree Algorithm provides the best performance. A pilot user evaluation carried out to evaluate the learning material recommendation performance shows a satisfactory results.

This approach can be applied not only for the selected Moodle LMS but other LMSs, as they would have the same artchitecture whereby user activities are logged in a database. Therefore, the research has positive implications, for e-learning systems in general. Limitations of the framework and the developed system are also discussed. The study concludes by providing insight into further research directions emerging out of this study.

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Abbreviations

1. MOOC – Massive Open Online Courses
2. LMS – Learning Management System
3. MOODLE – Modular Object–Oriented Developmental Learning Environment
4. CBT – Computer Based Training
5. LCMS – Learning Content Management Systems
6. CMS – Content Management System
7. VLE – Virtual Learning Environment
8. SCORM – Sharable Content Object Reference Model
9. MBTI – Myers–Briggs Type Indicator
10. FSLSM – Felder–Silverman Learning Style Model
11. ILS – Index of Learning Styles (Questionnaire)
12. API – Application Program Interface
13. LO – Learning Object
14. ADDIE – Analysis, Design, Development, Implementation, Evaluation
15. LSQ – Learning Styles Questionnaire
16. ACT – Active (preference in FLSLM)
17. REF – Reflective (preference in FLSLM)
18. SEN – Sensory (preference in FLSLM)
19. INT – Intuitive (preference in FLSLM)
20. VIS – Visual (preference in FLSLM)
21. VER – Verbal (preference in FLSLM)
22. WEKA – Waikato Environment for Knowledge Analysis
23. ARFF – Attribute–Relation File Format
24. k–NN – k Nearest Neighbor
25. LLA – Learning Syle Monitoring and Learning Profile Creation Agent
26. LPE – Learning Preference Estimator
27. AIA – Adaptive Content Presentation and Interface Enhancement Agent (AIA)
28. ERA – Expert Recommendation Agent
29. PDF – Portable Document Format

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Chapter 1

Introduction

1.1 Background of the Research

Universal access to education – the ability for every human being to have equal opportunity in education is considered a right in almost all countries. Achieving universal primary education is one of the millennium development goals adopted in the United Nations Millennium Declaration in September 2000. Yet as the target year of 2015 arrives, the goals are yet to be completely achieved.

Soon after humans learned to write, and scripts were used, recording information for the educational purpose was born. With time, this progressed to be more systematic, and study places or schools were established. The use of books created using printing presses dates back to the 15th century. Since then books have been a cornerstone in the propagation of knowledge. Learning is the process of obtaining knowledge and skill. Learning in a formal setup relied on student learners (Hereinafter, this thesis will use the term "learner" to refer to students), teachers (Hereinafter, this thesis will use the term "instructor" to refer to teachers), classrooms, writing boards, books, pens, pencils and paper.

The advent of technology has changed the classroom landscape dramatically within the last fifty years. Electronic devices such as microphones and speakers were initially used as aids for instructors. The terminology "distance learning" which was originally used for mail-order correspondence courses expanded with the use of radio and television which provided new mediums to expand as well as aid the classroom. The advent of the computer was the next "game changer". Multimedia personal computers provided learners with the ability to experience audio and visual material – a feature unavailable in books. In fact, educational books in this age supplemented the printed material with compact disks (CD) which had supplemental information, Audio and video where relevant. Self-learning by way of such CDs was also a concept born during this era.

The landscape of learning was further transformed with the advent of the Internet. The physical distance barrier was made irrelevant, as access to learning materials wherever in the world was only limited by data connectivity bandwidth. And while new technologies for communication have enabled higher bandwidth connections connectivity costs have been plummeting. E-learning or electronic learning as we know of today was born under these circumstances.

In the traditional education model, disparity was often discussed as a problem. When the access to education is costly, by way of tuition fees, study material, and other ancillary costs, students coming from families living close to or below a poverty line have limited options. This is especially true for higher education. This in turn, affects the student's skills, knowledge and qualifications, which have a strong connection to their occupational prospects. A worker with low knowledge, skills and qualifications in return gets only a limited salary. A vicious cycle is created when such workers have families, as they may border the poverty line.

Schools and more popularly universities embraced e-learning as a means to defeat this educational disparity. Further, e-learning can enable global classrooms to be created. As a result, Massive Open Online Courses (MOOCs) in, for example, Stanford University[1] and Harvard – MIT collaboration Edx[2] have attracted hundreds of thousands of learners. Yet the technology is not limited to these institutions as business organizations are also introducing the same technologies for cost-effective employee training and customer support.

While MOOCs are a relative new addition, the most commonly used software platform which enabled e-learning is known as Learning Management System (LMS). Many different vendors have developed LMS software, with varying degree of features. Modular Object Oriented Developmental Learning Environment (Moodle)("Moodle Learning Platform," 2015) is one of the most popular LMSs in use today with over 64,000 sites in 220 countries combining for a total of 79 million users.

This popularity stems possibly due to several key factors. Most commercial learning software is licensed on a per user basis, and enterprise license costs are extremely high. Moodle, on the other hand, is an open source product, and as such is available at no cost. The Moodle LMS has been developed with opportunities for third

[1] http://online.stanford.edu/courses

[2] https://www.edx.org

party plugins, and this has enabled its functionality to be enhanced by software developers.

The content which is stored on an LMS has to be developed with the learner in mind. In most of the time, however, courses hosted on LMS's tend to be offered in the same format for all learners of the course, irrespective of learner differences. The learner differences can occur due to numerous factors such as prior knowledge, analytical and cognitive abilities and capacities, motivation, etc. This single format offering has been identified as a limitation of LMS implementations, irrespective of whether commercial or open sourced (Sabine Graf & List, 2005).

When a user accesses the Internet in the present age and searches for products or services on an online shopping site, the experience is enhanced due to the availability of recommendation systems. They enable the shopper to get personalized recommendations. This scheme can be extended even for online learners. Personalizing the learning experience to suit the learner has been one of the sought after features in an e-learning environment in recent years. This personalization can be tried out using explicit information elicited from the learners such as by way of a questionnaire or by automatically modeling the users based on his/her actions performed in the LMS. The personalization strategy can be based on different dynamics. Using learning style preferences is one of them. A learner following a course may have a preferred way of learning which is exhibited by his attitudes and behaviors (Honey & Mumford, 1992) which can be identified as a "learning style."

1.2 Research Objectives and Scope

This thesis investigates how learning styles can be used to enhance LMSs. The main topic of this dissertation is detecting learning styles of learners in LMSs and the main research question is:

How can we enhance LMS using learning styles?

This research question formed the foundation for a set of aims and objectives upon which this dissertation is based. These are to:

1. Evaluate existing models of learning styles and select which of them can be applied for LMSs based learning environment.
2. Consider the selected learning styles and predict learning styles of learners in an LMS environment using a real student dataset.

3. Verify the predicted learning styles using an alternate approach.
4. Visualize each learner's learning style to enable the learners to get a better understanding of learning styles.
5. Visualize the learning styles of groups of learners to enable an instructor to get a condensed view of their learning styles.
6. Recommend content for learners using the selected approach and evaluate its effectiveness.

1.3 Thesis Contributions

This section elaborates on the contributions made by this research, which can be separated in terms of contributions to theory and practice.

1.3.1 Thesis contributions to theory

While there are many different learning style models, there has been limited comparison of the models, and especially their applicability to computing environments. This research has compiled a comprehensive literature survey of previous research and summarizes its suitability for e-learning.

The research introduces a framework which analyses learner behavior in an LMS and recommends content based on the learning styles. While this concept has been touched in brief by several previous researchers, this research describes the entire process involved, including exploring its effectiveness.

One of the unique contributions of this research is a scheme to visualize the learning styles of a learner. No previous researcher has documented any efforts to visualize learning styles.

1.3.2 Thesis contributions to practice

The learning style visualization model introduced in section 3.4.1.3 can be used not only to visualize the learning styles of a learner. This scheme can further be used to compare groups of learners against an individual learner, as well as analyze learning styles of learners in a classroom. This visualization is designed in a way that it can be integrated into an existing Moodle LMS as a module, and this scheme can benefit both learners and instructors. Four learner groups - two from Shimane University, Japan, one from University of Sri Jayewardenepura, Sri Lanka, and one from Siksil Institute of Business and Technology, Sri Lanka with 54, 8, 80 and 22 students respectively, were used for different performance evaluation of the framework and these performance indicators can be used by future researchers in this domain.

1.4 Thesis Organization

Chapter 2 describes a comprehensive bibliographic literature survey carried out to lay the foundation for the research. Several concepts which are at the core of this research are explained in detail. They include characteristics of e-learning, LMSs and more specifically Moodle LMS. Further, the process involved in creating content for LMS delivery is discussed. Learning styles is a core concept, and several learning style models which have been cited are discussed; especially with their relation to e-learning. Another topic which is explained is data mining, and its applications in e-learning. The Weka data mining tool, which is used within the subsequent few chapters, is also introduced in this chapter. The bibliographic survey focuses on the prior work conducted in LMSs, detection of learning styles in LMS, and content recommendation systems. The chapter further highlights ongoing research topics and provides a foundation for the exploratory study.

In Chapter 3, a framework which analyzes learner behavior in an LMS and recommends content based on the learning styles is presented. The rationale behind each system elements selection is further justified. Modules and sub-modules which comprise the system and their functionality, as well as technical aspects of the software design, are further explained in this chapter.

Chapter 4 describes efforts undertaken to examine the system performance compared with previous research as well as user evaluations and discusses the implications of this system.

Chapter 5 concludes by describing the summary of findings with reference to the environment and discusses limitations of the system and how they can attempt to be resolved. The final section of this chapter elaborates on future research directions.

Chapter 2

Background and Related Work

The literature survey aimed to analyze the existing research carried in related domains, as well as build the necessary background knowledge required for enhancing learning management systems using learning styles.

2.1 E-learning

The ability to learn is one of the key characteristics which is common to living beings, and especially humans. Learning activity has played a significant role in the development of historical civilizations. The Webster's dictionary refers to the term as "the act or experience of one that learns; knowledge of skill acquired by instruction or study; modification of a behavioral tendency by experience" ("Websters Dictionary Online," 2015). Learning activity has been studied extensively, and supported by numerous theories which underpin its foundation.

E-learning or electronic learning has its origins from the concept of distance education; which itself evolved from correspondence study programs. Correspondence study was first introduced by the University of London way back in 1858 as distance learning degrees via post. Distance education can be defined as an educational situation in which the instructor and learner are separated by time, location, or both. Distance education does not preclude the use of the traditional classroom.

The term e-learning can be defined depending on the context of use. If one were to gather its meaning from its extended form: electronic learning can be considered as "instruction that is delivered electronically, in part or wholly – via a web browser, through the Internet or an intranet, or through multimedia platforms such as CD-ROM or DVD" (B. Hall, 1997) as cited in (Clarey, 2008). The term e-learning has been used since the early 1960's with radio and television being the carrier in the early ages. The use of computers for e-learning came into the education mainstream in the 1990's with the usage of CD media – which gave rise to the term Computer Based Training (CBT). The advent of the World Wide Web created a path to a new dimension for e-learning. The first generation of web-based training relied on simple web browsers and had limitations in delivering interactive content – apart from basic text and simple graphics. Educational hypermedia systems was a term used to describe some of the first generation systems which either were browser based or client-server implementations.

With the emergence of technologies such as Macromedia Flash, more interactive content development was made possible. Nevertheless to use e-learning in educational establishments, a wider platform was required, as actors such as learners and instructors and elements such as courses or subjects need to be supported.

2.2 Learning Management Systems

2.2.1 General trend

Learning Management Systems (LMS) have been defined as "a software application or web-based technology used to plan, implement and assess a specific learning process" (Alias & Zainuddin, 2005). Several other terms used in e-learning are sometimes used as alternate term for LMS: learning content management system (LCMS), e-learning system, learning the platform, course management system and virtual learning environment (VLE). Graf comments that the concept of LMS support only at the course level, by considering the course as the smallest entity and that LCMS introduces the concept of learning objects and further supports instructors in creating, storing, and managing learning objects (Sabine Graf, 2007). Pinner suggests that out of the box the VLEs and LMS are the same things, but after implementation, depending on the way we intend to use them they become different and also provide different approaches to learning (Pinner, 2011). He further comments that VLEs are often characterized by constructivist pedagogical principals and often used as a place to collaborate and extend discussions rather than merely hosting tractable learning objects (Pinner, 2011). In this thesis, the term LMS is used as a term which covers all these terms.

As noted by Pinner, the use of e-learning and LMS is spread across a wide range of industries/sectors, with the highest portion being in schools and higher education (Pinner, 2014). When we consider the high prevalence of open source LMSs, one reason attributed could be the use of them by educational establishments, which may have developer communities to support them while constrained by budgets. The role played by an LMS may differ from institution to another. Supporting the full array of courses in a distance learning setup with one extreme, while the other would be like a supplemental technology-aided delivery method supporting traditional teaching, i.e. blended learning.

While software such as Blackboard ("Blackboard Educational Technology Platforms," 2014) and Desire2Learn are leading commercial products in terms of market share in universities in the United States (Green, 2013), the most widely used LMS in terms of total numbers of users, is Moodle (Elearning Industry, 2015).

2.2.2 Moodle

Moodle (Modular Object-Oriented Dynamic Learning Environment) was developed by Martin Dougiamas in 2001. It currently has over 64,000 registered sites in 220 countries, with over 79 million users ("Moodle Learning Platform," 2015). Moodle has been grounded on the social constructionist pedagogy, which details that individuals construct their knowledge collectively, rather than simply being received from an instructor or another source.

Moodle was originally identified as a course management system but now re-defined as a learning platform. Its popularity has increased gradually, one reason is that Moodle is written in PHP and makes it one of the most well-known and widely used e-learning software infrastructures. A few reasons for its wide acceptance can be listed as follows:

1. Freely available: Both the source code and binaries are distributed freely using the GNU general public license
2. Scalability: It can be scaled to accommodate several users; is served over 100,000 users in the University of Minnesota and over 200,000 in the Open University, UK.
3. Language support – Moodle has been translated into over 100 languages, and can be installed and configured as language packs. Multiple language packs can be supported on a single site.
4. Interoperability – Moodle can run on Windows, Mac Os, UNIX, Linux or any other platform which supports PHP and database server. It also supports mobile access and cross browser compatibility.
5. Portability – Content can be moved in/out from a Moodle installation to/from any SCORM compatible LMS (See section 2.4.2).

6. Extensive documentation – Moodle has been in use for over 13 years and has a large resource base in the moodle.org site.
7. Strong user community – Being an open source project it has a large user community together with an ever active forum. Yet it also has a full-time set of developers and certified Moodle partners to further develop the project.
8. Plugins – Plugins are tools which can be used to extend the core features of the Moodle system. They can be developed by third party developers. These include plugins for:
   - Activities – Provide activities in a course such as wikis, quizzes, assignments, achievement certificates.
   - Authentication – permit connectivity for external authentication sources
   - Blocks – provide small information displays or tools which can be moved around pages.
   - Themes – change the look and feel of a Moodle LMS or of a course by using HTML and CSS.
   - Reports – provide data views from Moodle for teachers and course administrators
   - Plagiarism – connect to external services and submit content for plagiarism detection

In order to install Moodle, one would require a PHP capable web server such as Apache and a database such as MySQL.

Figure 2-1. Moodle LMS Homepage at Shimane University (CERD)

2.2.3 Limitations of existing Learning Management Systems

LMS have been in use for over a decade now, and they have spread to many, higher educational establishments. Yet there have been issues with their usage. While the ability to customize features may be present, there will always be issues in tailoring a solution which claims to be an all-in-one solution.

Content creation is a process which requires careful monitoring, in order to keep to the learning outcomes expected of the course (see section 2.4). While the content prepared is designed with the learner in mind, learners who are subject to that content is not equal, and, therefore, may not absorb the information on an equal level. This can be due to numerous factors such as differences in prior knowledge, differences in analytical and cognitive abilities and capacities, differences in motivation, etc. Graf & List identified this issue of single format offering as a limitation of LMS implementations, irrespective of whether commercial or open sourced (Sabine Graf & List, 2005).

2.3 Adaptive Learning Management Systems

Adaptivity refers to the ability to change to fit circumstances. With respect to computing systems in and educational setup, De Crook et al. identified several characteristics of adaptive systems as listed below (De Crook et al., 2002).

1. Information should adapt to what a learner already knows (prior knowledge) or can do (prior skill).
2. Information should be able to adapt to a learner's learning capabilities.
3. Information should adapt to a learner's learning preferences or style.
4. Information should be able to adapt to a learner's performance level and knowledge state (i.e., the system should provide feedback).
5. Information should adapt to a learner's interests.
6. Information should be able to adapt to a learner's personal circumstances (location, tempo, etc.).
7. Information should adapt to a learner's motivation.

Graf suggests that in relation to adaptation in LMS, four different subcategories can be evaluated (Sabine Graf, 2007).

1. Adaptability – customizing the system for the needs of the educational institution by way of templates, language support, and user friendliness.
2. Personalization – facilities for each individual user to customize his/her own view of the system.
3. Extensibility – availability of APIs and other programming support for third party modules.
4. Adaptivity – automatic adaptation to the individual learners needs.

Profiling users is one method often mentioned as a strategy for providing adaptation. Different characteristics have been put to be used as the feature for user profiling in adaptive hypermedia systems – a precursor of modern e-learning systems. They include user's goals, knowledge, background, hyperspace experience and preferences (Brusilovsky, 1996). User's goals are connected to what the user aims to achieve such as accessing Information, or solving a problem or learning about a certain topic. User's knowledge relates to their intellectual abilities within a selected sphere of knowledge. Background refers to prior experiences which are outside the selected sphere of knowledge. Hyperspace experience relates to the familiarity of systems with the same look and feels in navigation.

Graf's study of existing LMS (Sabine Graf & List, 2005) notes the very little adaptivity in the study of nine open source LMSs. Later versions of Moodle (2.0 and later) support conditional activities such as enabling a lesson only once a student passes a quiz at an accepted level.

2.4 The Content Creation Process for Learning Management Systems

Setting up an LMS is only a step in the process of establishing an e-learning infrastructure. Developing contents for the LMS is a more long drawn out process which needs careful monitoring.

2.4.1 Instruction design

Instruction design has been defined as "*The systematic development of instructional specifications using learning and instructional theory to ensure the quality of instruction. It is the entire process of analysis of learning needs and goals and the development of a delivery system to meet those needs. It includes development* *of instructional materials and activities; and tryout and evaluation of all instruction and learner activities."* (Michigan, 1996). From a design perspective, there are a number of models which can be followed. The ADDIE (Analyze, Design, Develop, Implement, and Evaluate) model is one of the best-known ones. (Figure 2-2)

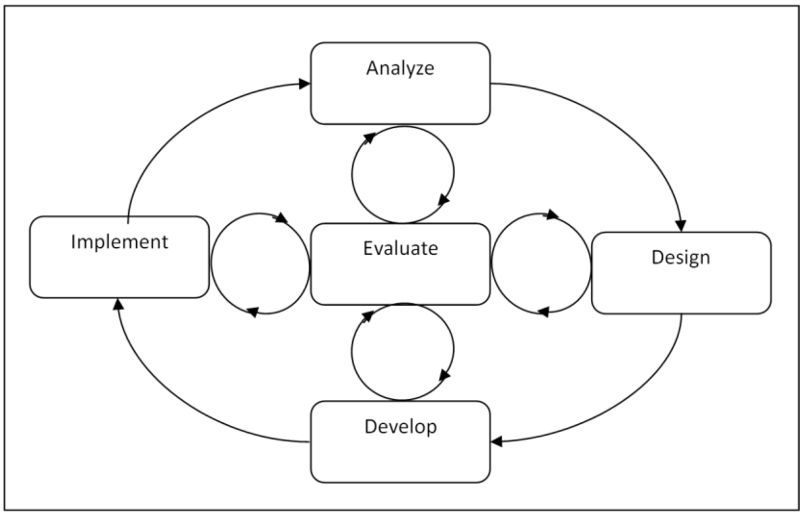

Figure 2-2. The ADDIE model

(From (Vendramin, 2004))

The first stage – analysis clarifies the problems and objectives with respect to the target audience. This includes the learning environment, and the existing knowledge and skills. The design stage determines the goals and tools used to measure performance. Further, it also determines testing methods, subject matter, and considers the resources available. The development stage is the time to develop an instructional material which was planned in the previous stage. This includes interactive materials, multimedia, instruction guides. Additional software such as authoring tools may be utilized to create the multimedia materials, and can involve more than one person. Few examples of software which can be used are Articulate and Captivate. Recently introduced cloud-based tools such as Elucidat[3] and Gomo[4] are rapid authoring tools.

In the implementation stage, the instructional material is deployed in the target LMS. The users of the system including instructors and other facilitators as well as learners should be adequately trained in its operation. In the final stage – evaluation, two methods are used. Formative evaluation is carried out during each stage of the ADDIE process while summative evaluation is carried out at the end of the course.

[3] https://www.elucidat.com

[4] http://www.gomolearning.com

2.4.2 Creating re-usable content for Learning Management Systems

One of the main issues in software engineering is software re-use. When it comes to e-learning, re-usability is important in a slightly different way. Code reusability is important to developers, but in the case of e-learning content reusability is equally or more important. In the first round of learning management systems, the content was changeable by users, but since each developer has different standards, the content was not interoperable each other. This meant content duplication and inconsistencies were common in learning environments.

The Sharable Content Object Reference Model (SCORM) introduced by the US Department of Defense's Advanced Distribution Team in 1999 changed this scenario. It is a technical reference model which ensures that all e-learning content and LMSs can work with each other. If an LMS is labeled as SCORM conformant, it can accept any content that is SCORM conformant, and any SCORM conformant content is compatible with any SCORM conformant LMS.

When it comes to making content SCORM compliant, it is important to granulize content into a form which can be handled easily so that its value to the learning process is not lost. The concept of learning objects was used for this purpose.

2.4.3 Learning objects

The term learning object or LO has been described in literature first in 1967 but has been used extensively in relation to e-learning since 1994. It has been defined as "Any entity, digital or non-digital, that may be used for learning, education or training" by the IEEE Learning Technology Standards Committee (LTSC) (IEEE Computer Society, 2005). Other definitions have included terms to define the granularity by saying that they are smaller units of learning typically from less than 15 minutes (Wisconsin Online Resource Center, 2010), as well as focus on the reusability: In the spirit of object-oriented programming breaking down educational content into smaller units which can be reused in different educational scenarios (Wiley, 2000).

In general, it would be possible to summarize a few characteristics of LOs.

- Each LO can be taken independently (self-contained)
- A single LO may be used in multiple contexts for multiple purposes (reusable)
- LOs can be grouped into much larger collections of content, including traditional course structures (aggregated)

- Every LO has descriptive information allowing it to be easily found by a search (tagged with metadata)

When considering the use of LOs in an LMS, it is expected that they could be packaged with SCORM compatibility to be ported to another LMS.

2.5 Learning Styles

The fact that humans do not learn equally, and differences in learning are observable was first documented by Aristotle by his observation of children in 334 B.C. (Reiff, 1992). The recent origin of learning styles can be attributed to the time period of early 1900’s when psychologists and educationalists forwarded theories which focused on relationships between memory and visual or oral instructional methods. The foundation and development of learning styles are intertwined between the domains of psychology and education, so much so that many different models have been documented with varying descriptions and scope. This is evidenced by the definition of learning styles itself: “a description of the attitudes and behaviors which determine an individual’s preferred way of learning” (Honey & Mumford, 1992) “educational conditions under which a student is most likely to learn.” (Stewart & Felicetti, 1992) cited in (Arden & Kuntz, 2015), and “characteristic strengths and preferences in the ways they (learners) take in and process information” (Felder & Silverman, 1988).

Coffield et al.’s categorization of families of learning styles (Coffield, Moseley, Hall, & Ecclestone, 2004) is one of the most comprehensive reviews of the models available in research today. The summarized list of learning styles has been prepared by Kanninen (Kanninen, 2008) in Table 2.1.

Table 2.1. Coffield's Families of Learning Styles

Author(s)	Assessment tool	Year introduced
Genetic and other constitutionally based learning styles and preferences including VAKT		
Dunn and Dunn	Learning Style Questionnaire (LSQ) Learning Style Inventory (LSI) Building Excellence Survey (BES)	1979 1975 2003
Gregorc	Gregorc Mind Styles Delineator (MSD)	1977
Cognitive structure		
Riding	Cognitive Styles Analysis (CSA)	1991
Stable personality type		
Apter	Motivational Style Profile (MSP)	1998
Jackson	Learning Style Profiler (LSP)	2002
Myers-Briggs	Myers-Briggs Type Indicator (MBTI)	1962
Flexibly stable learning preferences		
Allison and Hayes	Cognitive Style Index (CSI)	1996
Herrmann	Brain Dominance Instrument (HBDI)	1995
Honey and Mumford	Learning Styles Questionnaire (LSQ)	1982
Felder and Silverman	Index of Learning Styles (ILS)	1996
Kolb	Learning Style Inventory (LSI) LSI Version 3	1976 1999
Learning approaches and strategies		
Entwistle	Approaches to Study Inventory (ASI) Revised Approaches to Study Inventory (RASI) Approaches and Study Skills Inventory for Students (ASSIST)	1979 1995 2000
Sternberg	Thinking Styles	1998
Vermunt	Inventory of Learning Styles (ILS)	1996

Source: (Kanninen, 2008)

This study identified 71 models of learning styles out of which 13 important models were selected for categorization. The first family category relates to the concept that is learning styles and preferences are largely constitutionally based, including the four modalities: visual, auditory, kinesthetic, and tactile (VAKT). The second family category relates to the concept that learning styles reflect deep-seated features of the cognitive structure, including patterns of abilities. The third considers the learning styles as one component of a relatively stable personality type. The fourth family relates to the concept that learning styles are flexible, stable learning preferences. The final category describes learning approaches, strategies, orientations, and conceptions of learning rather than simply learning styles. (Coffield et al., 2004).

2.5.1 Myers-Briggs type indicator

In 1962, Isabel Briggs Myers and her mother Katharine Briggs published a booklet explaining the Myers-Briggs Type Indicator (MBTI) for classifying psychological preferences. MBTI is based on Carl Jung's typological theory and poses a number of questions (Versions include 93 and 126 item forms) related to four dimensions: extrovert-introvert, sensing-intuition, thinking-feeling, and judging-perceiving. The scales for the answers are bipolar, and the personality type calculated using the question scores place the respondent into one of 16 pre-determined personality types. Although its classification is based on personality, the same outlook has implications for learning behavior. As a ground-breaking classification, other models which succeeded MBTI have similarities to this approach.

2.5.2 Dunn and Dunn learning style model

Professors Ken and Rita Dunn originally proposed their model in 1974 and had been subjected to several refinements since then. Through their research carried out in schools, they observed distinct differences in the way students respond to the instructional material. Based on this research they identified five dimensions on which 20+ elements of the model are grouped (Dunn, 1984):

1. Environmental. The environmental dimension refers to the following elements: lighting, sound, temperature, and seating arrangement. For example, some people need to study in a cool and brightly lit room, while some others cannot concentrate unless they have music playing, and it is warm.
2. Emotional. This dimension includes the following elements: motivation, persistence, responsibility, and structure. For example, some people like to work on one activity at a time only starting another after finishing one, while others may like to perform several activities at the same time, multitasking in-between them. (Persistence element).
3. Sociological. The sociological dimension represents elements related to how individuals learn in association with other people: alone or with peers, with an authoritative adult or with a collegial colleague, and learning in a variety of ways or in routine patterns. For example, some people prefer to work alone when tackling a new and difficult subject, while some others prefer to work in a team (learning alone or with peer's element).

4. Physiological. The elements in this dimension are perceptual (auditory, visual, tactile, and kinesthetic), time-of-day energy levels, intake (eating or not while studying) and mobility (sitting still or moving around). For example, some people consider themselves to work/study best at night or in the morning (time-of-day element).
5. Psychological. The elements in this dimension correspond to the following types of psychological processing: hemispheric, impulsive or reflective, and global versus analytic. The hemispheric element refers to left and right brain processing modes; the impulsive versus reflective style describes how some people take decisions before thinking and others scrutinize the situation before making decisions. Global and analytic elements are unique in comparison to other elements because these two elements are made up of distinct clusters of elements found in the other four strands. The elements that determine global and analytic processing styles are sound, light, seating arrangement, persistence, sociological preference, and intake.

This model has been commercially marketed in 11 countries with 23 testing centers, and has four different assessment instruments based on the age of the subject – Ages 7-9, 10-13, 14-19 and 17+("International Learning Styles Network," 2015).

2.5.3 Kolb's learning style model

David Kolb introduced his Experiential Learning Theory in 1984 (Kolb & Kolb, 2005). It establishes four distinct learning styles based on a four-stage learning cycle and thus operates on two levels: In the first level, a four-stage cycle exists Concrete Experience (CE), Reflective Observation (RO), Abstract Conceptualization (AC), and Active Experimentation (AE), as illustrated in figure 2-3.

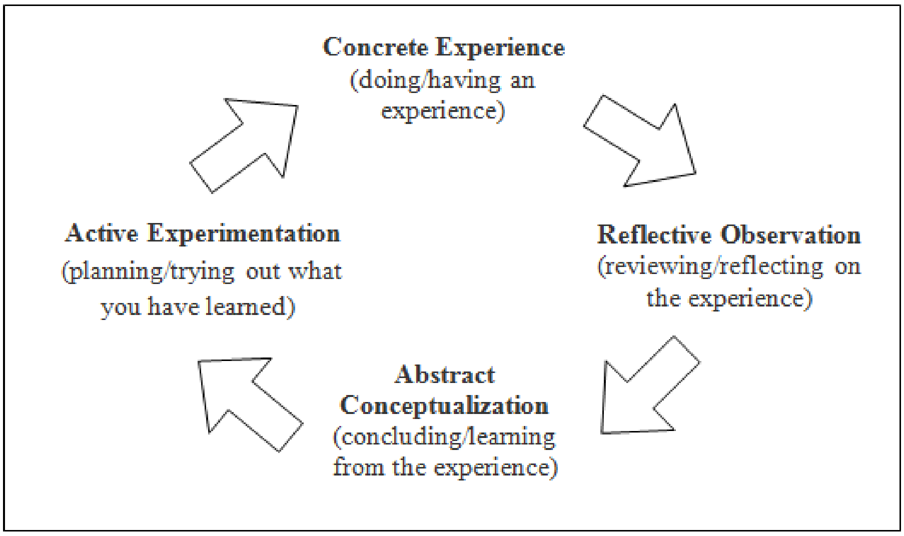

Figure 2-3. Kolb's Cycle (First Level)
(from (McLeod, 2010))

Kolb explains that different people naturally prefer a certain, single different learning style. Various factors may influence a person's preferred style, including social environment, educational experiences, or even the basic cognitive structure of the individual. Whatever influences the choice of style, the learning style preference itself is actually the product of two pairs of variables, or two separate 'choices' that we make, which Kolb presented as lines of the axis, each with 'conflicting' modes at either end.

A typical presentation of Kolb's two continuums is that the east-west axis is called the Processing Continuum (how we approach a task), and the north-south axis is called the Perception Continuum (our emotional response, or how we think or feel about it), as indicated in figure 2-4.

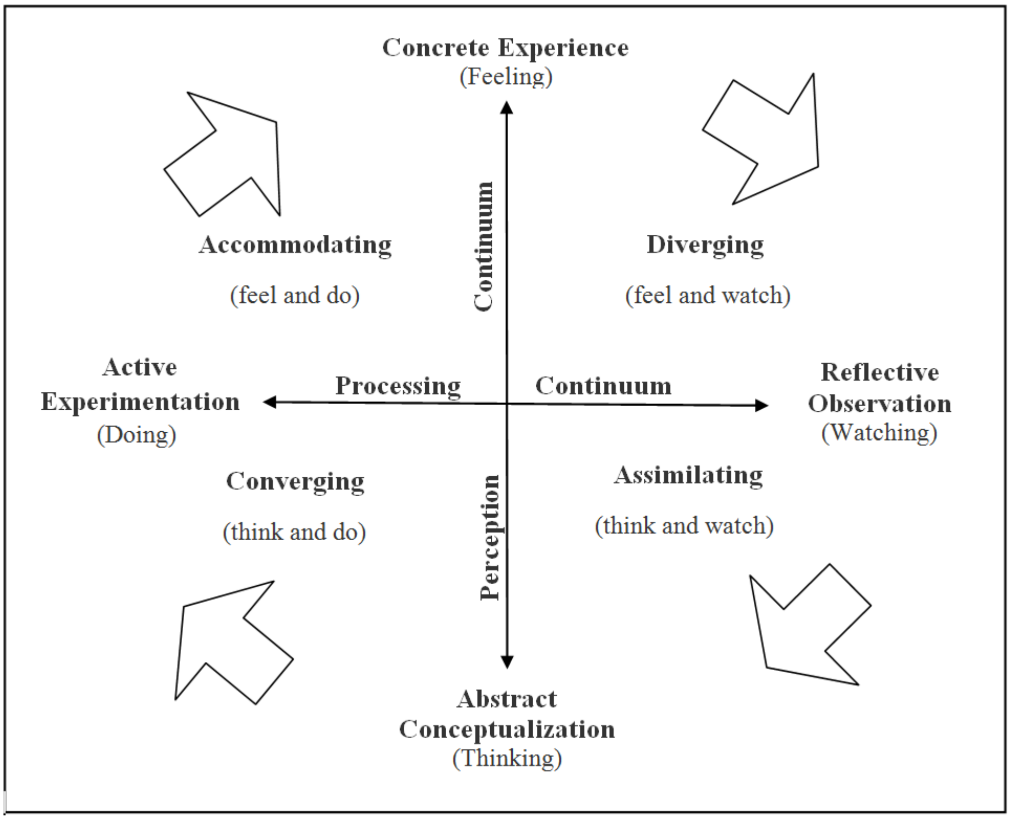

Figure 2-4. Kolb's Cycle (Second Level)

(from (McLeod, 2010))

Kolb's model is alternatively represented in a 2 × 2 matrix (Table 2.2).

Table 2.2. Kolb's Learning Styles in a 2 x 2 Matrix

	Doing (Active Experimentation)	Watching (Reflective Observation)
Feeling (Concrete Experience)	Accommodating (CE/AE)	Diverging (CE/RO)
Thinking (Abstract Conceptualization)	Converging (AC/AE)	Assimilating (AC/RO)

Source : (McLeod, 2010)

2.5.4 Honey and Mumford learning style model

Peter Honey and Alan Mumford's learning style model (Honey & Mumford, 1992) is based on Kolb's Experiential Learning Theory. It identifies four learning styles: activists, theorists, pragmatists, and reflectors based on an 80 question Learning Styles Questionnaire (LSQ) which was published in 1982. In 2000, they formulated a shorter, 40 question LSQ to enable learners to get a quicker route to evaluate their learning style.

2.5.5 Pask's Serialist/Holist/Versatilist model

Gordon Pask developed the conversation theory, out of his work with cybernetics where he proposed the human-machine interaction as a form of conversation. Its purpose was to explain learning in humans and machines, and stated that learning occurs through conversations about a subject matter. He identified two types of learners: Serialists who progress through a structure in a sequential fashion and Holists who look for higher order relations. He further stated that those who had a mixture of both can be considered as versatilists (Pask, 1988).

2.5.6 Felder and Silverman learning styles model

In 1988, Richard Felder and Linda Silverman published their learning style model which considered teaching practices that should meet the requirements of students with the full spectrum of styles (Felder & Silverman, 1988). In the Felder-Silverman learning style model (FSLSM), learners are characterized using values in four dimensions. The four dimensions are based on major dimensions in the field of learning styles and can be viewed independently of each other.

In the first dimension, the learner's preferred method of processing information is considered and marked as active (ACT) or reflective (REF). Active learners prefer to work in groups, and they do not learn in situations that require them to be passive and tend to be experimentalists. In contrast, reflective learners work better by themselves or with one other person at most. They do not learn much in situations that provide no opportunity to think about the information being presented and tend to be theoreticians.

In the second dimension, the type of information that the learner preferentially perceives is considered and marked as sensory (SEN) or intuitive (INT). Sensory learners prefer to learn facts and like to relate to practical, real-world situations while intuitive learners prefer abstract learning material such as theories and their underlying meaning. Intuitive learners are more comfortable with symbols than sensory learners.

In the third dimension, the sensory channel through which the learner most effectively perceives external information is considered and marked as visual (VIS) or verbal (VER). Visual learners prefer pictures, diagrams, graphs, or demonstrations, whereas verbal learners prefer spoken information or audio. FSLSM considers no other sensory channels such as touch, taste, and smell as these are relatively unimportant in most educational environments.

In the fourth dimension, how the learner progresses toward understanding is considered and marked as sequentially (SEQ) or globally (GLO). Sequential learners learn in small increments, and, therefore, have a linear learning progress, tending to follow logical stepwise paths toward solutions. Conversely, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without viewing connections; however, after learning sufficient material, they suddenly understand the entire picture. They can solve complex problems and put things together in novel ways, but find it difficult to explain how they did it.

The terms used in the FSLSM to identify the dimensions are not new, and some terms and their underlying concepts are shared with other learning style models.

1. Sequential learners (FSLSM model) are very much similar to the serial learner type in Pask's model.
2. Global learners (FSLSM model) have the same characteristic as holist learners in Pask's model.
3. The sensing–intuitive dimension of FSLSM Model has similar characteristics to that of MBTI.
4. Active learners in FSLM have similarities with activist learners in Honey and Mumford model, and accommodating learners in the Kolb's learning styles model.
5. Reflective learners in FSLM are similar with a reflector in Honey and Mumford model, and diverging learners in the Kolb's learning styles model.
6. Intuitive similar in FSLM to theorist in Honey and Mumford model, and assimilating learners of the Kolb learning styles model.
7. Sensing learners is related to pragmatist in Honey and Mumford model, and converging of the Kolb learning styles model.

While the FSLSM combines aspects of several learning style models, it differs from them in since it views learning styles as tendencies, suggesting that students have a inclination toward a specific learning style but could act differently in some situations.

In order to classify learners into each learning style model, each model has its own instruments. The Index of Learning Styles (ILS), which was developed by Felder and Soloman (Felder & Soloman, 1994), can be used as an instrument for assessing learning preferences in the four FSLSM dimensions. This instrument comprises 44 questions, with 11 questions for each dimension. The results of the questionnaire indicate an individual's learning preference in each dimension, with scores ranging from +11 to −11. This score can be read in the following manner. A score of 1–3 (either plus or minus) indicates that the learner is fairly balanced on the dimension of that scale. A score of 5–7 (either plus or minus) indicates that he/she has a moderate preference for one side of the dimension of the scale, and will more easily learn in a teaching environment that favors that dimension. A score of 9–11 indicates that he/she has a very strong preference for one dimension of the scale, and probably has considerable difficulty in learning in an environment that does not support that preference. The ILS Questionnaire and its Japanese translation are included in Appendix A and B.

2.6 Relevance and Criticisms of Learning Styles

The concept of learning styles has been in research and publications for nearly a century and has contributed to education in numerous ways. Many instructors/teachers are made aware of the subtle changes in students learning preferences. Therefore they need to prepare relevant content and to make the environment for learning stimulating and interesting. From the student's point of view, knowing his/her learning style provides insight into one's strengths, weaknesses, and habits thereby show them how to take advantage of their natural skills and inclinations. In situations where poor instructors hamper learning, it enables learners to access the most relevant study material for reducing stressful learning experiences.

While the positives from learning styles can be listed as above, not everyone agrees that they are as useful as mentioned. The proponent's claim of the use of learning styles has improved learning. The opponents of learning styles debate this, arguing that the very existence of different models, sometimes overlapping each other reflects that there is no single model which can be considered better than the others (Coffield et al., 2004). Another argument is that students learning may change over time and that depending on the age, they could change. Gender also has been discussed as a variable when it comes to learning styles.

A slightly different school of thought suggests that similar to the idea that there is no universal "right" way to teach or "right" way to learn/study, there is no single learning style theory that can be considered as best.

2.7 Use of Learning Styles in e-learning

Learning styles models were conceived for traditional learning. Yet, when considering e-learning environments, differences exist the types of activities that can be performed by a learner. Popescu (Popescu, 2010) suggests merging features from major learning style models into a new Unified Learning Style Model (ULSM) by considering technology enhanced learning which includes a number of dimensions:

1. Perception modality: visual vs. verbal
2. Processing information (abstract concepts and generalization vs. concrete, practical examples; serial vs. holistic; active experimentation vs. reflective observation; careful vs. non-careful with details)
3. Field dependence vs. field independence
4. Reasoning (deductive vs. inductive)
5. Organizing information (synthesis vs. analysis)
6. Motivation (intrinsic vs. extrinsic; deep vs. surface vs. strategic vs. resistant approach)
7. Persistence (high vs. low)
8. Pacing (concentrate on one task at a time vs. alternate tasks and subjects)
9. Social aspects (individual work vs. teamwork; introversion vs. extraversion; competitive vs. collaborative)
10. Coordinating instance (affectivity vs. thinking)

Some researchers (Felder & Silverman, 1988; S. Graf, Liu, & Kinshuk, 2010; Hsieh, Jang, Hwang, & Chen, 2011) agree that matching learning content with the learner's learning styles can benefit them to learn easily. However, in order to identify the learning styles of students, two approaches could be considered. They follow the user modeling categories introduced by Brusilovsky (Brusilovsky, 1996): Collaborative user modeling and automatic user modeling.

In collaborative user modeling, the user has to "collaborate" for the model to be complete. In the case of learning style user modeling achieved using the questionnaire instrument provided by the learning style model. Identifying students learning style using this scheme has been carried out with respect to Honey and Mumford (Sangvigit, 2012), MBTI (Radwan, 2014) and FLSLM (Kusumawardani, Prakoso, & Santosa, 2014; Morita, Koen, Ma, Wu, & Johendran, 2005; Park, 2005; Surjono, 2014). Savic and Konjovic presented a system that made recommendations using the ILS for an SCORM compatible Sakai LMS, by modifying the SCORM manifest file (Savic & Konjovic, 2009). Özpolat and Akar (Özpolat & Akar, 2009) developed a system that collected learner preference using explicit generic queries. Their system, based on the FSLSM, constructed a learner profile using a conversion unit-based keyword mapping. Furthermore, it built a learner model by processing the learner profile over a clustering unit that used the NBTree classification algorithm in conjunction with a binary relevance classifier.

While this method of using the questionnaire is simple to implement and provides quick feedback, it has its own criticisms. They include the fact that students learning styles may change during the course of the engagement, and that they are measured at only one time. It is also possible that when the students answer the questionnaire, they do not reveal their true learning style. Nevertheless, in our survey of literature we were unable to trace any visualization schemes of learning styles, even though measurement mechanisms were enabled in e-learning.

In the automatic user modeling, on the other hand, the accuracy or relevance is considered to be higher as it can be tested multiple times without interfering with the student's real actions performed on the system. In this way, automatic detection of learning styles in e-learning can be considered as much easier to perform and accurate than in traditional learning.

2.8 Detection of Learning Styles in Learning Management Systems

Recently researchers have explored the idea of automatically identifying learning styles to personalize the learning experience (García, Amandi, Schiaffino, & Campo, 2007; Sabine Graf & Kinshuk, 2006). These studies have adopted statistical as well as simple rule-based approaches. Most current LMSs follow CMS architecture and, therefore, share the CMS feature of logging events in a database. This includes activities such as accessing content, participating in quizzes and forums. Nearly, researchers who follow the data-driven approach use this log data to model automatically students' learning styles.

Chang et al. (Chang, Kao, Chu, & Chiu, 2009) used the k-nearest neighbor (k-NN) classification algorithm and genetic algorithms to classify and identify students' learning styles using a generic model. Garcia et al. (García et al., 2007) considered Bayesian networks to detect a student's learning style in a e-learning system. Protus (Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011) mines server logs to discover patterns of learning styles and learners' traits. It uses the collaborative filtering technique using AprioriAll algorithm.

Cha et al. (Cha et al., 2006) proposed an intelligent learning system with a specific user interface based on the FSLSM. Decision Trees and Hidden Markov model approaches are utilized in this system to predict learning styles. Despotović-Zrakić et al. (Despotović-zrakić, Marković, Bogdanović, Barać, & Krčo, 2012) presented a tool for adapting the Moodle LMS course material on the basis of a learner's learning preference, to which a data mining technique based on the K-means clustering algorithm was applied. Learners could be clustered into three groups on the basis of their behavior during a one-week period of using the LMS. Each cluster is a subset of FSLSM defined preferences.

Graf et al. introduced a simple rule-based technique for discovering learning styles from an LMS. This constituted as a mapping between the learners' behavior in an LMS and the FSLSM. (Sabine Graf & Kinshuk, 2008; Sabine Graf, Viola, & Kinshuk, 2007; Sabine Graf, 2007). For this experiment, they examined the generic features of an LMS rather than a particular product. In Table 2.3, gray cells represent patterns or behaviors which are irrelevant for each FSLSM learning style. The unmarked cells are relevant patterns or behaviors to at least one dimension. The "+" and "–" symbols indicate a high and low occurrence, respectively, for each learning style. For example, when we consider the first behavior pattern (content visit), active learners prefer less content visit than reflective learners because they prefer first to attempt exercises without going through content. Sensing and visual learners also less like to visit content than intuitive and verbal learners; therefore, the content visit is negative ("–") for active, sensing, and visual learner. It is positive ("+") for reflective, intuitive, and verbal learners. The content visit pattern is irrelevant for sequential and global learners, as represented by gray cells.

Table 2.3. Mapping online behavior for FSLSM

LMS Behavior	FSLSM Trend							
	Active	Reflective	Sensing	Intuitive	Visual	Verbal	Sequential	Global
Content visit	−	+	−	+	−	+		
Content stay	−	+	−	+				
Outline visit							−	+
Outline stay	−	+					−	+
Example visit			+	−				
Example stay	−	+	+	−				
Self-Assessment visit	+	−	+	−				
Self-Assessment stay	−	+	+	−				
Self-Assessment twice wrong	+	−						
Exercise visit	+	−	+	−				
Exercise stay	+	−						
Question detail			+	−			+	−
Question overview							−	+
Question facts			+	−				
Question concepts			−	+				
Question graphics					+	−		
Question text					−	+		
Question interpret							−	+
Question develop			−	+			−	+
Quiz revisions			+	−				
Quiz stay results	−	+	+	−				
Forum visit	−	+			−	+		
Forum stay					−	+		
Forum post	+	−			−	+		
Navigation skip							−	+
Navigation overview visit							−	+
Navigation overview stay							−	+

	Irrelevant Behavior
+	Relevant Positive Behavior
−	Relevant Negative Behavior

Source: (Sabine Graf, 2007)

2.8.1 Educational data mining

The term “data mining” is sometimes referred to as “knowledge discovery in databases”. It is the automatic extraction of implicit and interesting patterns from large data collections (Cristobal Romero, Ventura, Pechenizkiy, & Baker, 2010). The educational data mining community website (“The International Educational Data Mining Society,” 2015) defines educational data mining as “an emerging discipline concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students and the settings that they learn in.” While educational data mining originated in the late 1990s, another emerging field of study called Learning Analytics partially overlaps it. Learning Analytics has emerged within the last decade and is defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (“Society for Learning Analytics Research,” 2015). While educational data mining is mainly concerned with automated methods to reach its aims, learning analytics includes automated as well as human led methods to make sense of the data (Siemens & Baker, 2012).

Romero et al. (Cristóbal Romero & Ventura, 2010) proposed that the contribution provided by educational data mining activities can be classified into several categories:

1. Analysis and visualization of data
2. Providing feedback for supporting instructors
3. Recommendations for students
4. Predicting student performance
5. Student modeling
6. Detecting undesirable student behaviors
7. Grouping students
8. Social network analysis
9. Constructing courseware
10. Developing concept maps
11. Planning and scheduling

Using LMS data in an educational data mining approach to detect learning styles can contribute to categories II, V, VI, and VII. Most of the previous data mining studies contributed to categories III, V, and VII, as they considered only learner aspects.

One reason for the recent popularity and surge in the number of studies performed in the educational data mining domain is the availability of many algorithms for classifying and clustering data. Algorithms which have been used in the educational domain with respect to LMS and learning styles include Bayesian networks (García et al., 2007; Sabine Graf et al., 2007; Wen, Graf, Lan, Anderson, & Dickson, 2007), decision trees (Cha et al., 2006), hidden Markov models (Cha et al., 2006) and clustering algorithms (Despotović-zrakić et al., 2012).

Another reason is the appearance of powerful data mining tools such as DBMiner ("DBMiner," 2015). Another important reason has been the emergence of numerous open source public domain data mining tools such as Keel ("Keel," 2015), Weka ("Weka," 2015a), RapidMiner ("RapidMiner," 2015), R ("R Data Mining," 2015), and KNIME("KNIME," 2015). Evaluations of such tools have concluded that there is no single best tool and that each has advantages and disadvantages (Jovic, Brkic, & Bogunovic, 2014; Wahbeh, Al-radaideh, Al-kabi, & Al-shawakfa, 2010). Among them, WEKA is one of the most common and most cited.

2.8.2 Tool for data mining

Waikato Environment for Knowledge Analysis (WEKA) is a machine learning software that was developed at the University of Waikato, New Zealand. It was started as a project in 1992, at a time when learning algorithms were not unified and available for use on one platform. The forerunner to its current versions was developed in 1997 using java language.

Apart from supporting a large number of existing algorithms, Weka enables the addition of new algorithms by way of its framework and, therefore, permits researchers and developers to concentrate on the new algorithms itself, rather than having to focus on the supporting infrastructure and evaluation mechanisms (M. A. Hall et al., 2009). The publication of a series of books (Witten, Frank, & Hall, 2011) together with the support mailing list and a Weka e-learning course (WEKA MOOC), have added to its popularity.

Further, the ability for researchers to use the functionality of Weka using a GUI is also a plus point. A non-technical person could use the Weka Explorer GUI option from the initial screen (Figure 2-5) to easily analyze data.

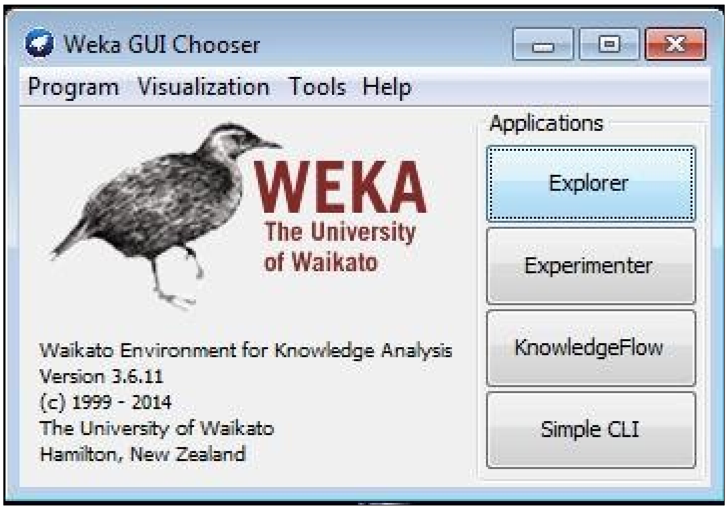

Figure 2-5. Weka GUI

2.8.2.1 Attribute-Relation file format

Weka uses a proprietary ARFF (Attribute-Relation File Format) to store data used for classification. It has two sections (Weka, 2015b) :

1. Header Section: Contains the relation declaration and attribute declarations
   - The @relation Declaration

     The relation name is defined as the first line in the ARFF file. The format is:

     @relation <relation-name>

     where <relation-name> is a string. It must be quoted if the name includes spaces
   - The @attribute Declarations

     Attribute declarations take the form of an ordered sequence of @attribute statements. Each attribute in the data set has its own @attribute statement which uniquely defines the name of that attribute, and it's data type. The order the attributes are declared indicates the column position in the data section of the file.

     The format for the @attribute statement is:

     @attribute <attribute-name> <datatype>

where the <attribute-name> must start with an alphabetic character. If spaces are to be included in the name, then the entire name must be quoted. The <datatype> can be any of the four types supported by Weka:

- Numeric
  - Real/integer numbers
- Nominal
  - defined by providing an listing for the possible values: {<nominal-name1>, <nominal-name2>,...}
- String
  - used to create attributes containing arbitrary textual values
- Date [<date-format>]

2. Data Section contains the data declaration line and the actual instance lines.
   - The @data declaration is a single line denoting the start of the data segment in the file.

     The format is:

     @data
   - The instance data

     Each instance is represented by a single line, with carriage returns denoting the end of the instance. Attribute values for each instance are delimited by commas. They must appear in the order that they were declared in the header section (i.e. the data corresponding to the n^{th} @attribute declaration is always the n^{th} field of the attribute). Missing values are represented by a single question mark, as in:

     @data

     4.4,?,1.5,?,Strong Active

2.8.2.2 Using Weka API

One of the main advantages of using Weka is that it can be called within programs written, for example, in java language. This is facilitated by the Weka API. In this situation, the data can be read and stored after classification using Weka's ARFF format or can be direct via a database such as MySQL. This requires a corresponding JDBC driver (Such as MySQL JDBC driver – connector/J) to be used.

The conversion between Weka's standard datatypes and SQL datatypes is as defined in the DatabaseUtils.props file which is part of the weka.jar external Jar file to be added to the project.

2.8.2.3 Performance measures

When classifying data using Weka, its GUI provides a number of performance measures as shown in Figure 2-6.

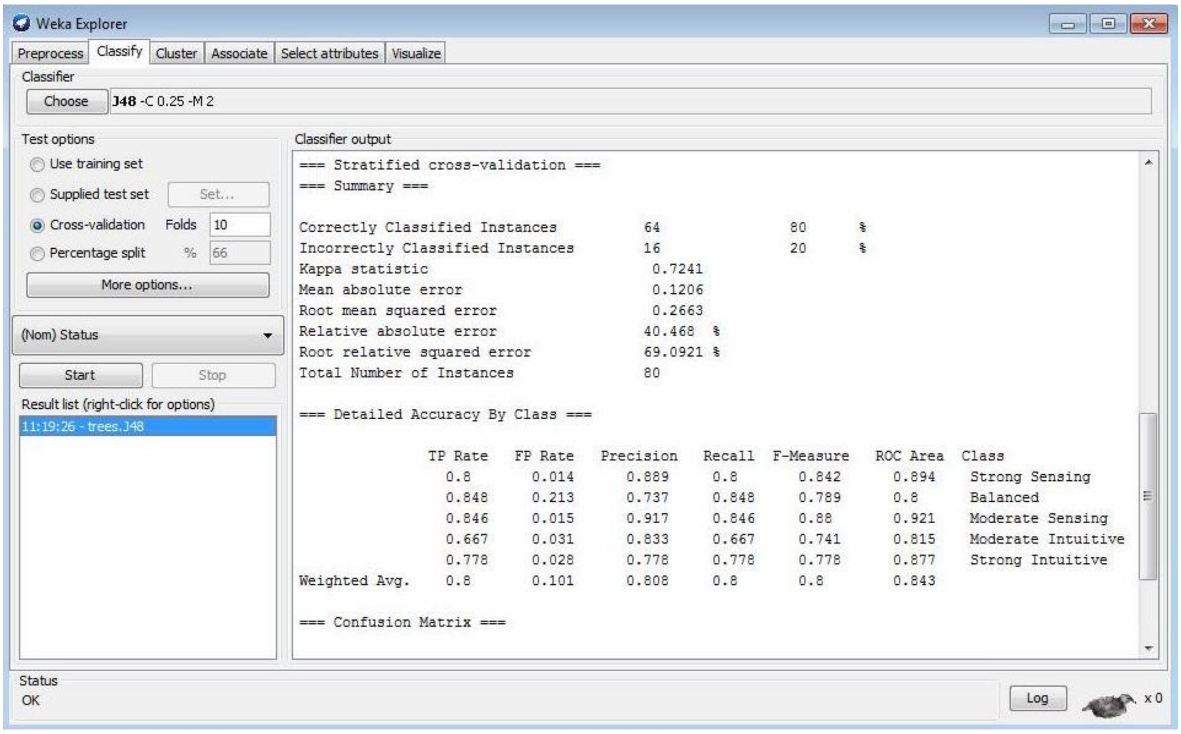

Figure 2-6. Weka classifier output

They can be explained as follows:

1. Correctly classified instances – the number of instances correctly classified, which is shown as a number as well as a percentage of the total instances submitted to classification. This has certain disadvantages as a performance estimate as it is not sensitive to class distribution.
2. Incorrectly classified instances - the number of instances incorrectly classified, which is shown as a number, as well as a percentage of the total instances submitted to classification.

3. Kappa statistic – measurement of the agreement between predicted and observed categorization of the dataset (Witten et al., 2011). A value of 1 indicates perfect agreement while 0 indicates a chance agreement.
4. Mean absolute error – the average of the absolute errors, where an absolute error is the absolute difference value between the prediction and the corresponding true value.
5. Root mean squared error – the square root of the mean squared error, where the mean squared error is the average of the square of every absolute difference value.
6. Total number of instances – the number of samples in a training / test dataset.
7. Confusion matrix – information about actual and predicted classifications done by a classifier such as a Weka.

Table 2.4. Confusion Matrix for two class variable

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

- true positive (TP): predicted to be positive and the actual value is also positive.
- false positive (FP): predicted to be positive, but the actual value is negative.
- true negative (TN): predicted to be negative and the actual value is also negative.
- false negative (FN): predicted to be negative, but the actual value is positive.

8. TP rate – rate of positives correctly classified (as a given class). Calculated as a fraction of the total positives = TP / (TP+FP).
9. FP rate – rate of negatives incorrectly classified (as a given class). Calculated as a fraction from the total negatives = FP / (FP+TN).
10. Precision – proportion of instances that are truly of a class divided by the total instances classified as that class = TP / (TP+FP).
11. Recall – proportion of instances classified as a given class divided by the actual total in that class (equivalent to TP rate).
12. F-measure – a variant of accuracy which is not affected by negatives.
calculated as 2 (Precision) (Recall) / (Precision + Recall).

13. Receiver Operating Characteristic (ROC) Area – ROC is a two-dimensional graph in which the false positive rate is plotted on the X axis, and the true positive rate is plotted on the Y axis. The ROC curve is considered to be a good evaluator for comparing classifiers. An optimal classifier will have an ROC area value approaching 1 with 0.5 being comparable for random guessing.
14. Class – the class label under consideration.

2.9 Personalizing Learning

The content in a learning management system can be overwhelming and diverse for a single person to absorb. To avoid information overload, personalization can be helpful. Personalization with relation to learners has been defined as tailoring and customizing learning experience to individual learners, and it is based on an analysis of learner's objectives, current status of skill/ knowledge and learning style preference (Sampson, Karagiannidis, & Kinshuk, 2002). Personalization can be performed either by the learners themselves or in a technologically assisted manner.

2.9.1 Recommender systems

Many online systems such as those found in shopping sites, where a lot of products are available for purchase, employ systems to suggest users on what best matches their buying taste. It is called a recommender system that facilitates this service.

When a user browses the Internet in the present age and shops for products or services on an online shopping site, the experience is enhanced due to the availability of recommendation systems. They enable the shopper to get personalized recommendations. Recommender systems can produce recommendations in one of following three ways:

1. Collaborative Filtering

   In this method, a large collection of data pertaining to users' past behavior and is used to analyze how similar they are to other users and are used for recommendations. Algorithms such as k-NN are used for this purpose. Amazon.com's recommendation follows this method (Linden, Smith, & York, 2003). One issue with collaborative filtering approach is that it depends on past data. So for new users or new items to recommend, it cannot recommend directly. This is referred to as the "Cold Start" problem affecting this collaborative filtering (Zhang, Tang, Zhang, & Xue, 2014).

2. Content-based filtering

   In this method, a profile of the user's preference is built, based on his/her own preferences. Therefore, content which is similar to the one which the user is currently engaged is recommended to the user.

3. Hybrid Recommender Systems

   In this method, multiple methods are combined to provide recommendations. This includes combining salient components of the previous methods with each other to reduce the problems associated with each method.

2.9.2 Recommender systems in e-learning

Since personalizing the learning experience to suit the learner has been one of the sought after features in an e-learning environment in recent years, recommender systems have been extended even for online learners. Recommendations can be applied in different ways to learning environments.

1. Recommending learning material which suitable based on what other learners with similar characteristics are accessing.
2. Based on peer reviews, the system could then give feedback to learners.
3. Recommending good answers to students who appear to have problems with a certain task.

Content-based recommender systems have been used to recommend PowerPoint slides-based image content to computer science students to increase student performance (Ghauth & Abdullah, 2011). They have further been used to provide recommendations using ontology considering learning styles (Kusumawardani et al., 2014). Collaborative filtering-based scoring algorithms have been used as an e-learning tool to evaluate the quality of student answers by considering relatively few peer ratings (Loll & Pinkwart, 2009). Hybrid approaches which used sequential pattern mining and attribute-based collaborative filtering have also been considered for recommending learning material (Salehi, Nakhai Kamalabadi, & Ghaznavi Ghoushchi, 2014).

2.9.3 Evaluating recommender systems

Recommender systems deal on one hand with users, as the recommendations are viewed by them. Therefore measuring the system with the user in mind is an important aspect of the evaluation of recommender systems. Pu et al. (Pu & Chen, 2010) developed a framework named ResQue to evaluate recommender systems. This framework considers four constructs a recommender system needs to fulfill from a user's point of view:

1. User's perceived qualities of the system.
2. User's beliefs as a result of these qualities in terms of ease of use, usefulness, and control.
3. User's subjective attitudes.
4. User's behavioral instincts.

While Pu et al. presented a 60 questionnaire instrument on a five-point Likert scale and also used reverse Likert scale they further presented a condensed 15 question instrument for obtaining evaluations promptly. This scheme has been used by many researchers (Dooms, De Pessemier, & Martens, 2011) in their evaluations.

2.10 Summary

This chapter covered the survey of previous research and constructed the necessary background knowledge for the study. Learning is an activity which is at the heart of human behavior. Technology has expanded the horizons of learning beyond traditional borders via e-learning. LMSs, which have been in used over the past 15 years, are commonly used in almost all higher education institutes today, albeit using different names. While they are common, they have suffered from common limitations in adaptability or personalization

The process involved in creating content for LMS plays an important role in the success of the system as more efforts are required to develop content appropriately. The notion of learning objects and reusability are key concepts in content development in e-learning.

Learning styles have been promoted as an important concept for the success of learning, and as e-learning is an extension of learning itself, the learning styles models have been increasingly projected to e-learning. The Felder-Silverman learning style model has been the most widely researched in relation to e-learning. It shares many similarities with certain aspects of most of the other prominent learning style models.

With relation to e-learning, researchers have experimented with methods to use learning styles to provide more relevant content to learners by matching their learning styles. Another related task has been to attempt to detect automatically the learning style preference by way of examining learner's online behavior or activity performed in an LMS. In the automatic detection of learning styles in an LMS, data mining has often been used. The content recommendation is a related task where similar solutions have experimented in e-learning.

Chapter 3

System Design & Architecture

This chapter explains the activities carried out during the preparation of content, setup of the hardware and software, and software development carried out.

3.1 System Overview

To facilitate the enhancement of an LMS by automatic detection of learners, learning styles and recommendation of contents to learners, we propose a following framework (Figure 3-1). The framework could be applied to any open-sourced LMS in the market.

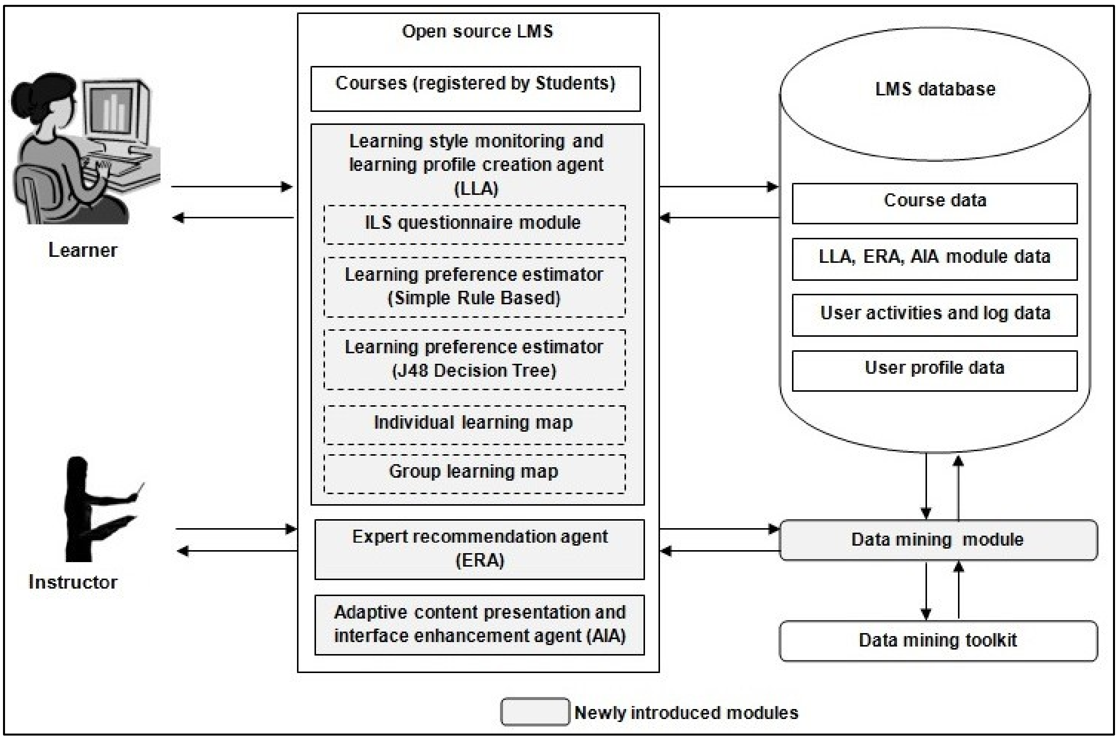

Figure 3-1. Framework for enhancing LMS using Learning Styles

from (Pitigala Liyanage, Gunawardena, & Hirakawa, 2016)

We selected the open sourced LMS Moodle, due to its wide usage and positives as identified in a survey of Open Sourced LMSs (Sabine Graf & List, 2005). The ability to easily add third-party modules as plugins was an important reason out of them. The FSLSM was selected as the chosen learning style model as it was the most frequently cited when considering e-learning (Carver C.A., Howard, & Lane, 1999; Cha et al., 2006; Dung & Florea, 2012; Sabine Graf, Kinshuk, & Liu, 2008; Sabine Graf, 2007; Kanninen, 2008; Klašnja-Milićević et al., 2011; Park, 2005; Savic & Konjovic, 2009; Surjono, 2014). Weka was selected as the data mining tool due to its wide application usage and API availability.

3.2 Content Preparation

Prior to preparing contents, an existing course conducted at an educational establishment was selected. Courses titled ICT 1321 – Introduction to Information Technology conducted at University of Sri Jayewardenepura (Dataset C2 in Appendix C), Sri Lanka and DBIT 1.1 – Introduction to Information Technology conducted at Siksil Institute of Business and Information Technology (Dataset C1 in Appendix C), Sri Lanka were selected. The content in these courses covered the Microsoft Word software and Introductory Information technology (Figure 3-2). Students following at

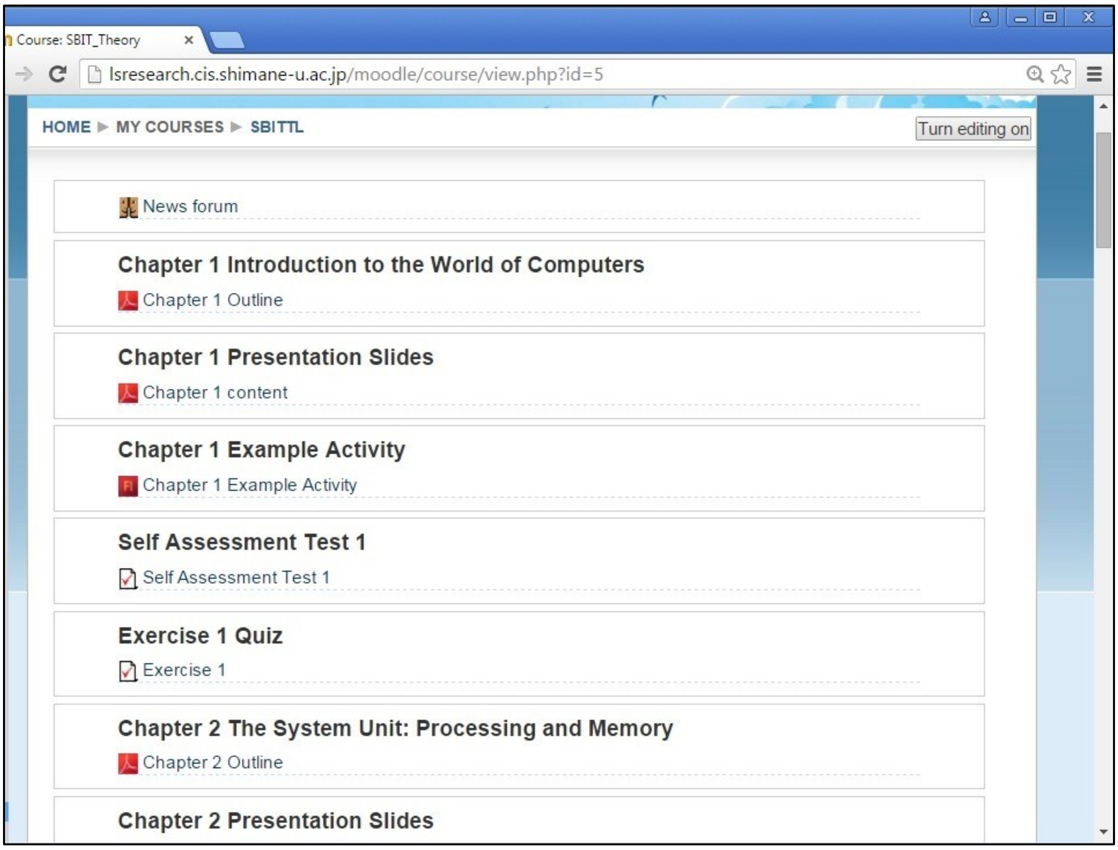

Figure 3-2. Introduction to Information Technology course from (Pitigala Liyanage et al., 2014)

both institutions were provided with a printed handbook, which has almost similar content.

The ADDIE model was followed by the content preparation activity, and the learning outcomes were as stated for the courses. The evaluation was based on quizzes and practical exercises.

The content prepared was to be hosted on three sites – two learning management system (Moodle) servers at each institution as well as a server hosted at Shimane University, Japan. The local servers were configured locally in December 2012 and administered remotely from Japan using TeamViewer. During the second phase of the system being in operation, a course titled “Human Computer Interaction / ヒューマン・コンピュータ・インタラクション” was hosted on the same server in Japan (Figure 3-3), and was used by undergraduate students in Shimane University (Dataset C3 & C4 in Appendix C). This course was used for the system evaluation of the recommendation module and is described separately in detail in sections 3.4.3.2 and 4.3.

Figure 3-3. Human Computer Interaction course

The content preparation was carried out using Techsmith Camtasia Studio, Camstudio and Macromedia Flash Software. The following is a breakdown of the 50 learning materials: 22 content objects, 8 outlines, 2 flash examples, 10 self-assessment quizzes, and 8 exercise quizzes.

3.3 Content Deployment

The main server was built on an Intel Corei5-370 CPU computer with 3.4 Ghz and 4GB Memory. It ran Microsoft Windows 7 64 bit OS with onboard RAID 1 configuration disks. The data was backed up incrementally on a daily basis to an external hard disk drive. The server was publicly accessible through the Internet.

Moodle version 2.3.2+ (Build: 20120920) was installed on top of a WAMPSERVER (Figure 3-4). WAMPSERVER version 2.2 contained Apache version 2.2.21, MYSQL version 5.5.20 and PHP version 5.3.10.

The language pack for Japanese was installed in addition to the original English language.

Figure 3-4. Experimental Moodle Installation

The developed system provides a facility to add metadata for learning materials such as outlines, contents, examples, self-assessments, and exercises. This metadata enables an automatic search of the type of contents that the learner has accessed. For example, if the learning material is an outline of Chapter 7, the name of the learning material can be any name, and the instructor is prompted to select the object type as an outline (Figure 3-5).

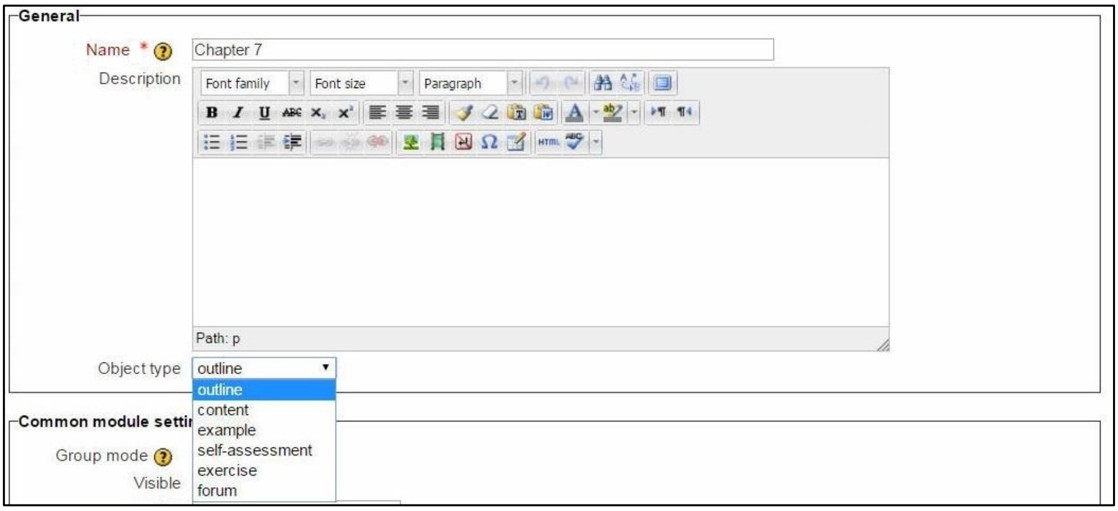

Figure 3-5. Adding learning material of different types

The same method is used for identifying metadata for questions in quizzes. The instructor can describe the type of question (detail, overview, facts, concepts, graphic, text, interpretation, or developmental) by selecting an appropriate item from a pull-down menu. These metadata are stored in the Moodle database.

3.4 System Functionality

The system comprises of three new modules written primarily in PHP. They are named as learning style monitoring and learning profile creation agent (LLA), adaptive content presentation and interface enhancement agent (AIA), and expert recommendation agent (ERA), to correspond to their functionality. A total of 15 files comprising of 5828 lines of PHP code and 12 files comprising of 821 lines of Java code contributed to the system. The Moodle database which consists of over 250 tables is supplemented with additional tables (refer to Appendix E) which are used to store data pertaining to the students learning behavior which makes up a user profile, as well as other configuration data and LO recommending data. The learners would be expected to be registered in the LMS as usual.

3.4.1 LLA module

This module can be divided into three sub-modules.

3.4.1.1 ILS questionnaire sub-module

One method by which the learner's learning style based on the FSLSM is evaluated is the use of a standard ILS questionnaire. Once a learner participates in the ILS questionnaire on the LMS, his/her learning style preferences are recorded in the mdl_ILS_value table of the Moodle database (Figure 3-6).

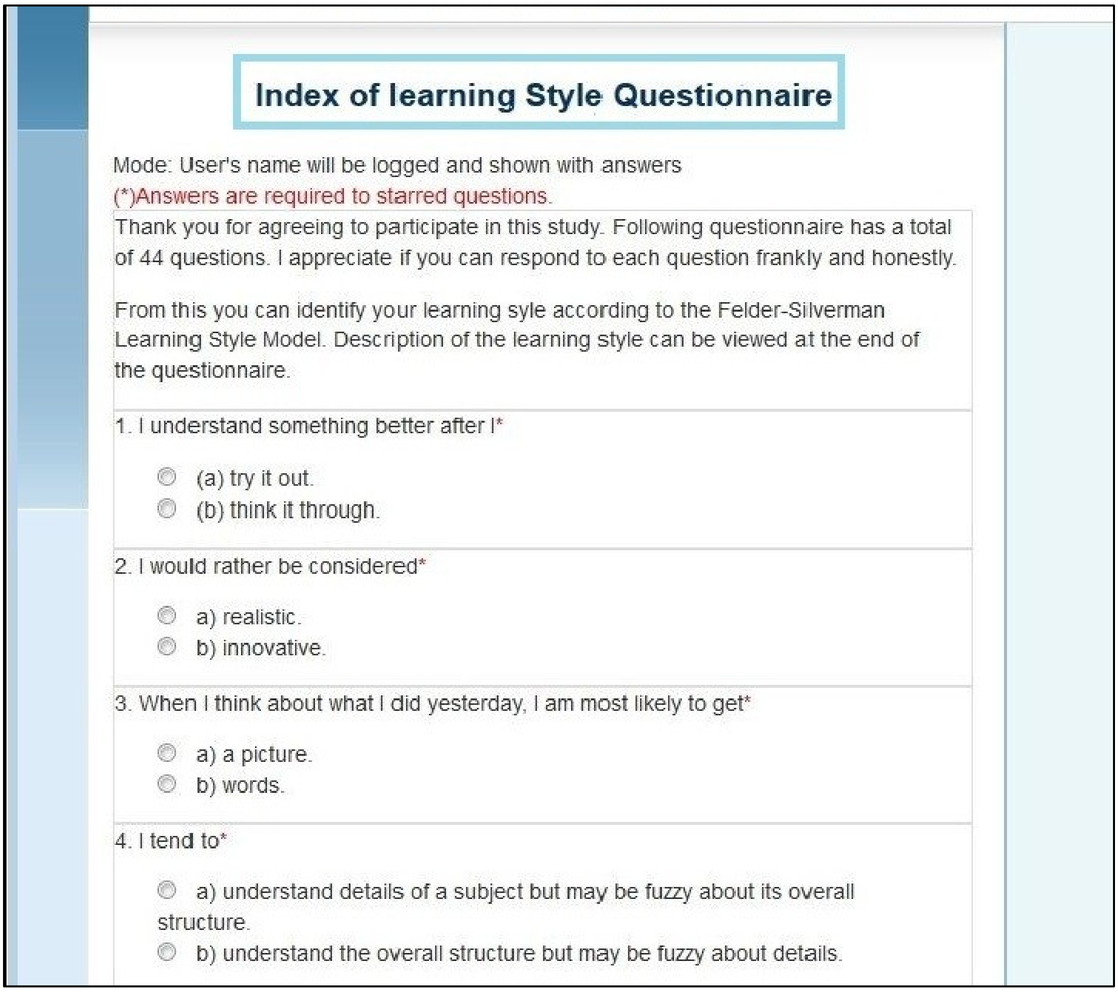

Figure 3-6. Index of Learning Styles Questionnaire on LMS
From (Pitigala Liyanage et al., 2016)

Per learner, four values would be stored. The ILS questionnaire results are further recorded as labels which describe the magnitude of the preference. For each of the four dimensions, the label can take one of five possibilities as listed below.

1. Strong preference for learning style 1
2. Moderate preference for learning style 1
3. Balanced (learning style 1—learning style 2)
4. Moderate preference for learning style 2

5. Strong preference for learning style 2

These labels are stored in the mdl_ILS_tracking table of the Moodle database. The learner is informed of his/her learning styles explanation using these labels, and a link to the original FSLSM site on the internet if he/she wishes to study the implications of each dimension (Figure 3-7).

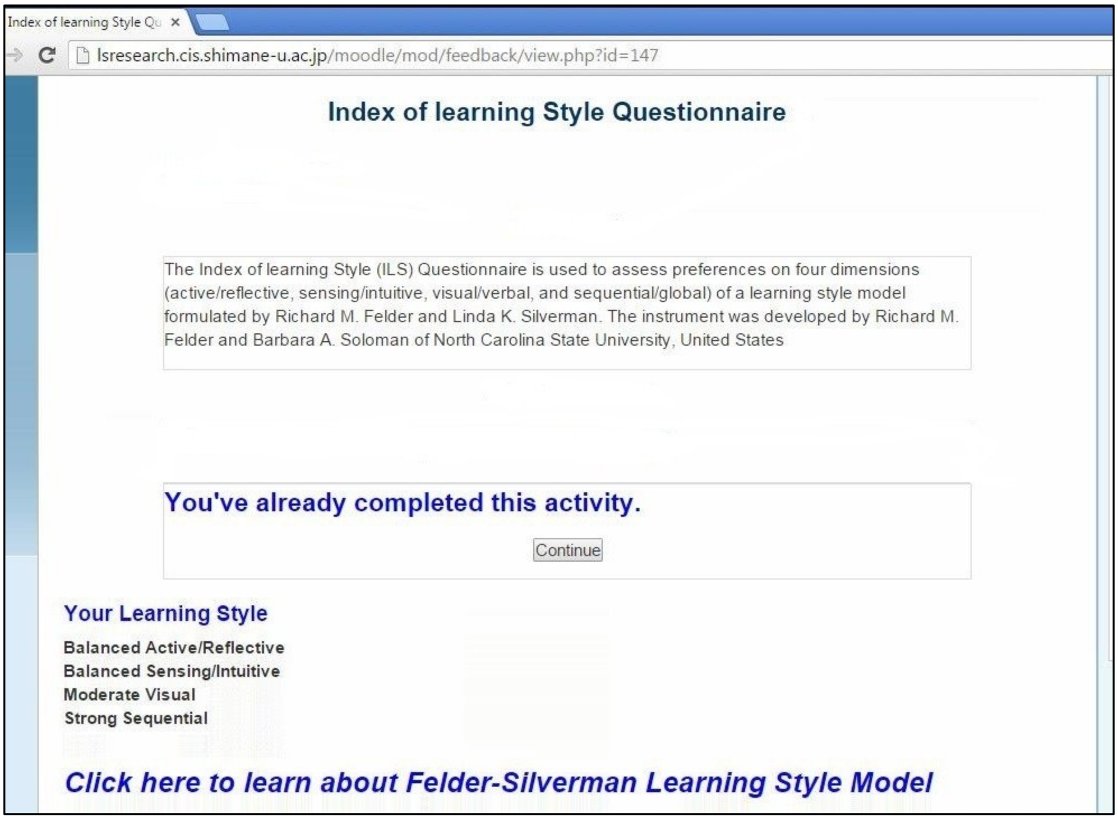

Figure 3-7. Learning styles estimated using ILS questionnaire

3.4.1.2 Learning preference estimator sub-module

As mentioned in section 2.9, while the explicit evaluation of learning styles is fast and can be done at any point, its reliability for long term use has been questioned. Asking the students to repeat the questionnaire several times is also not practical. Therefore, the Learning Preference Estimator (LPE) sub-module has been developed to address this deficiency. The learning preference estimator functionality is carried out using two methods.

3.4.1.2.1 Simple rule-based LPE

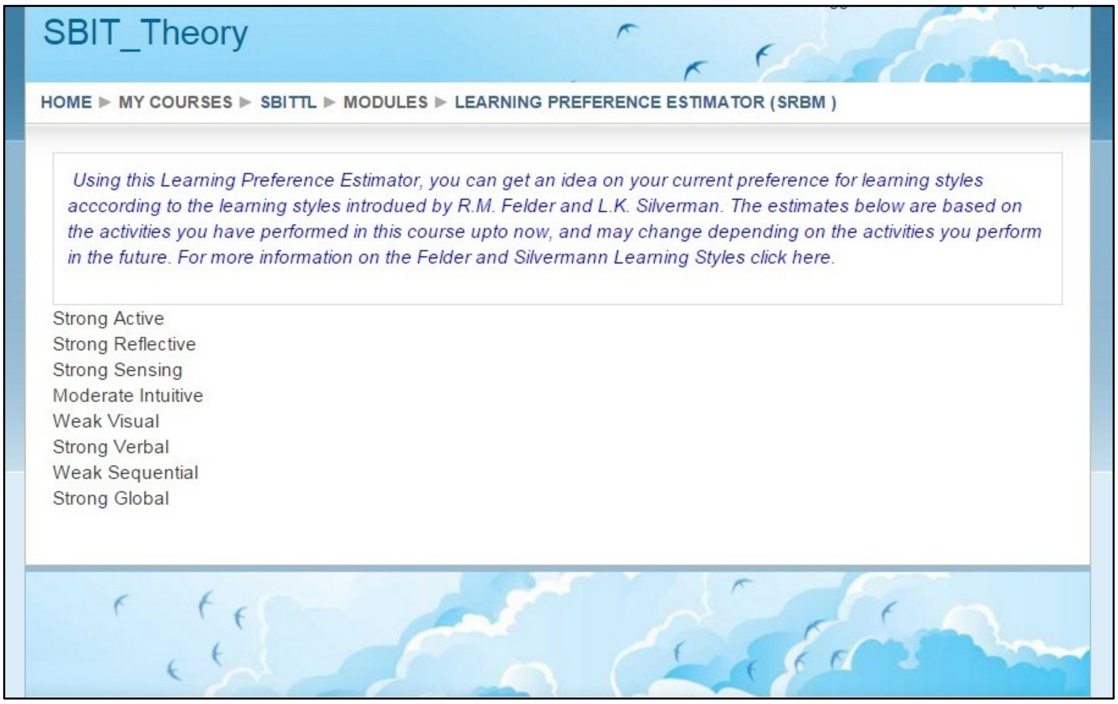

Figure 3-8. Simple Rule based LPE

In this approach, we consider the simple rule-based mapping provided by Graf et al. In our implementation, we did not consider the "content stay" and "outline stay" that have been adopted previously (Sabine Graf & Kinshuk, 2008; Sabine Graf et al., 2007; Sabine Graf, 2007), because it is difficult to gather meaningful data for these items from Moodle. Each LMS course material may contain different learning objects such as videos, quizzes, and exercises. As Table 2.3 illustrates, the learner's interaction behavior pattern with these objects and the time spent on them can be aligned with certain learning style preferences. For example, analyzing content-type learning objects (denoted Content Visit in Table 2.3), it is possible to find out the number of content-type learning objects the learner visited ($LOs_{VisitedContent}$). In addition, we can also identify the total number of content-type objects in the course ($LOs_{Content}$) from the Moodle database. These factors constitute the ratio of visits for content-type learning objects ($R_{VisitedContent}$):

$$R_{VisitedContent} = \frac{\sum LOs_{VisitedContent}}{\sum LOs_{Content}}$$

Table 2.3 reports that the content visiting pattern is associated with three dimensions of the FSLSM. Therefore, this ratio is used when evaluating the learner's preference for the active–reflective, sensing–intuitive, and visual–verbal dimensions.

Similarly, by analyzing time spent on visiting self-assessment-type objects (denoted Self-Assessment stay in Table 2.3), the instructor or an expert can estimate an expected time to be spent on each self-assessment-type learning object ($TES_{Self\text{-}assessment}$). From the Moodle log, it is possible to find out the time spent on each self-assessment-type object ($TS_{Self\text{-}assessment}$).

The sum of the time values for all self-assessment-type learning objects in the course produces the ratio of content stay time ($R_{TimeSpentSelf\text{-}assessment}$):

$$R_{TimeSpentSelf\text{-}assessment} = \frac{\sum TS_{Self\text{-}assessment}}{\sum TES_{Self\text{-}assessment}}$$

As Table 2.3 indicates, the self-assessment stay time pattern relates to two of the four FSLSM dimensions. As a result, the calculated ratio is relevant when evaluating the learner's preference for the active–reflective and sensing–intuitive dimensions.

This process of calculating ratios is repeated for all behavior patterns, which results in a ratio (R_i) for each behavior pattern. For each behavior pattern, i, if the ratio lies between a pre-determined upper threshold (UT_i) and a lower threshold (LT_i), the behavior is considered balanced. The values for UT_i and LT_i can be adjusted via the ERA module (Section 3.4.2), and the default values considered are those proposed by Graf et al.(Sabine Graf, Kinshuk, & Liu, 2009). If the ratio is less than the lower threshold, the behavior is considered negative. In contrast, if the ratio is higher than the upper threshold, the behavior is considered positive. After performing this process for all behavior patterns, we can calculate the average ratio for each learning style (R_{AVG}):

$$R_{AVG} = \frac{\sum_{i=1}^{n} R_i}{n}$$

where n is the number of relevant behavior patterns for the selected learning style. This calculation process is repeated for the eight FSLSM learning styles, resulting in the information reported in Table 3.1. The R_{AVG} scores express whether a learner has a weak, moderate, or strong preference for the selected learning style. This classification is performed by using two threshold values, the thresholds for moderate (TM) and strong (TS) preference, where typically TM = 0.3 and TS = 0.7.

Table 3.1. Sample scores (R_{AVG}) obtained for each learning style

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
0.71	0.11	0.21	0.36	0.8	0.77	0.74	0.31

For the above example in Table 3.1, this analysis would yield the result reported in Table 3.2, where S, M, and W indicate strong, moderate, and weak, respectively.

Table 3.2. Classification of learning styles on the basis of user preference

Dimension 1		Dimension 2		Dimension 3		Dimension 4	
ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
S	W	W	M	S	S	S	W

3.4.1.2.2 Data mining algorithm - based LPE

For the data mining algorithm - based LPE method, training data were obtained by merging the eight R_{AVG} values in the mdl_dimensions table together with the corresponding learning styles labels obtained by the mdl_ILS_tracking table. A sample dataset is given in Table 3.3.

Table 3.3. Sample data pertaining to a single student used in the training dataset.

Dimensions	Dimension 1		Dimension 2		Dimension 3		Dimension 4	
Learning styles	ACT	REF	SEN	INT	SEQ	GLO	VIS	VER
R_{AVG} values obtained from	0.41	0.06	0.79	0.03	0.15	0.58	0.07	0.22
Learning style labels obtained from mdl_ILS_tracking	Moderate active		Strong Sensing		Moderate Global		Balanced	

The collected data are transformed into the Weka-specific attribute-relation file format (ARFF). For each student, four instances pertaining to the four dimensions are recorded. Each instance records the two R_{AVG} values obtained for a dimension together with the corresponding ILS label. During pre-processing, we remove data that contained missing values. In addition, we attempt to eliminate bias toward the majority class due to imbalanced data in the dataset (Chawla, Bowyer, Hall, & Kegelmeyer, 2002). In our analysis, we found that the classes in the ACT/REF dimension were imbalanced in dataset C2 and the synthetic minority oversampling technique (SMOTE) was applied to the imbalanced dataset. In order to select the most appropriate data mining technique, the sample accuracy is considered as the main criterion. This experiment is explained in section 4.1

Data read from the MySQL server are transformed to ARFF before training a classifier. A new Moodle module was implemented in PHP to invoke program code for the classifier, which was prepared as an executable Java archive (JAR) file. When the system was first executed, ILS data are given to the classifier together with the R_{AVG} data for training. Once the training of the classifier is completed, the system is ready to perform classification. The result of classification as shown in Figure 3-9, i.e., a learning style, is then stored in the database. This classification is repeated four times, one each for each learning style dimension. This prediction is accessible via the LMS and is automatically re-evaluated once per day.

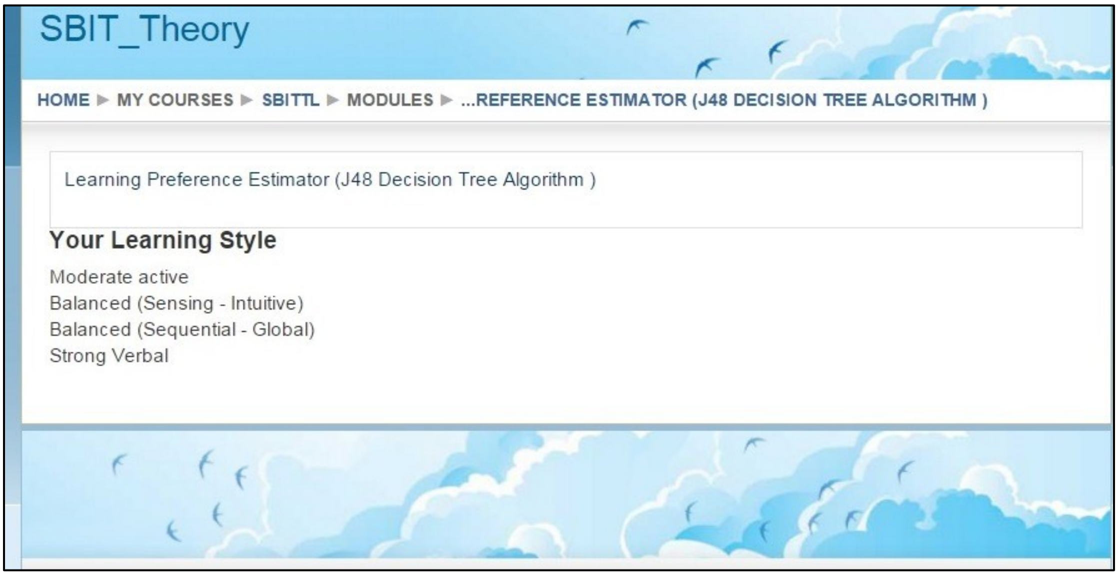

Figure 3-9. J48 Decision Tree LPE

It should be noted that, when a particular course commences for the first time, predicting learning styles of learners using data mining cannot be performed, as there is no log data on learner's behavior history of accessing learning objects. Therefore, all new users are expected to complete the ILS questionnaire. The learning style labels obtained using the ILS are handled together with the R_{AVG} values as training data, and prediction of a learning style becomes possible after few weeks of classes have passed. Up to that point, the system relies on the ILS result. When the course is re-run with a new set of students, the system does not require learners to run the ILS anymore, it needs to wait until the learner's access the learning objects (at least a week of interaction) before evaluation of relevance to past records. This approach is valid as long as the threshold values for the course in the ERA or LOs do not change.

3.4.1.3 Learning style maps

Visualization tools assist learners in grasping certain concepts easily and is widely used in e-learning. Nevertheless, as noted in section 2.9, we have found that no trials for visualization of learning styles had been done. Therefore, it was decided to develop a visualization tool which would enable learners and instructors to recognize learning style preferences visually. As the learning styles of students can change dynamically along the actions performed in the LMS; the learning map is automatically updated.

The map layout contains four quadrants, one for each dimension in the FSLSM, which enables plotting of the eight R_{AVG} values obtained from the LLA module. The scale for each dimension is from 0 to 1. The mapping sub module is developed using the GD graphics library using its PHP interface. This sub-module is executed once a day to automatically generate the learning style maps. This allows learners and instructors to view the latest learning styles. Two types of maps are generated: individual visualization and group visualization.

3.4.1.3.1 Individual learning style map

This visualization plots the eight R_{AVG} values pertaining to the user's learning preference as four coordinates (Figure 3-10). It assists the learner to comprehend his/her own learning style, rather than trying to understand learning style labels as text. Even if the learner had no previous experience of learning styles, the learner can easily get an overall picture of his/her own learning style and can identify which side of learning style he/she needs to become a balanced learner, and which type of learning material he/she needs to follow to excel in the course. This map can also be beneficial for an instructor who might want to investigate the learning styles of a selected learner.

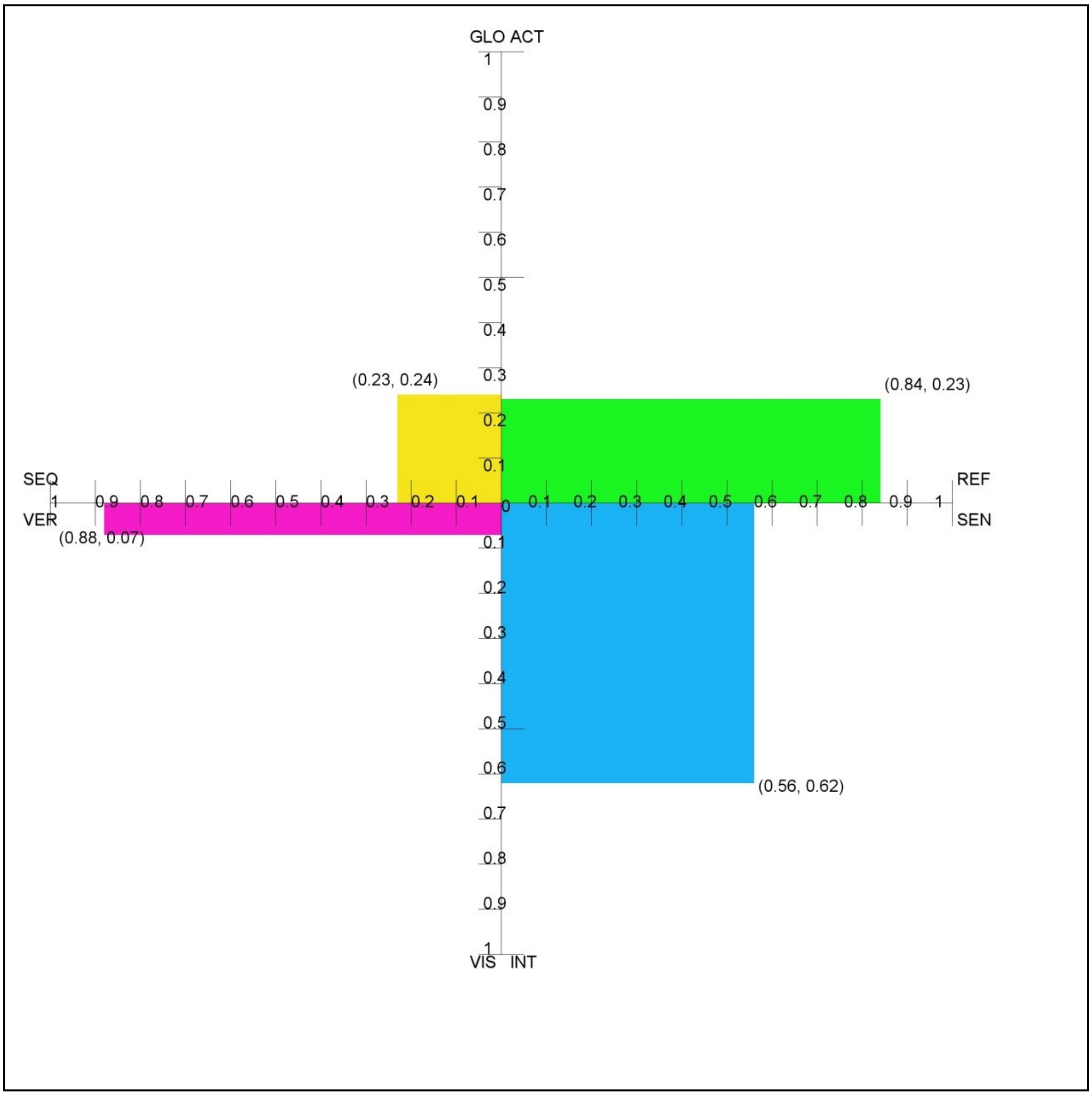

Figure 3-10. Individual Learning Style Map

3.4.1.3.2 Group learning styles maps

Although in e-learning individual users connect to the LMS individually from a computer in most cases, learning occurs socially in a classroom as well. As it is established in education through social comparison theory (Festinger, 1954) that humans yearn for evaluation of their abilities, we extend the learning map to visualize multiple learners' learning styles. Two types of maps are generated, considering the end user to be either a learner (Figure 3-11) or an instructor (Figure 3-12).

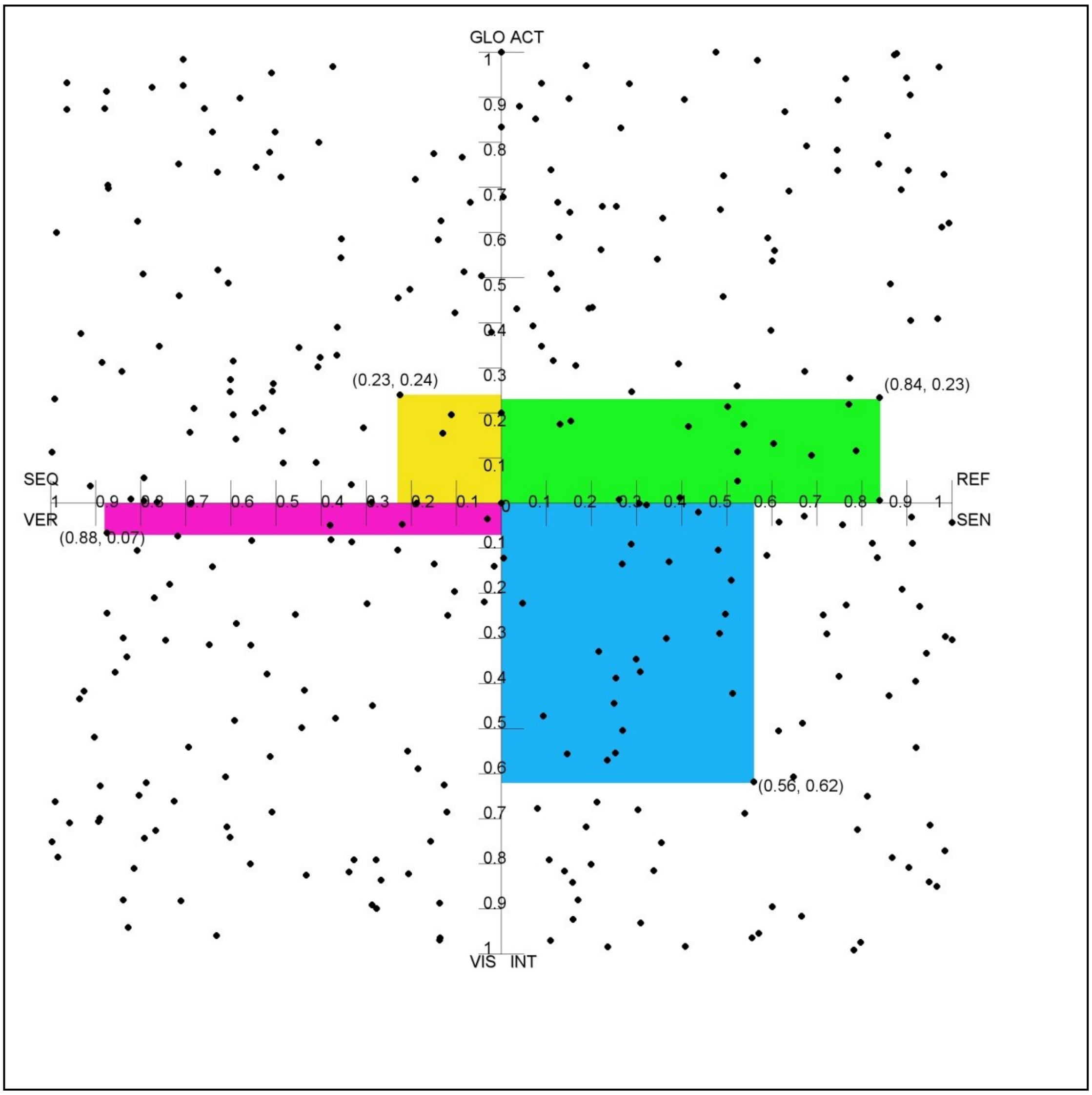

Figure 3-11. Group learning map for learner's use

When a learner likes to compare his/her learning style with others in the same class, the learner is allowed to get his/her individual learning style map as colored rectangles plus the all other learners' preferences marked using black dots. In order to protect the privacy of learners, the learner cannot select or identify each of the other learners in the class, neither is he/she permitted to select a subset of learners to visualize. Although this visualization is aimed mainly at the learner, it can also be used by the instructor as well. In this case, it is possible to select an arbitrary subset of learners (using their USERID) for comparison.

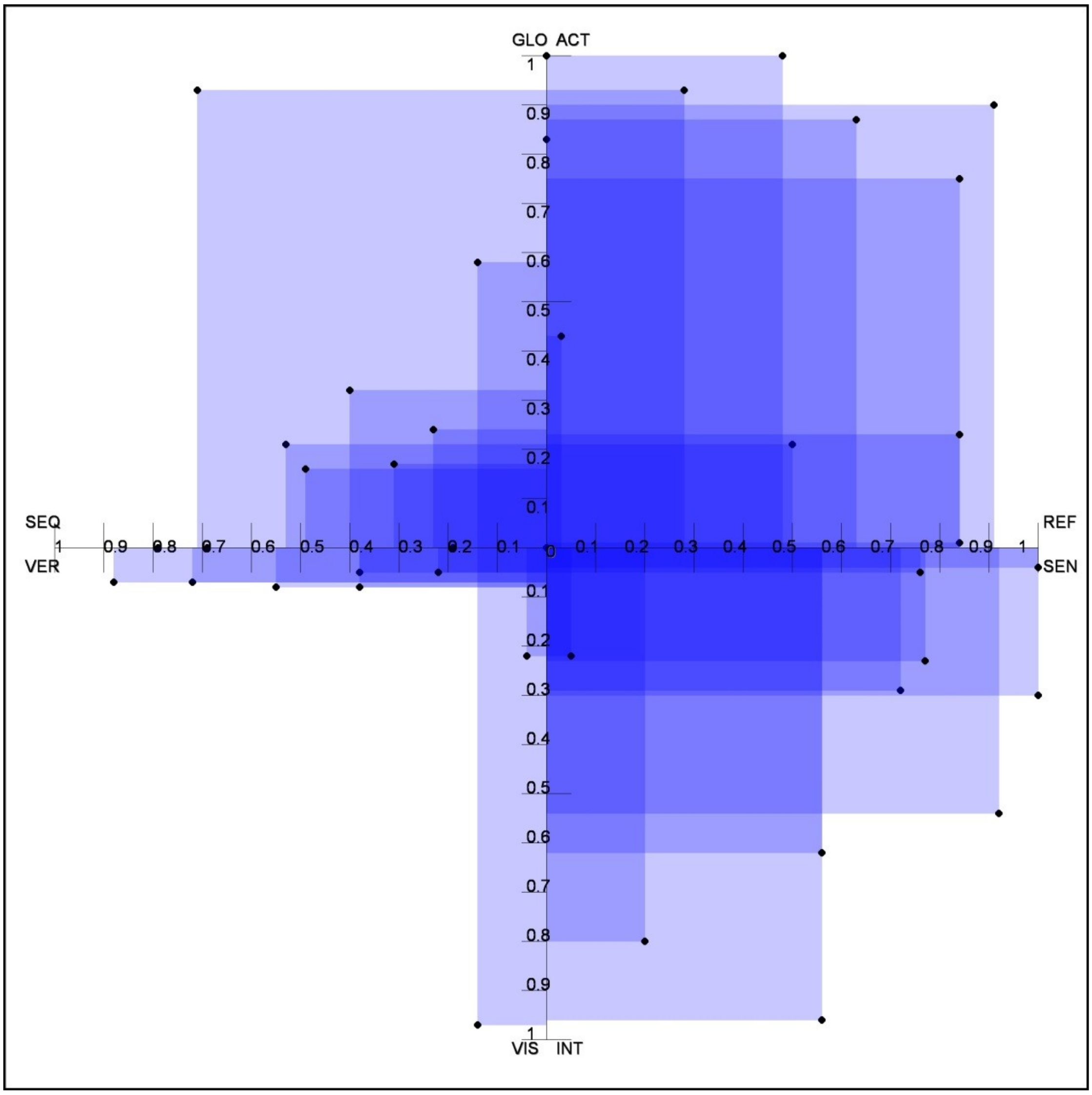

Figure 3-12. Group learning map for instructor use

The second map (Figure 3-12) is for exclusive use by the instructor. When the instructor needs to determine the diversity of learning styles in a student group or its subset by way of an overall view, this visualization is beneficial. An instructor may find this useful to modify course materials and/or lecturing styles to achieve the expected learning outcomes of the course more effectively.

When considering the example data plotted in Figure 3-12, the SEQ-GLO, ACT-REF, and SEN-INT dimensions exhibit no specific characteristics. Yet on inspecting the VER-VIS dimension a rather distinctive feature is noted: one student exhibits a strong visual learning style, but the rest mainly exhibit a verbal learning style. An instructor viewing such a class should consider the content of the course. If the course contains slides shows and videos (visual material), it would be better to supplement the material with audio to address the concerns of the verbal learner.

3.4.2 ERA module

The ERA module is a module accessible by the instructor only and enables him/her to fine tune the conditions which contribute to the estimation of the learning styles. As explained in the functionality of the LLA (section 3.4.1), for each of the eight learning preferences, the ratio (R_i) is compared against a set of threshold values of UT and LT to determine whether a learner's behavior for a particular dimension is a relevant positive behavior, relevant negative behavior, or irrelevant. These thresholds are calculated using configuration settings in the ERA.

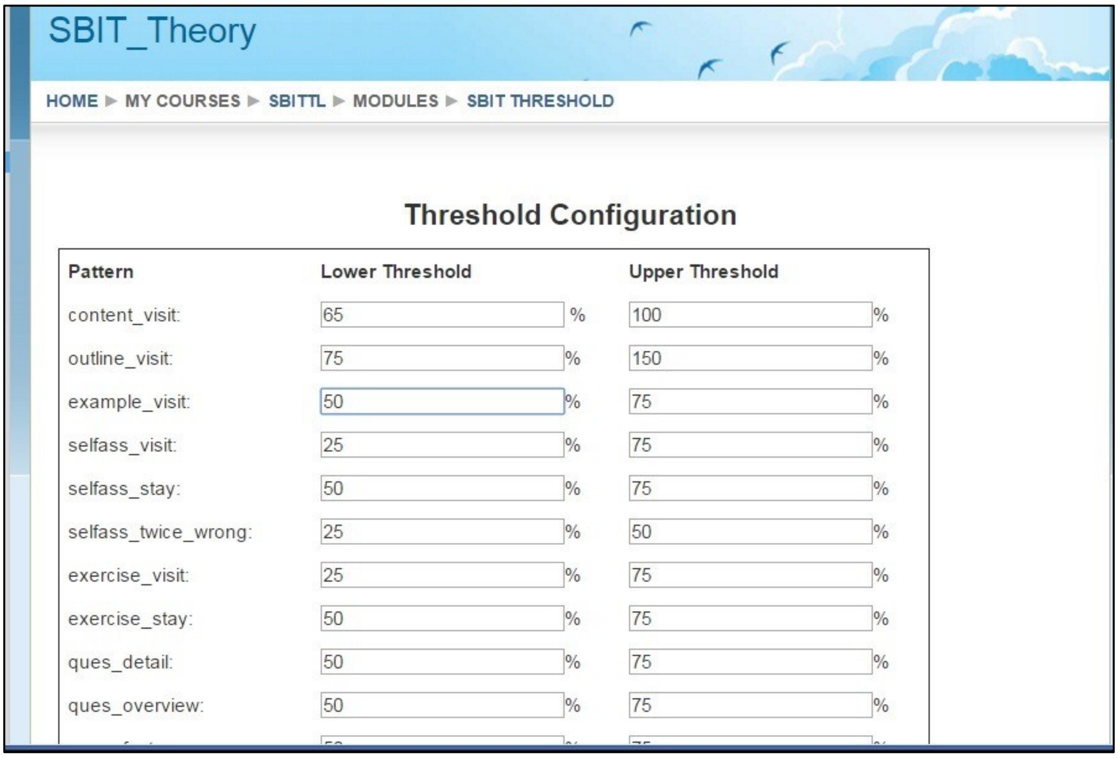

Figure 3-13. Threshold configurations

Using an interface shown in Figure 3-13, the instructor can modify the UT_i and LT_i values of all behavior patterns identified in Table 2.3. The values are configured as percentages as indicated in figure. The threshold settings are set per course, and can vary from course to course. The table mdl_lec_threshold is used to store threshold values.

3.4.3 AIA module

The purpose of AIA module is to recommend content according to the learner's learning style. The content adapted for the learner is provided on a screen as recommended material that the learner may be tempted to click and follow, and thereby altering the LMS interface for him/her. Two approaches are investigated to reach this goal.

3.4.3.1 Using static mapping of content

Using the study of related literature, we formulate the following mapping between each learning preference and activities performed/learning objects accessed with respect to an LMS by users who possess the said learning preference. This can be used to recommend learning objects which are suitable for the listed activities. Tables 3.4 to 3.7 follow each of the learning style dimensions.

Table 3.4. Learning styles to Activity mapping for ACT/REF

Active	Reflective
• Self-assessment tests • Chat, forum posting • Multiuser mind map tools • Multiple choice questions • Guessing exercises	• Outline of lecture/session • Case studies • Slideshows • Forum viewing • Using online help • Content viewing • Examples • Single-user mind map tool • Summaries of lecture/session • Result pages view

Source : (Pitigala Liyanage, Gunawardena, & Hirakawa, 2013)

Table 3.5. Learning styles to Activity mapping for SEQ/GLO

Sequential	Global
• Detailed questions • Step-by-step exercises • Pages with few links	• Outline of lecture/session • Lecture/session summaries • Pages with multiple links • Overview questions • Navigation skip • Navigation overview pages

Source : (Pitigala Liyanage et al., 2013)

Table 3.6. Learning styles to Activity mapping for VIS/VER

Visual	Verbal
• Graphics • Tables • Flowcharts, charts • Images • Demonstrations/videos • Colored or highlighted text • Slides with multimedia and animations	• Text-based material • Audio objects • Lesson objectives and Content objects • Text slideshows with audio

Source : (Pitigala Liyanage et al., 2013)

Table 3.7. Learning styles to Activity mapping for SEN/INT

Sensing	Intuitive
• Examples • Exercises • Self-assessment tests • Questions about facts • Detail questions • Hands-on activities • Practical material • Slideshows • Case studies • Navigation using arrows	• Content viewing • Questions about concepts • Concepts and theories • Conceptual maps • Definitions • Algorithms

Source : (Pitigala Liyanage et al., 2013)

Providing recommendations for learning style preferences has to be related to the magnitude of the preference the learner possesses, and at certain conditions recommendation of LOs may not be meaningful. For example, if a learner possesses a weak sensing as well as a weak intuitive preference (which are opposite preferences on the same dimension), it may not be meaningful to recommend material. In order to facilitate orderly recommendations, a conditional recommendation scheme is proposed.

Two conditional thresholds are introduced for this purpose: the conditional thresholds for strong ($CT_S = T_S - T_M = 0.4$) and conditional thresholds for moderate ($CT_M = T_M = 0.3$) are used in situations where two learning style preference levels are adjoined to each other. If, for a given dimension, the level of learning style 1 (element on one side) is moderate, and that of learning style 2 (element on another side) is weak; if their learning style levels are separated by a score of more than CT_M, it is possible to recommend materials relevant to learning style 1.

Table 3.8. Recommendation matrix for a given learning style dimension i

		Learning Style 2 Level		
		Weak	Moderate	Strong
Learning Style 1 Level	Weak	NR	LS2*	LS2
	Moderate	LS1*	NR	$LS2^{+}$
	Strong	LS1	$LS1^{+}$	NR

Source : (Pitigala Liyanage, Gunawardena, & Hirakawa, 2014)

The recommendations to be provided for each pair of learning styles in a certain dimension i (i can be 1–4) is denoted in Table 3.8. LS1 denotes learning style 1, and LS2 denotes learning style 2; for example, for dimension 1, LS1 is active, and LS2 is reflective. NR indicates that no recommendation is possible. An underlined item denotes a conditional recommendation. Situations, where CTM is used, are denoted by an asterisk (*), whereas those where CT_S is used are denoted by a plus sign (+).

While this method of labeling content at the time of entering is possible, it adds a burden to the instructor, who must tag the content appropriately for it to be successful. The next approach aims to remedy this problem.

3.4.3.2 Using collaborative filtering approach

In this approach, the learner does not need to explicitly complete the ILS. Hence if the course is running for the first time, ILS is needed because, to use the data mining, no previous data is available and few weeks are needed to gather learner’s log data. This scheme is ideally suited for courses which are repeatedly run without significant change of content materials. This approach requires the use of a data mining toolkit and a suitable algorithm for providing the recommendations. We selected Weka as the toolkit, as it was already configured for use with Moodle based on our use of data mining in section 3.4.1.2.2. The Instance Based learner (IBk) algorithm, which is the WEKA implementation for the k-NN algorithm is chosen as the algorithm. The value of k was considered as 1 for the experiments.

Assuming that a course of a certain subject matter has been conducted once, for each user, eight R_{AVG} values contain the learning style preference. (This can be achieved by using the data mining approach in section 3.4.1.2.2, and does not need the ILS). However for the first time and beginning of the course, we need to collect ILS data.This data is stored per user in the mdl_ILS_value table. But after few weeks we can use mdl_Dimension table which store R_{AVG} instead of mdl_ILS_value table. Further, from the Moodle log, it is possible to examine whether the learner accessed each and every resource in the course. In Moodle, each resource is identified using the unique ID known as CMID (Course Module ID). For each learner, we merge the mentioned data from the two tables using the userID as the key. If the course has N learners and M resources, this results in N x M records, each describing whether the learner has accessed the CMID or not. This data is stored in a table named mdl_training_ibk, and is taken as the training data for data mining. First time of the newly introduced course, if the learner needs to get the recommendations for LOs, during the first week, he/she require filling the ILS questionnaire. An extract from this table is provided in Table 3.9.

Table 3.9. Extract from mdl_training_ibk table

User ID	CMID	ILS								Access Status
		ACT	REF	SEN	INT	SEQ	GLO	VIS	VER	
1	100	4	7	9	2	7	4	11	0	1
1	101	4	7	9	2	7	4	11	0	0
1	102	4	7	9	2	7	4	11	0	0
2	100	6	5	2	9	5	6	8	3	0
2	101	6	5	2	9	5	6	8	3	1
2	102	6	5	2	9	5	6	8	3	1

When the same course is re-run again, after new learners register and use the LOs for a short time, based on their access to material, it is possible to obtain R_{AVG} values pertaining to their learning style. This data can be used to recommend suitable material – out of the ones they have yet to access. Instead of Tables 3.9 through 3.11, ILS data for eight learning styles columns, R_{AVG} values of eight learning styles used. The test data file which is generated per learner is stored in a file series named as mdl_testing_ibk_userid, where user ID varies. When the course is run, it is possible that two learners may use the system simultaneously, and in such situation, the system needs to permit concurrency in database handling. It is due to this reason that the testing dataset is stored individually per learner. However, in order not to overburden the database with a large number of tables, once testing is completed, mdl_testing_ibk_userid table is deleted from the database. This testing dataset has the following structure:

Table 3.10. Extract from mdl_testing_ibk_3 table

User ID	CMID	ILS								Access Status
		ACT	REF	SEN	INT	SEQ	GLO	VIS	VER	
3	100	4	7	9	2	7	4	11	0	?
3	101	4	7	9	2	7	4	11	0	?
3	102	4	7	9	2	7	4	11	0	?

In this case, for CMID100-102 learner bearing user ID 3 has not accessed either of them and these data required to predict. Once training has been performed using the previous dataset in Weka, by providing this test dataset, the resulting dataset (mdl_cfresults) will indicate whether or not the material identified by the corresponding CMID should be recommended or not.

Table 3.11.Extract from mdl_cfresults table

User ID	CMID	ILS								Recommend (1=yes)
		ACT	REF	SEN	INT	SEQ	GLO	VIS	VER	
3	100	4	7	9	2	7	4	11	0	1
3	101	4	7	9	2	7	4	11	0	0
3	102	4	7	9	2	7	4	11	0	0

The mdl_cfresults table recommendations are merged into a master recommendation table for all learners of the system identified as mdl_links. It has the following structure.

Table 3.12. Extract from mdl_links table

User ID	Course ID	CMID	Link	Recommend (1=yes)
3	6	100	<ahref=http://lsresearch.cis.shimane-u.ac.jp/moodle/mod/quiz/view.php?id=220>要旨 3（Topic 3 Exercise) 	1
3	6	101	<ahref=http://lsresearch.cis.shimane-u.ac.jp/moodle/mod/resource/view.php ? id=241>pdf 資料（Topic 5 Content) 	0
3	6	102	<ahref=http://lsresearch.cis.shimane-u.ac.jp/moodle/mod/resource/view.php ?id=285>pdf 資料（Topic 9 Content） 	0

The Moodle LMS page footer is modified to enable reading relevant links from this file, where only the links for the logged in user are displayed when the recommendation status is 1. Once a learner has clicked the link the recommendation setting of that link is set to 0, as the learner has already visited it and does not need that recommendation anymore.

At a given instance, the learner may not find all such recommendations to be useful. In a course, dependencies may exist between resources, such that for each CMID, another CMID, which must have been followed previously (priorCMID) exists, i.e., if system want to recommend the Chapter 3 LO, assume that Chapter 3 LO cannot be read without the knowledge of Chapter 1 LO and Chapter 2 LO, consequently system recommends Chapter 3 LO only after the Chapter 1 LO and Chapter 2 LO viewed. There can be multiple priorCMIDs can be present, as well as multiple levels of dependencies in a course. A separate table, mdl_priority handles stores these relations which must be provided by the course instructor. When a user logs in, the footer will only display the content which has been cleared of suitable content as its priorCMIDs have been accessed by the user previously. This requires recursive searching in the mdl_priority for a given CMID.

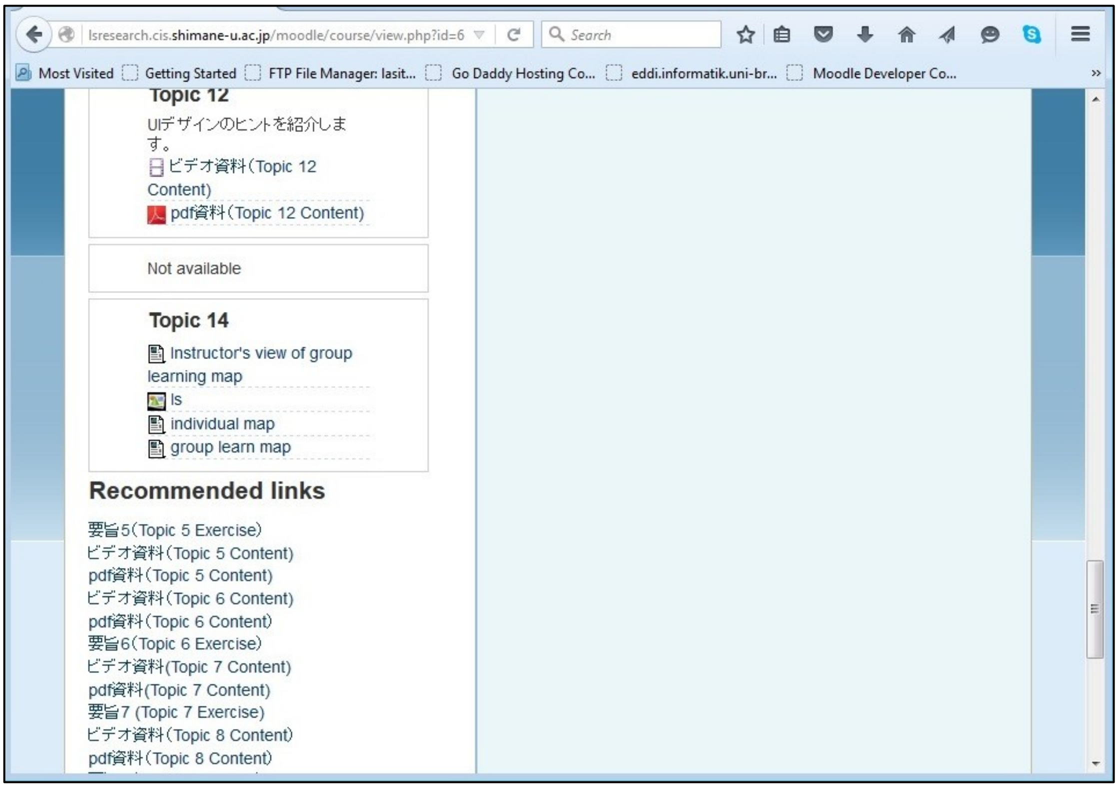

Figure 3-14. LOs recommending AIA

To address the cold start problem affecting recommendation systems, which makes recommendations based on this scheme impossible during the first run of the course, we propose the static mapping of content described in section 3.4.3.1 to be adopted during the first run of the course. In the case of the second run, once the learners start accessing content in the first week, the system should enable recommendation.

3.5 Summary

This chapter introduced a framework which can be applied to any open source LMS for the purpose of enhancing its usage by using learner's learning styles. For the implementation, Moodle was selected as the suitable LMS due to its wide usage and plugin support. The FSLSM was chosen as the learning style model due to its frequency of use in e-learning. Weka was chosen as the data mining tool of choice due to its ability to easily integrate with external programs through its API.

The framework introduces three new modules which would operate on a Moodle and are referred as LLA, ERA, and AIA. Several new tables are added to the Moodle database and a separate module to enable data mining to be carried out on data stored in the Moodle database. The building of user profiles which store characteristics pertaining to the learning styles is one of the main features of this framework.

The LLA module contains several sub-modules – one for the ILS questionnaire, two for estimating learning preference, and another for visualizing learning styles using a map. The ERA module enables fine tuning of the threshold settings for each course by the course instructor.

The AIA module permits recommendation of learning material either by using a static mapping or by using a collaborative filtering based content recommendation system.

Chapter 4

Evaluation and Results

This chapter describes experiments carried out to select the best data mining algorithm for detecting learning styles and to evaluate the performance of the newly introduced modules described in section 3.4.

4.1 Data Mining Algorithm for Learning Styles Prediction

As explained in section 3.4.1.2.2, learning styles, preference estimation can be performed by using a data mining technique. However, as mentioned in section 2.8.1 different algorithms have been used in the past. In order to select the best algorithm, an experiment was carried out. Dataset C2 was used for the experiment. Four algorithms were selected for the evaluation.

- J48 – The open source Java Implementation of the C4.5 algorithm used in the Weka data mining tool (Decision Tree Algorithm)
- Bayes Net – Bayesian Network Classifier
- Naïve Bayes Classifier (a particular class of Bayesian network where the features are class-conditionally independent)
- Random Forest – Forest of Random classification trees

During the first week of the course, the students were requested to participate in the ILS questionnaire. The results are summarized in Appendix C.

The sample accuracy rate was considered as the main criterion for determining the most suitable data mining technique. Results of the performance evaluation obtained using weka are presented in Tables 4.1 to 4.4. The accuracy rates are estimated usign the 10-fold cross validation method. Two additional criteria (i.e., precision and receiver operating characteristic (ROC) area) given by Weka, are also presented.

As visible from the table data, the J48 classifier exhibits reasonably high performance. The only exception was the performance in the active and reflective dimension, where the random forest method yielded a sample accuracy of 72.77% compared to 65.26% obtained by J48. Since correctly classified instances can be insensitive to class distribution at times, when selecting the best technique precision rates for each class and the ROC area values must be taken into account. An ROC curve was created by plotting the true positive rate against the false positive rate for different threshold settings. An optimal classifier should have ROC values that are closer to 1. By considering the data shown in Tables 4.1 to 4.4, we conclude that J48 is the most appropriate method for our dataset. The correctly classified instances i.e. sample accuracy rates obtained are 65.26%, 80.00%, 90.00%, and 81.25% for the ACT/REF, SEN/INT, SEQ/GLO, and VIS/VER dimensions, respectively.

Table 4.1. Performance in ACT/REF dimension

		J48	Bayes net	Random Forest	Naïve Bayes
Correctly Classified Instances		65.26%	63.84%	72.77%	59.62%
Precision	Moderate Active	0.865	0.718	0.892	0.857
	Balanced	0.483	0.608	0.6	0.568
	Strong Active	0.667	0.541	0.625	0.541
	Strong Reflective	0.816	0.804	0.868	0.571
	Moderate Reflective	0.487	0.5	0.645	0.5
ROC Area	Moderate Active	0.916	0.932	0.957	0.91
	Balanced	0.742	0.841	0.846	0.772
	Strong Active	0.827	0.887	0.908	0.827
	Strong Reflective	0.904	0.93	0.984	0.851
	Moderate Reflective	0.763	0.89	0.833	0.807

Source : (Pitigala Liyanage et al., 2016)

Table 4.2. Performance in SEN/INT dimension

		J48	Bayes net	Random Forest	Naïve Bayes
Correctly Classified Instances		80.00%	66.25%	72.50%	56.25%
Precision	Moderate Sensing	0.917	0.556	0.667	0.692
	Balanced	0.737	0.769	0.65	0.514
	Strong Sensing	0.889	0.667	0.889	0.583
	Strong Intuitive	0.7	0	0.875	0.4
	Moderate Intuitive	0.909	0.55	0.818	0.75
ROC Area	Moderate Sensing	0.921	0.824	0.867	0.885
	Balanced	0.813	0.809	0.77	0.649
	Strong Sensing	0.894	0.846	0.918	0.863
	Strong Intuitive	0.885	0.731	0.844	0.814
	Moderate Intuitive	0.815	0.807	0.87	0.749

Source : (Pitigala Liyanage et al., 2016)

Table 4.3. Performance in SEQ/GLO dimension

		J48	Bayes net	Random Forest	Naïve Bayes
Correctly Classified Instances		90.00%	81.25%	88.75%	85.00%
Precision	Moderate Global	1	0.692	0.818	0.727
	Balanced	0.86	0.85	0.857	0.804
	Strong Global	0.8	0	1	1
	Strong Sequential	1	1	1	1
	Moderate Sequential	0.938	0.75	0.933	1
ROC Area	Moderate Global	0.794	0.802	0.773	0.78
	Balanced	0.891	0.814	0.918	0.897
	Strong Global	0.893	0.792	0.997	0.824
	Strong Sequential	0.944	0.915	0.996	0.98
	Moderate Sequential	0.992	0.986	0.997	0.995

Source : (Pitigala Liyanage et al., 2016)

Table 4.4. Performance in VIS/VER dimension

		J48	Bayes net	Random Forest	Naïve Bayes
Correctly Classified Instances		81.25%	61.25%	78.75%	60.00%
Precision	Moderate Visual	0.6	0	0.714	1
	Balanced	0.833	0.661	0.833	0.673
	Strong Visual	0.75	0.5	0.667	0.545
	Strong Verbal	1	0	0.714	0.2
	Moderate Verbal	0.875	0.4	0.778	0.455
ROC Area	Moderate Visual	0.846	0.6	0.782	0.618
	Balanced	0.856	0.79	0.746	0.679
	Strong Visual	0.897	0.704	0.891	0.728
	Strong Verbal	0.811	0.707	0.892	0.861
	Moderate Verbal	0.718	0.695	0.828	0.715

Source : (Pitigala Liyanage et al., 2016)

4.2 LLA Functionality Evaluation

The LLA functionality was evaluated by comparing the predicted learning styles (LLA functionality) against the results obtained by using the ILS questionnaire. For each dimension, the percentage of learners whose preference was accurately predicted by the two approaches, i.e. simple rule-based and data mining was calculated. In the case of simple rule-based, we considered two datasets.

When considering studies that have attempted to predict learning styles, comparing performance is an important component. The precision the evaluation method proposed by Garcia et al. (García et al., 2007) has been commonly used in previous studies. To compare the performance of our trial with that of existing trials, we used the same formula proposed by Garcia et al.

$$\text{Precision} = \frac{\sum_{i=1}^{n} \mathrm{Sim}(\mathrm{LS_{FW}}, \mathrm{LS_{ILS}})}{n} \times 100$$

Here, LS_{ILS} and LS_{FW} are the learning styles obtained by the ILS and that obtained by the chosen method, respectively. The parameter n is the number of students in the course. The function Sim calculates the similarity between LS_{ILS} and LS_{FW}. If the magnitude of LS_{ILS} is equal to that of LS_{FW} Sim takes 1, 0 if they are opposite, and 0.5 if one is neutral and the other is an extreme value. The accuracy rate given by Weka differs from the precision rate in the above because the weight 0.5 is not considered in the calculation (Pitigala Liyanage et al., 2016).

Table 4.5 compares the precision rates obtained by approaches in this research with those of other studies, including our own previous study. Garcia et al. (García et al., 2007) applied Bayesian networks to an artificial intelligence course with 40 students. Graf et al. (Sabine Graf et al., 2008) estimated learning styles using an SRBM for a Web Engineering course with 43 students. Dung and Florea (Dung & Florea, 2012) also used an SRBM to estimate learning styles for an artificial intelligence course with 44 students. In one previous study (Pitigala Liyanage et al., 2014) we performed two trials using an SRBM, while in another (Pitigala Liyanage et al., 2016) we used a data mining approach.

Table 4.5. Precision rate comparison

Authors	ACT/REF	SEN/INT	SEQ/GLO	VIS/VER
Garcia et al. (García et al., 2007)	58.00%	77.00%	63.00%	−
Graf et al. (Sabine Graf et al., 2008)	79.33%	77.33%	73.33%	76.67%
Dung and Florea (Dung & Florea, 2012)	72.73%	70.15%	65.91%	79.54%
SRBM Dataset C1(Pitigala Liyanage et al., 2014)	63.64%	77.27%	77.27%	72.73%
SRBM Dataset C2 (Pitigala Liyanage et al., 2014)	65.00%	75.00%	77.50%	76.25%
Data Mining Dataset C2 (Pitigala Liyanage et al., 2016)	70.89%	84.38%	91.25%	82.50%

The precision rate obtained for the ACT/REF dimension is consistently slightly lower than those for the other dimensions across all three datasets. Further, when comparing with other researchers too, the performance in ACT/REF dimension is not the best. Plausibility for this could be due to the fact that courses involved in the datasets are blended learning classes, where classroom lectures provided face to face content delivery. The LMS sessions were supplemental. Further, the most course materials were made available to learners as a printed textbook. It is possible that students may not have chosen to read the same content on the LMS when the printed notes were available. Furthermore, the ACT/REF dimension dataset was imbalanced.

Nevertheless, out of the three datasets, and overall when compared with the previous studies, the data mining approach with dataset C2 has obtained the best precision rates.

4.3 User-Centric Feedback for AIA

The AIA module gives recommendations to a learner. In order to evaluate the AIA module's effectiveness and usefulness, an user test is carried out. A questionnaire is applied as the instrument to measure explicit feedback and performance due to its ease of quantifying feedback and ability to anonymously provide feedback.

4.3.1 Experiment setup

"Human Computer Interaction / ヒューマン・コンピュータ・インタラクション" mentioned in section 3.2 was chosen as a course for experimental trial. During its first run, we collected learning styles of 54 learners. (Dataset C3). These learners were not provided recommendations, while their learning styles were logged using the data mining technique explained in section 3.4.2.2. During the second run, this C3 data was used to evaluate and provide recommendations to 8 subjects (Dataset C4).

4.3.2 Evaluation procedure

The evaluation framework presented by Pu et al. (Pu & Chen, 2010) was considered for this purpose. While it was aimed at recommending items (such as those for purchase), it was suitably modified to recommend learning materials, and a questionnaire having 17 questions was developed based on the 60 questions questionnaire developed by Pu et al. The questionnaire is enclosed in Appendix D. The questions and responses for questions 2, 4 and 10 are set in the reverse Likert scale (to increase validity) while other questions responses are set in the Likert scale. Questions 1 – 6 belong to the category user perceived qualities. On questions 1 and 2, measure the perceived accuracy which is the degree to which users feel the recommendations match their interests and preferences of the subject. Questions 3, 4 measure the relative accuracy, question 5 measures the context compatibility, and the question 6 measures the interface adequacy under user perceived qualities. Questions 7 – 13 come under user beliefs category. Question 7 measures the perceived ease of use, Question 8 measures the ease of preference elicitation, Questions 9 and 10 measure ease of decision making, Questions 11 and 12 measure perceived usefulness, and Question 13 measures control/transparency of the system under user beliefs category. Questions 14 and 15 were formulated under the category of user attitudes. Questions 16 and 17 were formulated under behavioral intentions category as explained by Pu et al. (Pu & Chen, 2010). The questionnaire was provided to subjects via email, whereby they could connect to the Internet and use a google form to submit their feedback anonymously.

4.3.3 Results

Out of the 8 learners in dataset C4, 7 learners responded to the request. There were no fake samples (i.e. users who had answered every question with the same value) or incomplete feedback. The analysis is carried out considering the same constructs of the evaluation framework on perceived qualities of recommenders introduced by Pu et al. (Pu & Chen, 2010) which was used as a guideline during the questionnaire preparation.

1. User perceived qualities

   Figure 4-1 shows a result of that the question 1: 3 students found the system preference to be indifferent while the 4 others agreed with the question.

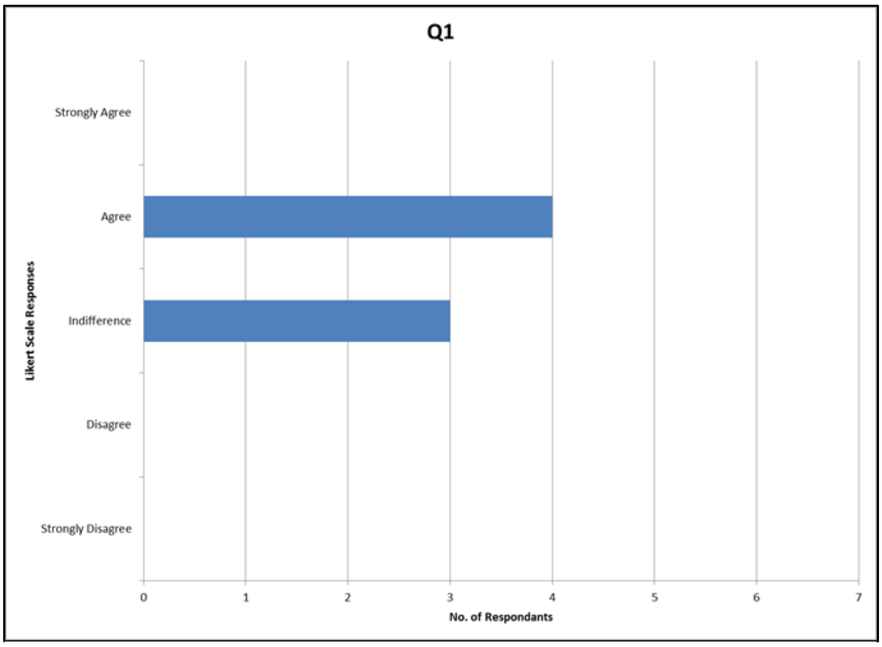

Figure 4-1. A result of the question 1: The learning materials recommended to me via links matched my learning preference.

Figure 4-2 shows a result of the question 2: 1 student found the system preference to be indifferent, 1 student agrees while 5 others disagreed with the question.

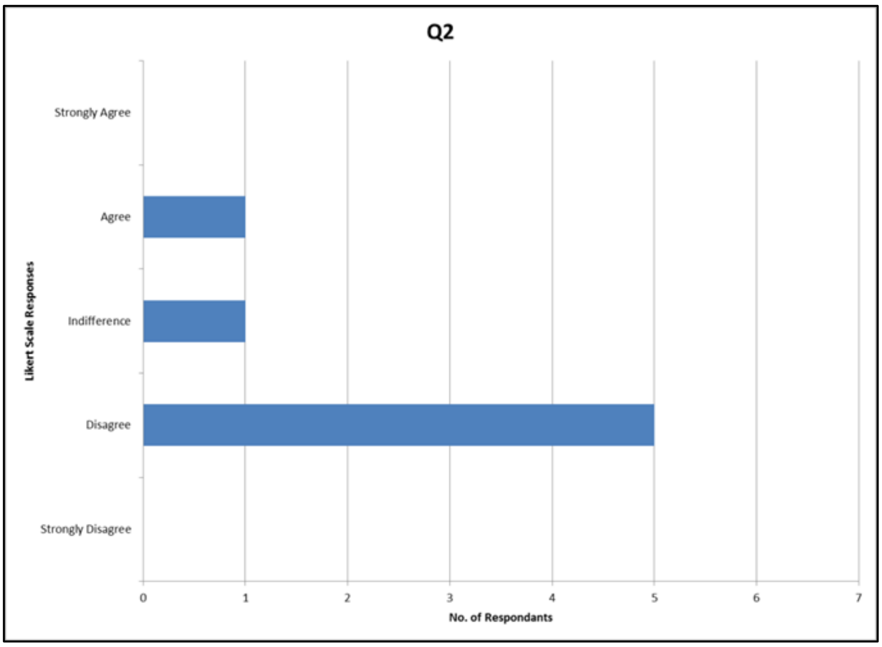

Figure 4-2. A result of the question 2: I am not interested in the links recommended to me

Figure 4-3 shows a result of question 3: 4 students found the system preference to be indifferent while the 3 others agreed with the question.

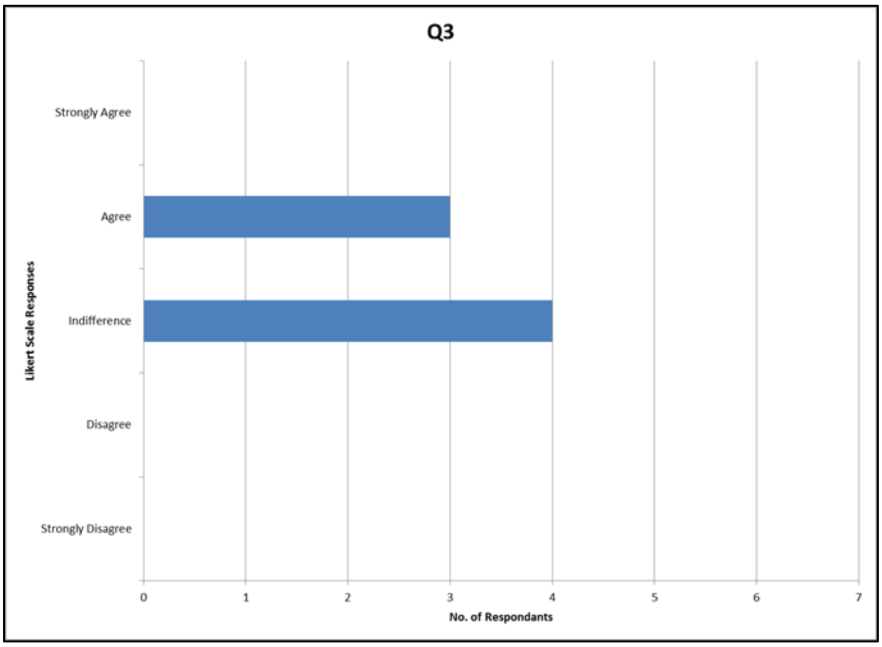

Figure 4-3. A result of the question 3: The recommendation I received better fits my learning preference than what I may receive from a friend.

Figure 4-4 shows a result of question 4: 4 students found the system preference to be indifferent while the 3 others agreed with the question.

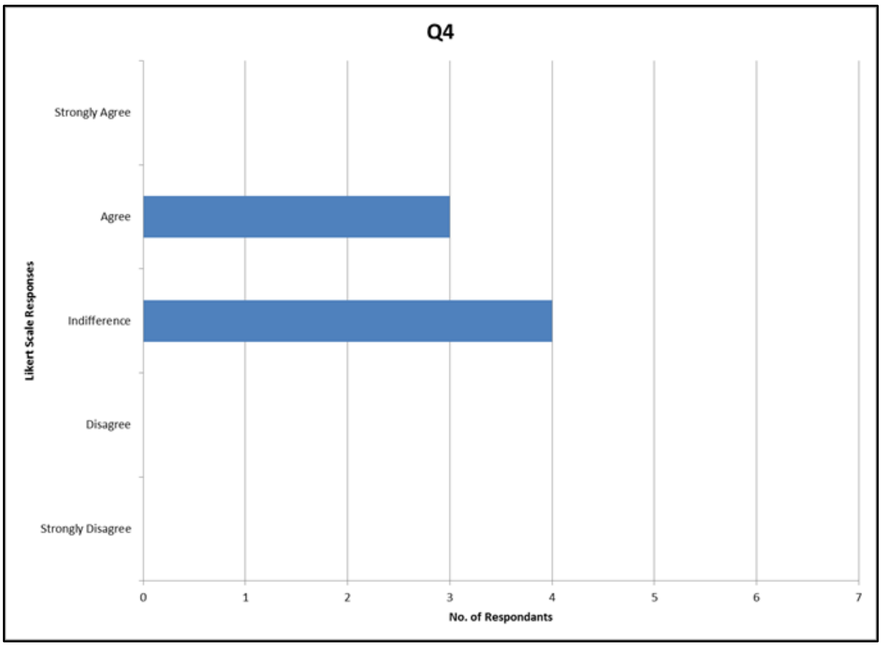

Figure 4-4. A result of the question 4: A recommendation from my friends better suits my learning preference than the recommendation from this system.

Figure 4-5 shows a result of question 5: 4 students found the system preference to be indifferent while the 3 others agreed with the question.

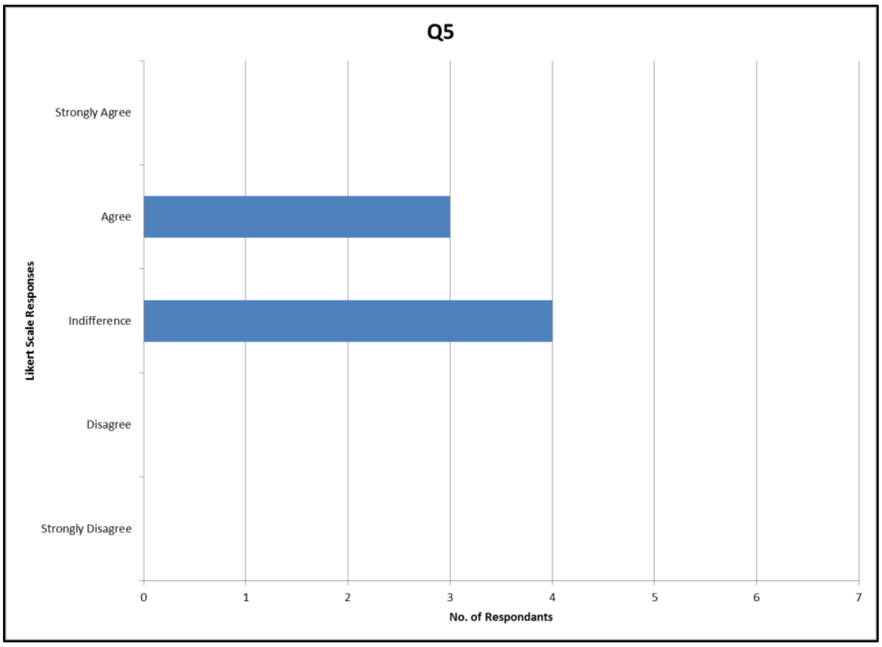

Figure 4-5. A result of the question 5: The recommendations are timely.

Figure 4-6 shows a result of the question 6: all 7 students agreed with the question.

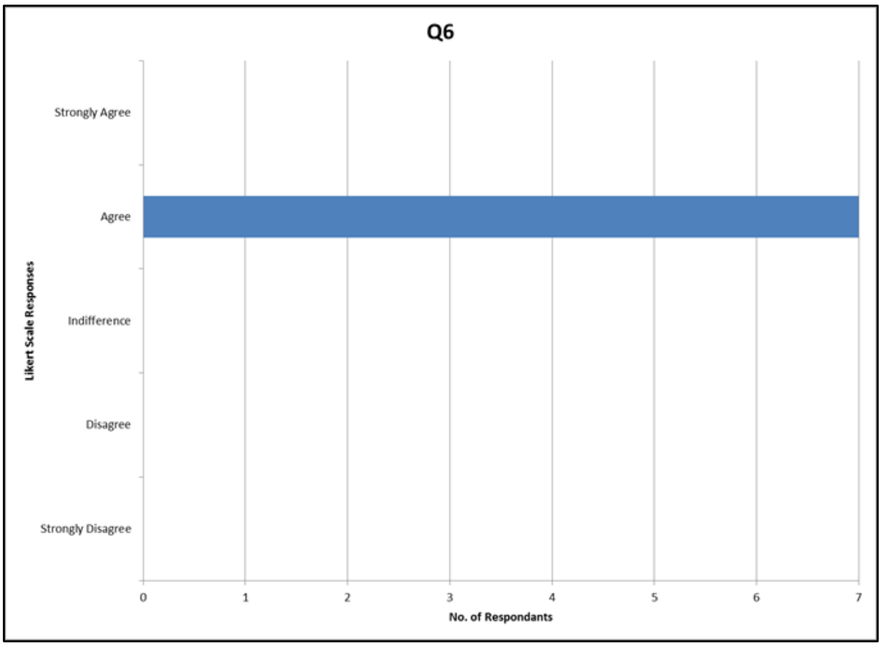

Figure 4-6. A result of the question 6: The layout of the recommender system interface is attractive and adequate.

2. User beliefs

Figure 4-7 shows a result of question 7: 2 students strongly agreed, 4 students agreed while the 1 other disagreed with the question.

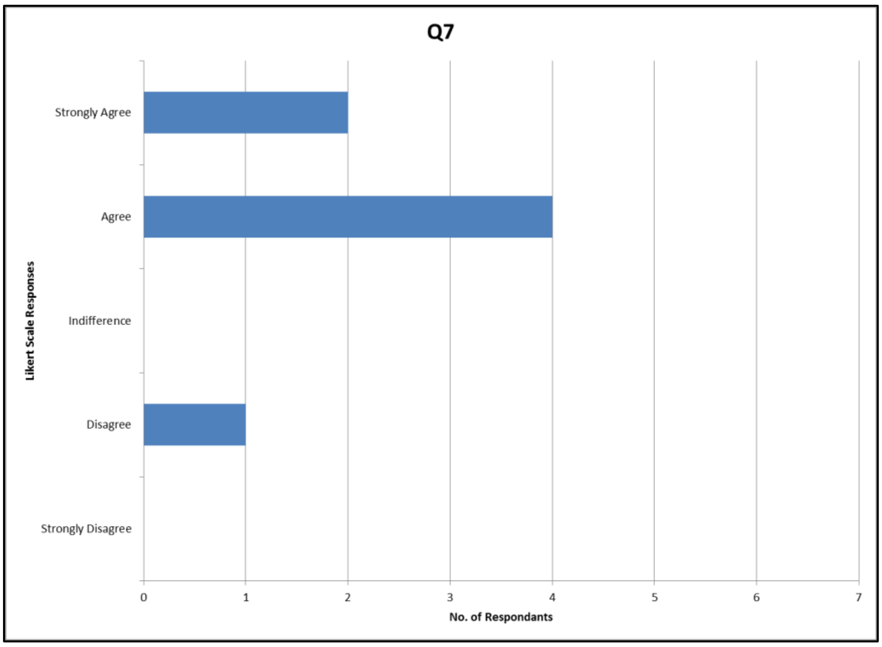

Figure 4-7. A result of the question 7: I became familiar with the recommender system very quickly.

Figure 4-8 shows a result of question 8: 3 students strongly agreed, 3 students agreed while the 1 other feels indifferent with the question.

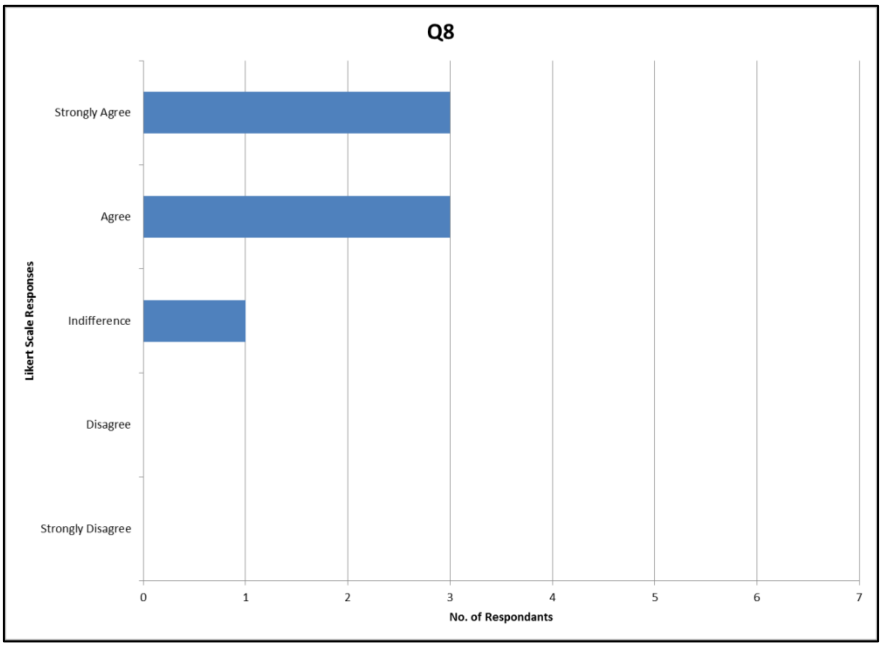

Figure 4-8. A result of the question 8: I found it easy to tell the system about my learning preferences. (By Using Questionnaire)

Figure 4-9 shows a result of question 9: 2 students strongly agreed and 5 students agreed with the question.

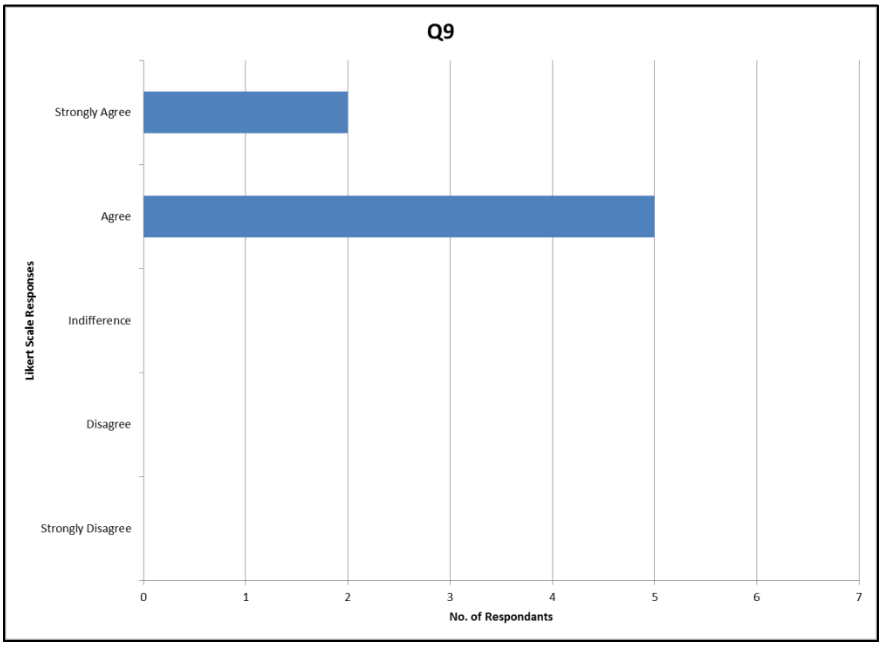

Figure 4-9. A result of the question 9: Finding the learning materials to learn with the help of the recommender is easy.

Figure 4-10 shows a result of question 10: 6 students disagreed, and 1 student feels indifferent with the question.

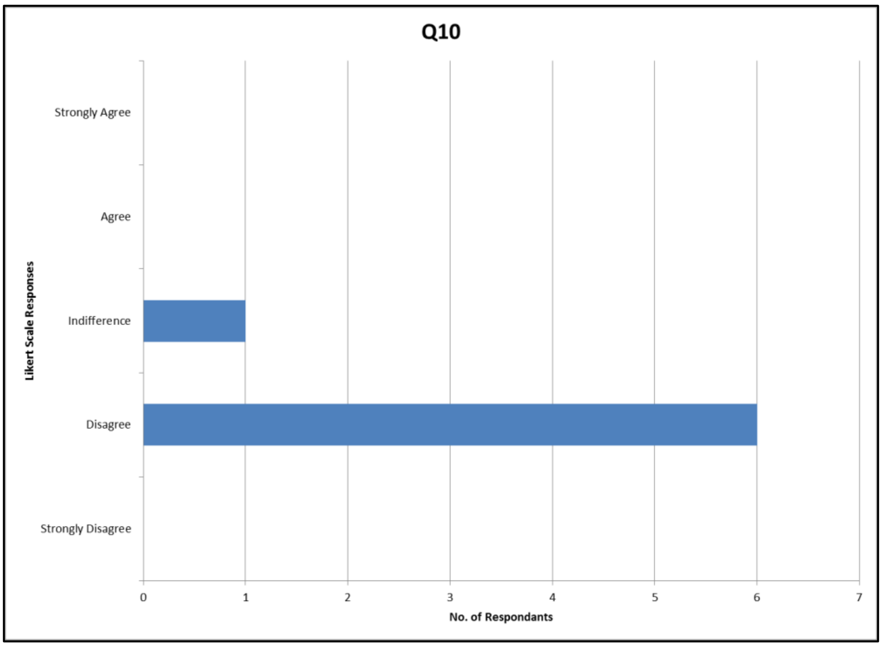

Figure 4-10. A result of the question 10: Finding learning materials to learn, even with the help of the recommender system, consume too much time.

Figure 4-11 shows a result of question 11: 4 students agreed, and 3 students feel indifferent with the question.

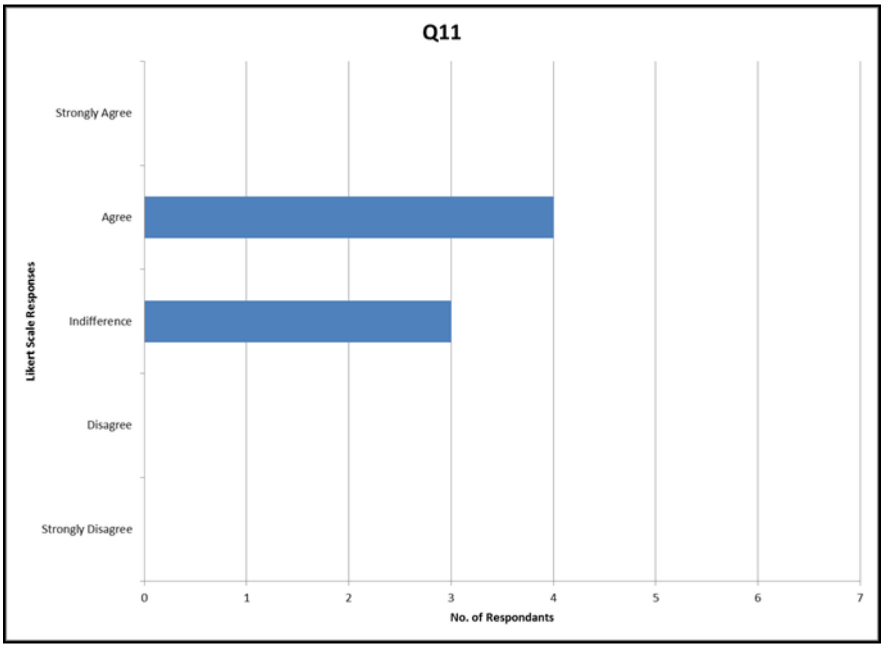

Figure 4-11. A result of the question 11: The recommender system effectively helped me find the ideal learning materials.

Figure 4-12 shows a result of question 12: 4 students agreed, and 3 students disagreed with the question.

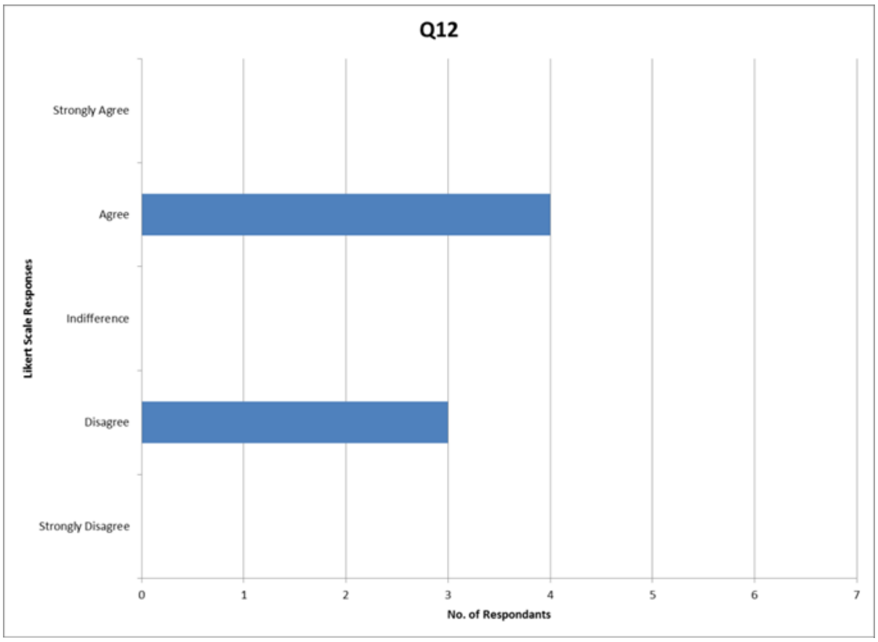

Figure 4-12. A result of the question 12: I feel supported to find what I like with the help of the recommender system.

Figure 4-13 shows a result of question 13: 4 students agreed, 2 students disagreed while 1 other feels indifferent with the question.

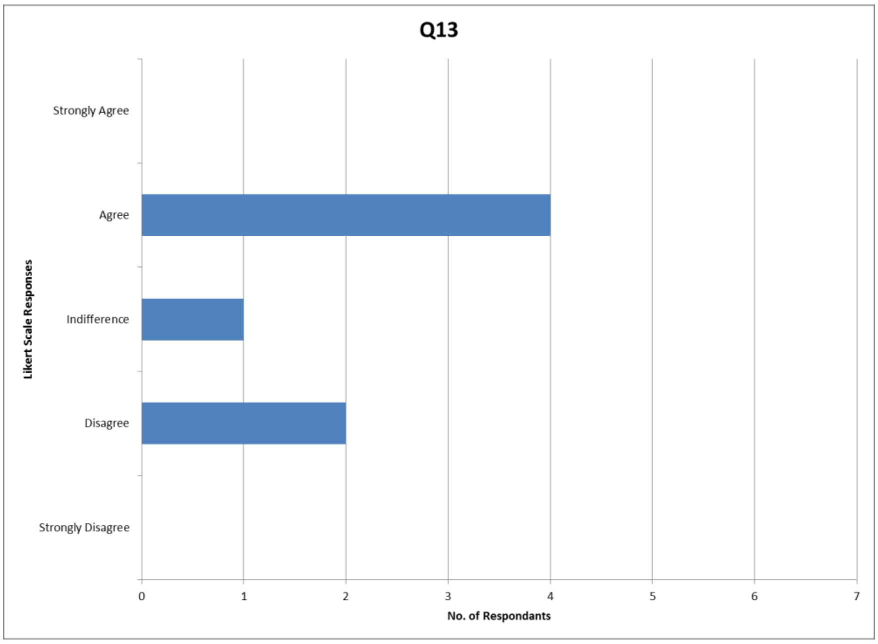

Figure 4-13. A result of the question 13: I understood why the links were recommended to me.

3. Attitudes

Figure 4 -14 shows a result of that the question 14: 5 students agreed, 1 student disagreed while 1 other feels indifferent with the question.

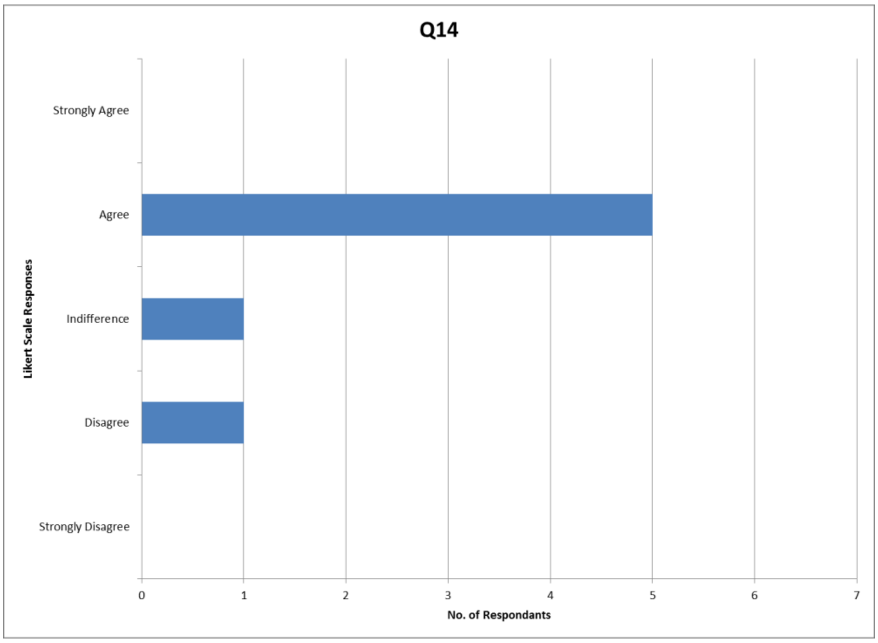

Figure 4-14. A result of the question 14: Overall, I am satisfied with the recommender system.

Figure 4 -15 shows a result of question 15: 5 students agreed, while 2 other feel indifferent with the question.

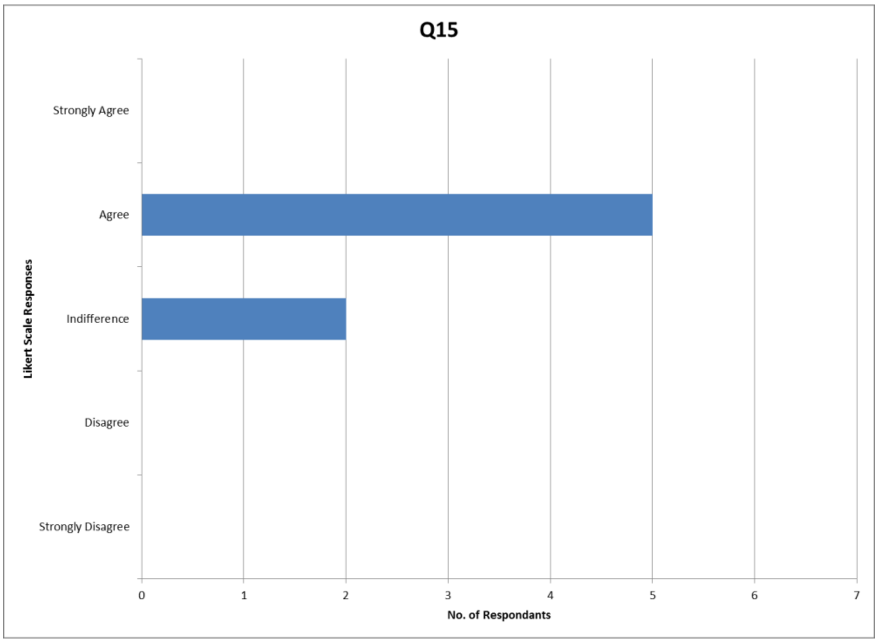

Figure 4-15. A result of the question 15: The recommender system can be trusted.

4. Behavioral Intensions

Figure 4 -16 shows a result of that the question 16: 6 students agreed, while 1 other feels indifferent with the question.

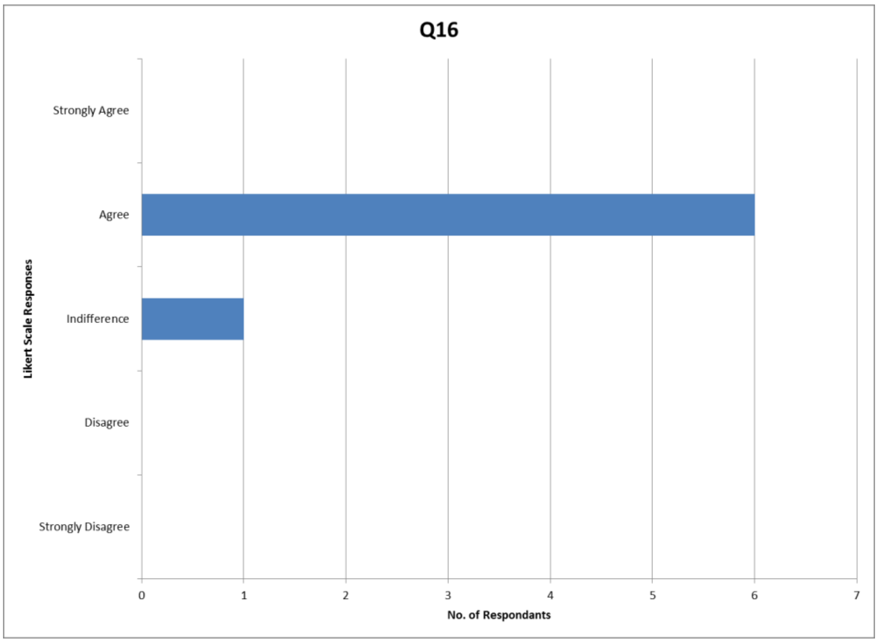

Figure 4-16. A result of the question 16: If a recommender such as this exists, I will use it to find the learning materials to learn.

Figure 4 -17 shows a result of question 17: 6 students agreed, while 1 other feels indifferent with the question.

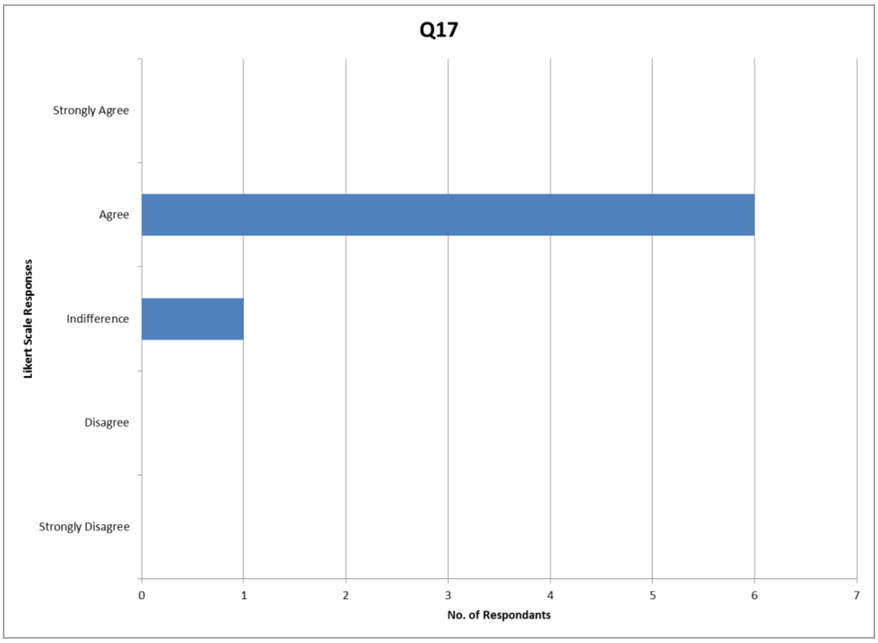

Figure 4-17. A result of the question 17: I will use this type of recommender system frequently.

Overall, the majority of learners have responded positively to the evaluation.

4.4 Summary

This chapter described the different experiments carried with respect to performance. First, out of four possible algorithms, an experiment concluded that the j48 algorithm performed the best. Secondly, using a common precision rate comparison, the performance of selected datasets was examined with respect to two learning preference estimation approaches discussed in section 3.4.1.2. The data mining approach provided the best precision rate. Finally, a user evaluation of the recommending system was performed using a questionnaire. The questionnaire was based on the Pu et al.'s evaluation framework proposed for evaluating recommender systems, and used the 5 point Likert scale. The questions were grouped into four constructs along the framework and, in summary, the participants' responses are positive towards the course recommendations.

Chapter 5

Conclusion

5.1 Summary of Findings

This research addressed several research questions formulated at the commencement. While several learning style models were studied, the most cited and experimented one – the FSLSM was considered suitable. Another contributing factor is the mapping between certain preferences of the FSLSM and elements of other learning styles. We selected the open source Moodle LMS as the choice for further study. By considering a rule based mapping between learning styles and learner behavior in a LMS, the framework developed was used to evaluate the learning styles of a pilot group of 22 learners. The learner behavior was examined using the log files. The precision was calculated by comparing the results against the responses received to the ILS questionnaire. The same experiment was carried out using a different learner group of 80 learners, which provided a slightly better precision rate.

Considering the capabilities of data mining technique, several data mining algorithms have been applied for evaluation. We have found that the J48 decision tree algorithm performed the best for our dataset C2. Two visualization maps aimed at learners were developed to permit a learner examine own learning styles as well as group learning behavior. Both visualizations can benefit the instructor by providing an opportunity to align the learning materials to match the learners' learning styles.

The learning styles were used to recommend learning content using a recommendation system. The content filtering approach was adopted with the k-nearest neighbor algorithm. Pilot evaluations carried out with 7 learners suggested the results were promising.

5.2 Limitations

There still remain limitations in this study, and possible solutions are explained in this section. Out of the number of learning style models published in research, this research focused on the FSLSM. While it has been the most cited model, there is no conclusive evidence that it is the best model. Therefore it maybe worthwhile to examine whether other models can also be used in e-learning. In the

Moodle LMS, technical limitations result in the inability to track the time spent on certain content such as PDF and slides. Unless third party desktop tracking software is used, it is impossible to figure the time up. Therefore the time spent in content cannot be evaluated. For example a user could click a link, and the user log records it as followed. But it is possible that the user opened the file, and immediately closed it. Additional desktop software could assist to track such situations. While this research omitted the time spent attribute which caused missing values, it was not possible to measure the impact of this omission.

From an experiment point of view, the sample data used belongs to one learner group and they follow a single course within a LMS. Nevertheless in the practical scenario, the LMS can have more than one course followed by the same learner. If a learner participates in two courses, two R_{AVG} would be recorded. In reality one would expect a learner to have one learning style at a given time, i.e. the R_{AVG} values should be equal. But it is possible that in reality they have two different values. Valid reasons for this situation could include the learner preference varying for each course due to difference of subject matter. Another could be that the learner preference may vary depending on the type of learning materials used in the LMS (i. e., audio, video, graphics, and text). The threshold values used to estimate learning styles set in the ERA can also influence the R_{AVG} as they can be fine-tuned by the course instructor. To address this limitation, one solution could be to calculate the R_{AVG} value as the average values among the multiple courses.

In the selection of the algorithm used for prediction of learning styles, four algorithms were considered. Yet further experiments need to be performed to validate whether other algorithms are unsuitable for similar data mining-based predictions of learning styles. The factors that affect the choice of algorithm are yet to be determined and needs further investigation.

In the ERA module, the instructor must fine-tune the thresholds per course, and they play an important role in determining how the system classifies individual learning preferences. During the first week of a course, the default values based on the literature can be used as the settings. But the threshold configuration requires additional awareness by the instructor, and burdens the instructor. Ideally, a tool which graphically presents performance metrics, maybe better. Another solution would be to figure a method by which these settings are automatically calibrated.

On evaluating methods for learning style prediction, every researcher obtains a different dataset and does not contain a common dataset. This relates to privacy concerns of the institutions. Ideally if a common dataset exists, it can be helpful for comparison purposes.

In content recommendation, if new contents are added to the system, there is no possibility to recommend them to users as there is no previous content-related data on them. This relates to the "cold start" problem found in recommendation systems. Although we proposed a static mapping, further investigations need to be carried out to explore more dynamic recommendations. Further in our experiment, for content recommendation using weka, we applied the k-nearest neighbour algorithm where k is considered 1, while we did not explore other k values. Evaluations need to be carried out to different learner groups using different k values. Another possible improvement is on obtaining implicit feedback. For explicit feedback, user involvement is essential whereas implicit feedback, user involvement is not essential. While explicit feedback is quick as we used the evaluation questionnaire, the user's relative feelings may not be sufficient to get a complete understanding of the recommendation. Tracking clicks or hyperlinks by learner is a possible alternative which provides an implicit feedback of which content was accessed.

5.3 Future Work

The use of learning styles in an LMS environment is applied in this research and mostly in research for tertiary education. The use of LMS which can identify learner's learning styles need not be limited to Universities or adults in general and can be extended to secondary and primary education. However the validity of extending existing learning styles to learners of such age groups, uncertain. Further research needs to be carried out to identify learning style models suitable for children so that they can be applied for LMS in primary and secondary learning.

The SCORM container does not currently store any information pertaining to its suitability for different learning style models. However, given that the SCORM standard is widely accepted in LMSs, it's worthwhile exploring whether SCORM or its successor Tin Can API can integrate learning style metadata to enable tighter integration of learning styles into the LMS.

Currently, no plugin is available on the Moodle developer site to enable users to evaluate their learning styles. It would be possible to introduce a scheme to enable learners to evaluate their learning style as well as visualize it. A future work would be to upload a fully complaint Moodle LMS plugin to the official developer plugin site to enable learners around the world to experience the concept of learning styles as well as visualize their peers learning styles.

At present the learning styles measurements (R_{AVG}) values are only stored once, i.e. changes in the learning styles are not recorded in the database. However, learning styles of learners may change with time. While storing them is certainly possible, a more innovative visualization learning map is required to present time varying learning style preferences.

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Appendices

Appendix A – ILS Questionnaire

(Available at http://www.engr.ncsu.edu/learningstyles/ilsweb.html)

Barbara A. Soloman
Richard M. Felder

North Carolina State University

For each of the 44 questions below select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently.

1. I understand something better after I
    a. try it out.
    b. think it through.

2. I would rather be considered
    a. realistic.
    b. innovative.

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

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

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

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

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

8. Once I understand
    a. all the parts, I understand the whole thing.
    b. the whole thing, I see how the parts fit.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

36. When I am learning a new subject, I prefer to
    a. stay focused on that subject, learning as much about it as I can.
    b. try to make connections between that subject and related subjects.

37. I am more likely to be considered
    a. outgoing.
    b. reserved.

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

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

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

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

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

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

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

Appendix B – Japanese translation of the ILS Questionnaire

Prepared by Kiyoto Hinata with kind permission of the author, Professor Richard Felder. (Available at http://eng.alc.co.jp/newsbiz/hinata/2010/10/post_761.html)

For each of the 44 questions below select either "a" or "b" to indicate your answer. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently. When you are finished selecting answers to each question, please select the submit button at the end of the form.　以下の 44 項目の質問のそれぞれにつき、(a) と (b) のうちいずれか当てはまるものをクリックしてください。ひとつの質問に対して回答はひとつとします。いずれも自分に当てはまるという場合、頻度として多い 方を選んでください。回答を終えたら、最後にある submit をクリックしてください。

1. I understand something better after I
(a) try it out.
(b) think it through.
自分の理解が深まるのは、
(a) 実際に試してみてからだ
(b) 考え抜いてからだ

2. I would rather be considered
(a) realistic.
(b) innovative.
自分のことは人にはこう思ってもらいたい、
(a) 現実的実際的人間だ、と
(b) 斬新かつ画期的なことをする人間だ、と

3. When I think about what I did yesterday, I am most likely to get
(a) a picture.
(b) words.
きのう何をしていたかを思い出そうとする場合、たいていは
(a) イメージが浮かぶ
(b) 言葉が浮かぶ

4. I tend to
(a) understand details of a subject but may be fuzzy about its overall structure.
(b) understand the overall structure but may be fuzzy about details.
どちらかと言えば、
(a) 学習内容の細かい点はわかっていても全体像が今ひとつつかみ切れないということがある
(b) 全体像はわかっていても、細かい点となると今ひとつつかみ切れないということがある

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

新たなことを勉強しようという場合、
(a) そのことについて話をした方が理解しやすい
(b) そのことにつきあれこれ考えた方が理解しやすい

6. If I were a teacher, I would rather teach a course
(a) that deals with facts and real life situations.
(b) that deals with ideas and theories.
自分が教師だとしたら、
(a) 事実認識や現実の状況を扱う科目の方が教えやすい
(b) 観念や理論を扱う科目の方が教えやすい

7. I prefer to get new information in
(a) pictures, diagrams, graphs, or maps.
(b) written directions or verbal information.
新たな情報に接し、学ぼうという場合、
(a) イラスト、図表、グラフ、地図を使う方がいい
(b) 書面による説明その他言葉が入っている方がいい

8. Once I understand
(a) all the parts, I understand the whole thing.
(b) the whole thing, I see how the parts fit.
自分が納得する際の手順は、
(a) すべての要素を把握したところで、全体がわかってくる
(b) 全体がわかったところで、個々の要素の位置づけがわかる

9. In a study group working on difficult material, I am more likely to
(a) jump in and contribute ideas.
(b) sit back and listen.
難しいテーマの勉強会に参加しているとして、
(a) 随時発言し、自分の考えを述べる方だ
(b) 黙って聞いている方だ

10. I find it easier
(a) to learn facts.
(b) to learn concepts.
比較的楽に勉強できるのは対象が
(a) 事実のときだ
(b) 概念のときだ

11. In a book with lots of pictures and charts, I am likely to
(a) look over the pictures and charts carefully.
(b) focus on the written text.
図版やチャートが豊富な本を読んでいる場合、
(a) 図版やチャートをじっくりと見る感じだ
(b) テキストの方をじっくり読む感じだ

12. When I solve math problems
(a) I usually work my way to the solutions one step at a time.
(b) I often just see the solutions but then have to struggle to figure out the steps to get to them.
数学の問題を解いている場合、いつも、
(a) 最終的な解答に向け一歩ずつ計算していく
(b) 最終的な解答はぱっとわかるが、そこに行くまでのプロセスで苦労する

13. In classes I have taken
(a) I have usually gotten to know many of the students.
(b) I have rarely gotten to know many of the students.
これまで出てきた授業を振り返ると、
(a) おおぜいの学生と知り合いになるのが普通だ
(b) 滅多に他の学生たちと知り合いになったりしない

14. In reading nonfiction, I prefer
(a) something that teaches me new facts or tells me how to do something.
(b) something that gives me new ideas to think about.
ノンフィクションを読むとすれば、
(a) 新たな事実を知ることができたり、何かのやり方を知ることができるものを選ぶ
(b) 考えさせてくれる新たな視点に触れることのできるものを選ぶ

15. I like teachers
(a) who put a lot of diagrams on the board.
(b) who spend a lot of time explaining.
好きな教師のタイプは、
(a) 視覚教材を多用する教師だ
(b) 説明に時間をかけてくれる教師だ

16. When I'm analyzing a story or a novel
(a) I think of the incidents and try to put them together to figure out the themes.
(b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.
フィクションその他小説を読み解く場合、
(a) 書かれている出来事をつなげていってテーマを探ろうとする
(b) 読み終えると自然にテーマはわかるので、あとは、振り返って直接関係する出来事を探すという手順になる

17. When I start a homework problem, I am more likely to
(a) start working on the solution immediately.
(b) try to fully understand the problem first.
課題を家に持ち帰っている場合、たいていは、
(a) すぐに解決策を見いだそうとする
(b) まずは何が問題かをしっかり見きわめようとする

18. I prefer the idea of
(a) certainty.
(b) theory.
どちらかと言えば、惹かれるのは、
(a) 確実性だ
(b) 理論だ

19. I remember best
(a) what I see.
(b) what I hear.
一番記憶に残るのは、
(a) 見たことだ
(b) 聞いたことだ

20. It is more important to me that an instructor
(a) lay out the material in clear sequential steps.
(b) give me an overall picture and relate the material to other subjects.
自分にとって大事なのは、講師が
(a) 素材を明確な順序で示してくれることだ
(b) 全体の中で素材が他とどう関係しているかを示してくれることだ

21. I prefer to study
(a) in a study group.
(b) alone.
勉強のやり方としては、
(a) 勉強会形式で仲間と勉強する方が好きだ
(b) ひとりで勉強する方がいい

22. I am more likely to be considered
(a) careful about the details of my work.
(b) creative about how to do my work.
人には、
(a) 細部まで細かく詰めていると思われることが多い
(b) 仕事の進めぶりがクリエイティブだと思われることが多い

23. When I get directions to a new place, I prefer
(a) a map.
(b) written instructions.
初めて行く場所への道順を教わるなら、
(a) 地図で示してもらった方がいい
(b) 書いて説明してあるものの方がいい

24. I learn
(a) at a fairly regular pace. If I study hard, I'll "get it."
(b) in fits and starts. I'll be totally confused and then suddenly it all"clicks."
勉強のペースは、

(a) かなり一定しており、頑張って勉強すれば「わかる」
(b) 一定しておらず、まるでわからなくなったかと思うと，ある時、突然、すべてが「わかる」

25. I would rather first
(a) try things out.
(b) think about how I'm going to do it.
自分で好むのは、
(a) まずはやってみることだ
(b) 始める前に段取りを考えることだ

26. When I am reading for enjoyment, I like writers to
(a) clearly say what they mean.
(b) say things in creative, interesting ways.
趣味の読書の場合、
(a) 言いたいことを端的に言う作者が好きだ
(b) 他にない、おもしろい言い方をする作者が好きだ

27. When I see a diagram or sketch in class, I am most likely to remember
(a) the picture.
(b) what the instructor said about it.
クラスで図やスケッチが示された場合、一番頭に残るのは、
(a) どういう絵だったかだ
(b) 講師がそれについて言ったことだ

28. When considering a body of information, I am more likely to
(a) focus on details and miss the big picture.
(b) try to understand the big picture before getting into the details.
ひとまとまりの資料を読みこなす必要のある場合、
(a) 細かい部分に頭が行き、全体像を見落とす傾向にある
(b) 細かいことは後回しにし、全体像を把握しようとする傾向にある

29. I more easily remember
(a) something I have done.
(b) something I have thought a lot about.
より記憶に残るのは、
(a) 実際に自分がやったことだ
(b) いろいろと考えを巡らした事柄だ

30. When I have to perform a task, I prefer to
(a) master one way of doing it.
(b) come up with new ways of doing it.
課題を与えられた場合、自分が好むのは、
(a) 既存の解決方法を自分のものにすることだ
(b) 新たな解決法を見いだすことだ

31. When someone is showing me data, I prefer
(a) charts or graphs.
(b) text summarizing the results.
誰かがデータを見せてくれる場合、自分が好むのは、
(a) チャートやグラスを使ってくれることだ
(b) 結果がまとめてあるテキストを見せてくれることだ

32. When writing a paper, I am more likely to
(a) work on (think about or write) the beginning of the paper and progress forward.
(b) work on (think about or write) different parts of the paper and then order them.
論文やレポートを書く場合、
(a) 最初の部分を考えたり、書き上げたりしてから、次へと進む傾向にある
(b) 部分部分を考えたり、書き上げてから、それを整理する傾向にある

33. When I have to work on a group project, I first want to
(a) have "group brainstorming" where everyone contributes ideas.
(b) brainstorm individually and then come together as a group to compare ideas.
グループで取組む課題がある場合、自分が最初にやりたいのは、
(a) グループ全体としての「ブレスト」を行い、各人の意見を出し合うことだ
(b) メンバー各自が単独で「ブレスト」を行なってから、グループで集まって成果を比較しあうことだ

34. I consider it higher praise to call someone
(a) sensible.
(b) imaginative.
人をほめる場合、
(a) 「現実的・実際的」という言い方の方がより大きな賛辞だと思う
(b) 「想像力が豊か」という言い方の方がより大きな賛辞だと思う

35. When I meet people at a party, I am more likely to remember
(a) what they looked like.
(b) what they said about themselves.
パーティーなどで出会った人については、
(a) 容姿を覚えていることの方が多い
(b) その人が自分自身につきどんなことを言ったのかを覚えている方が多い

36. When I am learning a new subject, I prefer to
(a) stay focused on that subject, learning as much about it as I can.
(b) try to make connections between that subject and related subjects.
新たなことを学習しようという場合、自分の好みは、
(a) そのことに集中し、できるだけ多くを学び取ろうとすることだ
(a) そのことが他の事項との兼ね合いの中でどのようなものかを見定めることだ

37. I am more likely to be considered
(a) outgoing.
(b) reserved.

人の目には、
(a) 外向的、社交的だと思われがちだ
(b) 内気と見られがちだ

38. I prefer courses that emphasize
(a) concrete material (facts, data).
(b) abstract material (concepts, theories).
何かを学ぶコースを選ぶ場合、
(a) 事実やデータといった具体的な素材を扱うものの方が好きだ
(b) 概念や理論といった抽象的な素材を扱うものの方が好きだ

39. For entertainment, I would rather
(a) watch television.
(b) read a book.
くつろいだり、気晴らしをするためには、
(a) テレビを見ている方がいい
(b) 本を読む方がいい

40. Some teachers start their lectures with an outline of what they will cover. Such outlines are
(a) somewhat helpful to me.
(b) very helpful to me.
教師によっては、講義の冒頭で説明しようとしていることの「あらまし」を述べる人もいますが、こうした「あらまし」は、
(a) 多少なりとも助けになる
(b) 大変助かる

41. The idea of doing homework in groups, with one grade for the entire group,
(a) appeals to me.
(b) does not appeal to me.
グループごとに課題が与えられ、成績評価もグループごとという方式は、
(a) いいと思う
(b) いいと思わない

42. When I am doing long calculations,
(a) I tend to repeat all my steps and check my work carefully.
(b) I find checking my work tiresome and have to force myself to do it.
長い計算をするような場合、
(a) 何度も計算過程をチェックし、注意深く進めるのが普通だ
(b) チェックをすること自体が面倒だが、やらない訳には行かないと無理にやっている感じだ

43. I tend to picture places I have been
(a) easily and fairly accurately.
(b) with difficulty and without much detail.
自分が行ったことのある場所を見たままに再現するような場合、

(a) そのイメージを比較的簡単かつ正確に描写できる
(b) そのイメージを思い起こすのが難しく、また、大雑把でしかない

44. When solving problems in a group, I would be more likely to
(a) think of the steps in the solution process.
(b) think of possible consequences or applications of the solution in a wide range of areas.
グループで問題解決に取組む場合、
(a) 解決のプロセスにおける個々のステップに焦点を合わせる傾向にある
(b) 他の分野や領域まで視野に入れながら解決策にどのような可能性や応用例がありうるかを考える傾向にある

Appendix C – Summary of ILS Questionnaire results for each Dataset

1. Dataset C1: Siksil Institute of IT (22 Students)

	Number of learners	Percentage
Strong Active	0	0%
Moderate Active	0	0%
Balanced	16	73%
Moderate Reflective	6	27%
Strong Reflective	0	0%
Total	**22**	**100%**
Strong Sensing	2	9%
Moderate Sensing	0	0%
Balanced	14	64%
Moderate Intuitive	6	27%
Strong Intuitive	0	0%
Total	**22**	**100%**
Strong Global	0	0%
Moderate Global	5	23%
Balanced	17	77%
Moderate Sequential	0	0%
Strong Sequential	0	0%
Total	**22**	**100%**
Strong Visual	2	9%
Moderate Visual	7	32%
Balanced	10	45%
Moderate Verbal	3	14%
Strong Verbal	0	0%
Total	**22**	**100%**

2. Dataset C2: University of Sri Jayewardenepura (80 Students)

	Number of learners	Percentage
Strong Active	3	4%
Moderate Active	10	13%
Balanced	54	68%
Moderate Reflective	10	13%
Strong Reflective	3	4%
Total	**80**	**100%**
Strong Sensing	10	13%
Moderate Sensing	13	16%
Balanced	33	41%
Moderate Intuitive	15	19%
Strong Intuitive	9	11%
Total	**80**	**100%**
Strong Global	5	6%
Moderate Global	13	16%
Balanced	38	48%
Moderate Sequential	15	19%
Strong Sequential	9	11%
Total	**80**	**100%**
Strong Visual	9	11%
Moderate Visual	9	11%
Balanced	43	54%
Moderate Verbal	11	14%
Strong Verbal	8	10%
Total	**80**	**100%**

3. Dataset C3: Shimane University - Human Computer Interaction Course (54 Students)

	Number of learners	Percentage
Strong Active	2	4%
Moderate Active	10	19%
Balanced	36	67%
Moderate Reflective	6	11%
Strong Reflective	0	0%
Total	**54**	**100%**
Strong Sensing	5	9%
Moderate Sensing	10	19%
Balanced	33	61%
Moderate Intuitive	5	9%
Strong Intuitive	1	2%
Total	**54**	**100%**
Strong Global	2	4%
Moderate Global	6	11%
Balanced	25	46%
Moderate Sequential	13	24%
Strong Sequential	8	15%
Total	**54**	**100%**
Strong Visual	4	7%
Moderate Visual	7	13%
Balanced	39	32%
Moderate Verbal	3	6%
Strong Verbal	1	2%
Total	**54**	**100%**

4. Dataset C4: Shimane University – Human Computer Interaction Course (8 Students)

	Number of learners	Percentage
Strong Active	0	0%
Moderate Active	3	38%
Balanced	4	50%
Moderate Reflective	1	13%
Strong Reflective	0	0%
Total	**8**	**100%**
Strong Sensing	1	13%
Moderate Sensing	2	25%
Balanced	5	63%
Moderate Intuitive	0	0%
Strong Intuitive	0	0%
Total	**8**	**100%**
Strong Global	0	0%
Moderate Global	0	0%
Balanced	6	75%
Moderate Sequential	2	25%
Strong Sequential	0	0%
Total	**8**	**100%**
Strong Visual	3	38%
Moderate Visual	4	50%
Balanced	1	13%
Moderate Verbal	0	0%
Strong Verbal	0	0%
Total	**8**	**100%**

Appendix D – Content recommender system user evaluation questionnaire

レコメンドシステム評価用アンケート票

Dear Sir/Madam,

Thank you for agreeing to participate in this study. The following questionnaire has a total of 17 questions, which should not take more than 15 minutes of your valuable time. The questions are based on user evaluation of the learning materials recommender system. I appreciate if you can respond to each question frankly and honestly. It will enable me to evaluate the system properly.

You do not need to write any personal details in this questionnaire, and as such your identity will not be revealed at any time. The responses given individually will also be kept confidential. Data will be used only for statistical analysis only.

アンケートにご協力いただきましてありがとうございます。質問票は17の質問項目からなっており、15分程度のお時間を頂戴したいと思います。本アンケートは、開発中の学習素材レコメンド（推薦）システムの評価を目的としています。システム評価を意味のあるものとするために、率直かつ正直にご回答ください。

記載したくない項目はスキップしてもらって構いません。回答は統計的に処理され、個々の回答が開示されることはありません。

Please indicate your level of agreement in the following statement in terms of you. Shown below is the description of letters appearing on top of the cages corresponding to the level of agreement.

1	2	3	4	5
Strongly Disagree まったく同意できない	Disagree 同意できない	Indifference どちらともいえない	Agree 同意できる	Strongly Agree 非常に同意できる

回答にあたっては、５段階の該当する数字の個所にチェックをお願いします。それぞれの数字（段階）の意味は次の通りです。

		1	2	3	4	5
1.	The learning materials recommended to me via links matched my learning preference. お勧めリンクで提示された素材は自分の学習スタイル（関心）に合致するものだった。					
2.	I am not interested in the links recommended to me (reverse scale). 推薦された内容に魅力はなかった。					
3.	The recommendation I received better fits my learning preference than what I may receive from a friend. 推薦内容は、同級生から教えてもらうものよりも、自分の学習スタイル（関心）に見合うものだった。					
4.	A recommendation from my friends better suits my learning preference than the recommendation from this system (reverse scale). 同級生に教えてもらうお勧め情報は、システムから推薦されるものよりも、自分にとって有意義であった。					
5.	The recommendations are timely. お勧め情報は時を得たものである。					
6.	The layout of the recommender system interface is attractive and adequate. システム操作画面のレイアウトは魅力的で適切である。					
7.	I became familiar with the recommender system very quickly. システムにすぐに慣れることができた。					
8.	I found it easy to tell the system about my learning preferences. (By Using Questionnaire) 自分の学習スタイルについてのシステム入力は簡単だった（質問票への回答）					
9.	Finding the learning materials to learn with the help of the recommender is easy.					

	システムのおかげで学ぶべき素材を見つけることが簡単であった。					
10.	Finding learning materials to learn, even with the help of the recommender system, consume too much time. システムの支援があっても学ぶべき素材を見つけることは難しかった。					
11.	The recommender system effectively helped me find the ideal learning materials. システムのおかげで申し分ない素材を獲得することができた。					
12.	I feel supported to find what I like with the help of the recommender system. 自分の欲するものが何かということをシステムが教えてくれた。					
13.	I understood why the links were recommended to me. お勧めリンクの推薦理由を理解することができた。					
14.	Overall, I am satisfied with the recommender system. 全般的にいって、システムに満足している。					
15.	The recommender system can be trusted. システムの振る舞いは信頼できる。					
16.	If a recommender such as this exists, I will use it to find the learning materials to learn. 同様のシステムが実用に供された場合、勉学にシステムを使おうと思う。					
17.	I will use this type of recommender system frequently. 同様のリコメンドシステムを将来は頻繁に使うと思う。					

Appendix E – Moodle database tables used for learning style detection and recommending LOs

Type of Table	Moodle Table	Attributes extracted /description
original	mdl_user	User identification number
	mdl_course	Course identification number
	mdl_log	User-performed activities in Moodle LMS
	mdl_quiz	No. of contents, outlines, examples, exercises, self-assessments available; no. of times content visit, outline visit, example visit, exercise visit, self-assessment visit; no. of correctly answered questions about details, overview knowledge, facts, concepts, graphics, text, interpreting solutions, developing new solutions; time spent on self-assessment tests, exercise, examples
	mdl_resource	No. of contents, outlines, examples, exercises, self-assessments available; no. of times content visit, outline visit, example visit, exercise visit, self-assessment visit
	mdl_scorm	
	mdl_forum	No. of forums available, no. of times forum viewed, time spent on forum
	mdl_question_attempts	No. of times giving wrong answer for the same quiz twice; no. of correctly answered questions about details, overview knowledge, facts, concepts, graphics, text, interpreting solutions, developing new solutions
	mdl_question_attempt_steps	
	mdl_question	No. of correctly answered questions about details, overview knowledge, facts, concepts, graphics, text, interpreting solutions, developing new solutions
	mdl_quiz_question_instances	
	mdl_quiz_attempts	Time spent on self-assessment tests, exercise, examples
	mdl_course_modules	Available LOs data (CMID)
	mdl_modules	Available and newly added modules data
Newly added	mdl_lec_threshold	Instructor's recommended thresholds for course activities.
	mdl_dimensions	Student's average ratio for each learning style (R_{AVG})
	mdl_ils_tracking	ILS questionnaire data pertaining to a student, learning style predicted by ILS
	mdl_ils_value	
	mdl_traindata_act_ref	J48 Decision tree learning style detection training data for ACT - REF dimension
	mdl_traindata_sen_intt	J48 Decision tree learning style detection training data for SEN - INT dimension
	mdl_traindata_seq_glo	J48 Decision tree learning style detection training data for SEQ - GLO dimension
	mdl_traindata_vis_ver	J48 Decision tree learning style detection training data for VIS -VER dimension
	mdl_testdata_act_ref	J48 Decision tree learning style detection testing data for ACT - REF dimension
	mdl_testdata_sen_intt	J48 Decision tree learning style detection testing data for SEN - INT dimension
	mdl_testdata_seq_glo	J48 Decision tree learning style detection testing data for SEQ - GLO dimension
	mdl_testdata_vis_ver	J48 Decision tree learning style detection testing data for VIS -VER dimension
	mdl_results_act_ref	J48 Decision tree learning style detection predicted results data for ACT - REF dimension
	mdl_results_sen_intt	J48 Decision tree learning style detection predicted results data for SEN - INT dimension
	mdl_results_seq_glo	J48 Decision tree learning style detection predicted results data for SEQ - GLO dimension
	mdl_results_vis_ver	J48 Decision tree learning style detection predicted results data for VIS -VER dimension
	mdl_training_ibk	Collaborative filtering training data
	mdl_testing_ibk_userid	Collaborative filtering testing data
	mdl_cfresults_ibk_userid	Collaborative filtering results data
	mdl_links	Recommended LOs links
	mdl_priority	dependencies among LO and Prior LO required to view (what type of LO need to followed first)