Learning Path Construction in e-Learning – What to Learn and How to Learn?

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A Thesis presented for the degree of

Doctor of Philosophy

School of Engineering and Computing Sciences

University of Durham

United Kingdom

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November 2012

Dedicated to

My Supervisors -Dr. Frederick Li and Prof. Rynson Lau

For their guidance and help

and

My Parents

For their care and support

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Abstract

Whether in traditional or e learning, it is important to consider: what to learn, how to learn, and how well students have learned. Since there are various types of students with different learning preferences, learning styles, and learning abilities, it is not easy to provide the best learning approach for a specific student. Designing learning contents for different students is very time consuming and tedious for teachers. No matter how the learning process is carried out, both teachers and students must be satisfied with students' learning performance.

Therefore, it is important to provide helpful teaching and learning guidance for teachers and students. In order to achieve this, we proposed a fined-grained outcome-based learning path model, which allows teachers to explicitly formulate learning activities as the learning units of a learning path. This allows teachers to formulate the assessment criteria related to the subject-specific knowledge and skills as well as generic skills, so that the pedagogy could be defined and properly incorporated. Apart from defining the pedagogical approaches, we also need to provide tailored learning contents of the courses, so that different types of students can better learn the knowledge according to their own learning abilities, knowledge backgrounds, etc. On the other hand, those learning contents should be well-structured, so that students can understand them. To achieve this, we have proposed a learning path generation method based on Association Link Network to automatically identify the relationships among different Web resources. This method makes use of the Web resources that can be freely obtained from the Web to form well-structured learning resources with proper sequences for delivery. Although the learning path defines what to learn and how to learn, we still needed to monitor student learning progress in order to determine proper learning contents and learning activities in an e-Learning system. To address the problem, we proposed the use of student progress indicators based on Fuzzy Cognitive Map to analyze both performance and non-performance attributes and their causal relationships. The aim is to help teachers improve their teaching approaches and help students reflect their strengths and weaknesses in learning. . This research focuses on the intelligent tutoring e-Learning system, which provides an intelligent approach to design and delivery learning activities in a learning path. Many experiments and comparative studies on both teachers and students have been carried out in order to evaluate the research of this PhD thesis. The results show that our research can effectively help teachers generate high quality learning paths, help students improve their learning performance, and offer both teachers and students a better understanding on student learning progress.

Keywords: Learning path, learning activity, learning outcome, student learning progress, learning resources.

Declaration

The work in this thesis is based on research carried out in the School of Engineering and Computing Sciences, University of Durham, England. No part of this thesis has been submitted elsewhere for any other degree or qualification and it is all my own work unless referenced to the contrary in the text.

Acknowledgments

I would like to extend my appreciation and gratitude to the following persons for their contributions to this research study.

First and foremost, I must thank my supervisor Dr. Frederick Li and Prof. Rynson Lau for their invaluable academic guidance over the past few years, for their patience to teach me to prepare papers and talks, and also for their help and care for my personal life. Their constructive criticism and comments are highly appreciated. Without their advices, support and encouragements, this thesis would be impossible. They are truly great mentors for me.

Especially, I would like to thank Prof. Rynson Lau again for inviting me to visit his research lab in City University of Hong Kong for 3 times, 6 months in total. I am so appreciate these valuable opportunity to work over international cooperation, and provide me a lot of chances to participate in some international conferences where I learned a lot do contribute to my research and future career.

I would like to thank Prof. Uden and Dr. Ivrissimtizis who are my examiners, and they have helped me a lot to find out the problems of this thesis. I cannot have this degree without their helps.

I also want to acknowledge Prof Xiangfeng Luo for advising me many bright ideas to overcome the academic problems, and also guiding me in programming in details. I greatly appreciate that he supported me to visit his research lab in University of Shanghai for six months. I have learned many things from his group and had an enjoyable time there.

I acknowledge University of Durham for its funding support over my PhD.

Many thanks also go to Qingzheng Zheng, Wei Lu, Yang Zhuang, Steven Huang for their friendship.

Most of all, my wholehearted thanks go to my mother and father for their unconditional love, support, companion, encouragement, concern, understanding and inspiration.

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Chapter 1

1.Introduction

1.1.Research Overview

e-Learning can provide various technological support to assist teaching and learning. This technological support mainly includes developing learning contents to instruct learning, setting up learning environments to engage learning, designing platforms and tools to enhance learning, organizing and standardizing learning resources to make the learning contents reusable and more formal. Constructing learning path is to organize a set of Units of Learning (UOL) in sequence and to plan how student learning will happen, which is actually a critical topic in designing platforms and tools. Because a learning path contains the information about what to learn and how to learn, it can help teachers manage student learning and help students improve their learning efficiency. There are different types of e-Learning systems, including the traditional e-learning system, adaptive e-Learning system, instructional design system, intelligent tutoring system, and service-oriented e-learning system. They are used to focus on long-distance e-Learning system, but now they focus on different aspects of the e-Learning systems by providing adaptive teaching approaches and feedbacks, consistent and reliable learning materials, curriculum sequencing mechanisms, and Web services, respectively. More details about these e-Learning systems are given in section 2.2.2. Our research provides an intelligent service to design the learning activities and to arrange the learning path, so that it can be applied to intelligent tutoring system. Learning path construction (or curriculum sequencing) organizes a series of learning activities that are disseminated with proper teaching approaches to build up student knowledge. As defined in the work of [Brus92], Intelligent Tutoring System relies on curriculum sequencing mechanisms to provide students with a learning path through learning materials, this research on learning path construction is one of the major work in Intelligent Tutoring System. Existing methods [Farr04, Yang05, Chen08, Lim009] formulate learning paths based on knowledge elements. While this allows the e-Learning systems to work out and organize suitable instructional contents based on the knowledge elements, such as the difficulty levels and the topic categories of the knowledge elements. However, such a formulation is not comprehensive enough.

The main concerns of various studies on learning path construction include how to generate the learning contents for each UOL, how to design the UOL to support different forms of learning activities, and how to identify the relationships among UOLs and delivery them in sequence. Our research focus on providing an intelligent tutoring system to construct learning path which can pedagogically design teaching strategies based on learning outcomes, generate learning resources adaptive to different students, and analyse student learning progress in terms of their performance related attributes as well as non-performance related attributes. During the learning process of each UOL, we need to monitor student learning progress and evaluate student learning performance, so that we will be able to construct the best learning paths for different types of students according to their learning abilities and preferences, etc.

1.2. Definition

Before clarifying the motivation of this research, I would like to introduce some terminologies, which are all very important concepts of this research. This research improves the **e-Learning** systems and aims to help students achieve their **learning outcomes**. We generate **learning resources** and construct **learning paths** based on **learning activities** to provide them what to learn and how to learn. We also measure their **learning progress** to provide more details about student learning to guarantee their learning qualities.

1.2.1.e-Learning

e-Learning aims to support learning and teaching, transfer knowledge and skills through web and electronic machines . e-Learning techniques provide various forms of electronic tools and platforms, teaching and learning approaches, learning environments, etc. Current research in e-Learning mainly focuses on several broad aspects, such as *technology enhanced learning*, *learning resource organization and standardization*, and *e-Learning platforms and tools*. *Technology enhanced learning* [Wang05] is technology-based learning and instructional systems, where students acquire skills or knowledge with the help of teachers, learning support tools, and technological resources. Technology enhanced learning investigates the use of information and communication technologies to help students learn effectively through a course of study by pedagogically making learning contents more accessible and providing students with better learning environments. *Learning resource organization and standardization* [Totk04] design models for organizing learning contents, so that the contents can be easily adopted by different e-Learning systems and reused in various instructional contexts. On the other hand, *e-Learning platforms and tools* [Dagg07], also known as Virtual Learning Environments (VLE), use a mix of communication technologies and focus on the design and development of the hardware and software components of e-Learning systems over Web 2.0 for two-way interaction. *Adaptive e-Learning methods* [Jere10] tend to find out an effective way to guide students to learn according to students' interests, so that the learning process could be adjusted for different students.

1.2.2.Learning Outcomes

Learning outcomes explain what students are expected to achieve at the end of a period of learning, which are expressed by the level of competence to be obtained by the students [Wage08]. Learning outcomes are measurable, so that they could be used to measure student learning performance, which could be cognitive, skill-based, and affective learning outcomes. Learning outcomes are always being defined by descriptive verbs [Nash]. For example, to define the terms, to compare the two ideas, to compute the possibility, etc. Learning outcomes are set to be the criteria of assessing student learning performance. Subject-specific knowledge and skills, and generic skills could be used to measure learning outcomes by assessing formative or summative assignments or examinations. For example, students are expected to describe/explain knowledge concepts and reach some knowledge levels [Chen05, Guzm07], to apply research skills [Mitr01, Feng09], or to develop some learning behaviors [Gres10]. However, learning outcomes in this work can only apply to limited aspects of learning, which cannot support different designs of learning activities and cannot be applied to different knowledge disciplines.

1.2.3. Learning Resources

Learning resources [Kara05, Meli09] refer to the structured learning materials or learning contents that can help students understand some knowledge concepts and achieve their learning outcomes. Learning resources could be represented by different types of media [Leac07], such as text, audio, or video, and are associated with attributes including knowledge domains, complexities, importance degrees, as well as the relationships among each other. These attributes of learning resources can facilitate course design that is adaptive to students [Kara05] who have different knowledge backgrounds, knowledge levels, etc. In fact, it is not easy to automatically obtain these attributes from complex and loosely connected learning contents and to use them to form well-structured learning resources. It is not enough to only identify suitable learning resources for a student. It is also necessary to provide students with the relationships among learning resources, because these relationships explain how knowledge concepts are related each other, helping students gain a better understanding and improve their learning performance.

1.2.4.Learning Activity

A learning activity is a UOL guided by certain teaching approaches based on some learning outcomes, which is used to construct teaching and learning approaches. It can be formulated in different forms to facilitate different learning environments in which different kinds of learning activities require different learning styles and different learning outcomes. During a learning activity (*LA*), a student will follow a particular teaching approach that applies to the student's own characteristics, and achieve some learning outcomes in the learning process. A learning activity is independent of learning contents, which makes the pedagogies being reused in different knowledge disciplines. The way to deliver the learning activities indicates a sequence of learning.

Existing works [Farr04, Liu05, Chen06, Hern06, Lim009] generally adopt lecturing and Q&A as learning activities. However, the situation can be complicated in practice. First, each learning activity may be very different in nature from the others, so it requires to be delivered through a different form, such as lecture, presentation, practical, etc. Also, each learning activity can be carried out through different learning modes, such as individual learning, and collaborative learning. A specific or even multiple assessment methods may be required to determine the student's learning performance. Second, in different subject disciplines, even the same type of learning activity may need a very different kind of assessment method. For example, a "practical" activity for a programming course may focus on training up the students' problem-solving and application skills, while the same activity for a piano course may focus on fingering and sight-reading. Such practical requirements are so complex that it becomes difficult to implement a learning path construction system that generically addresses all of them. This explains why most existing methods allow only lecturing and Q&A as learning activities, even though this significantly restricts their usefulness.

During a learning activity, a student can achieve some learning outcomes by learning the content of it. SCORM [Su06] and IMS Learning Design (IMS-LD) [Hern06, Amor06] are the major existing standards for designing learning path on the basis of Unit of Learning. The sequencing of SCORM controls the order, selection and delivery of a course, and organizes the UOLs into a hierarchical structure. The UOLs are actually designed based on given learning materials and only model a single student's need. However, SCORM only concerns learning contents and the sequence of UOL delivery, but not considers teaching approaches and different types of learning outcomes evolved in a UOL. IMS-LD is a data structure holding information about the UOLs and their learning outcomes. It comprises UOLs modeling what to learn, and supports UOLs modeling how to learn, based on the learning outcomes of UOLs. A UOL and its contents are separated, so that the designed UOL can be reused. However, IMS-LD needs teachers to define the pedagogical structure without given clear guidance.

1.2.5.Learning Path

Learning path (or *curriculum sequencing*) construction [Brus92] is fundamental to the education process, which comprises a series of learning activities for the student to build up certain knowledge and skills. It refers to the organization of learning activities in a proper sequence, so that students can effectively study a subject area. Different forms of learning activities can support the implementation of different teaching approaches in a learning path. Obviously, if we can adaptively produce a learning path according to a student's learning performance and preferences, it will help the student master knowledge and skills more efficiently.

There are different methods proposed for designing learning paths. Melia and Pahl [Meli09] directly generate the best learning path for different students within their Courseware Model (CM). However, the CM only allows UOLs to be organized one after another according to the student model, such that students cannot follow UOLs in parallel for learning. In practice, some UOLs are complementary to each other, where students can learn more efficiently if students can study those UOLs in parallel. In addition, the student model only considers students' initial knowledge and learning outcome. Many other critical factors, e.g., learning style, that affect students' learning preferences are not considered. Liu and Yang [Liu05] adopt an incremental approach. They first identify the key elements of a learning path (the initial, the target and the essential UOLs) and then incrementally work out the successive UOLs connecting these key elements. This method also considers asking a student to retake a UOL or to follow a re-designed learning path if necessary. Hernandez-Leo et al. [Hern06] propose a semi-automatic method that allows teachers to design the learning path based on pre-defined Collaborative Learning Flow Patterns (CLFPs), where a CLFP involves a flow of tasks. However, CLFPs do not support flexible combination of these tasks. So, if a teacher chooses a template pattern, a student has to use all the tasks included in the pattern.

1.2.6.Student Learning Progress

Student learning progress reflects the changes of student learning performance in different aspects over time, which is the process of determining the learning performance of the student according to learning outcomes [Good09]. Student learning progress not only shows how much knowledge and how well a student has learned, but also provides with the changes of the student's learning performance, which has become a popular topic over time [Mart07]. During the learning process, student learning performance is changing after a period of learning. Their learning abilities and knowledge levels may be improved or may stay as the same. It would take different efforts for different students to make the same learning progress. We need to monitor student learning progress and analyze the contributions of different factors on their learning performance.

With the help of student learning progress, teachers can design learning path [Kwas08], adjust course settings (e.g. difficulty level, updating learning contents), update student profiles, group students who have the same learning style, (e.g. it may deduce that if there are a group of students who perform better on 'Analyze' knowledge level, they are more likely to be reflective students who prefer to process information through introspection.), and also provide better instructions to students. Teaching and learning can be improved according to student learning progress which is reflected from student or course attributes.

1.3. Motivation

This section discusses about why the research of learning path construction is worth studying. The advance in the Internet and mobile technologies significantly improves the accessibility of the Web to nearly anytime and anywhere. Together with the emerging Web standards, such as HTML5, CSS3 and WebGL, the Web has become a popular platform for developing applications. Particularly, e-Learning is considered as one of the potentiality killer-applications, and comprehensive learning platforms can be easily developed by exploiting learning resources available on the Web.

The Web provides a shared workspace for students to interact and learn through cooperation, while different forms of Web-based communication technologies allow individual students to learn at their own pace [Li08]. Normally, it is not easy for a student to manage the student's study on the student's own because of lacking self-control, limited individual learning experience, especially when the student knows nothing about the course. Even if students would like to learn, they are still confused with what to learn at first and then next and not sure what they can achieve. We need a method to make students know clearly not only what to learn, but also how to learn and how to improve.

Internet also provides a lot of useful Web resources that can be freely obtained from authenticated Websites, such as Wikipedia, BBC, Reuters, etc., where the contents, quality and presentation styles can be guaranteed and suitable for learning. If these Web resources can be converted to well-structured learning resources which have relationships in between and contain attributes as the criteria to select suitable learning resources, then we can automatically generate the knowledge structure on the basis of the learning resources. The knowledge structure builds up the relationships of the knowledge concepts as well as the relationships of learning resources.

During the learning process guided by the learning path, students are making progress to obtain more knowledge as well as improving their learning abilities. It is necessary to monitor what they have achieved and analyze which factors would affect their learning progress, so that they can provide the information to further manage their learning. However, it is not easy for a teacher to design learning activities for different students, especially there are too many factors that may affect their learning qualities. Monitoring student learning progress help us analyze how an attribute affects a student's learning performance on another attribute. Students can understand their own learning performance and how to improve. On the other hand, teachers can adjust their teaching approaches. Both parties can identify main parameters that affect student learning progress and their developments in different attributes.

1.4. Challenges

The discussion in the last section motivated us to do the research of learning path construction, but there are some challenges need to be solved. This section discusses about the technical problems that we need to address. Though a lot of novel ideas in this area have been proposed in recent years, learning path construction and student progress measurement are still having some problems.

(1) **Appropriate learning resources**. In order to help students achieve their learning outcomes, they are required to study corresponding learning resources. Although it will be straightaway to acquire suitable learning resources from authentic institute, or to create them by designers, it is either expensive or very time consuming. These ways can only acquire limited resources, and sometimes, the learning resources are out of date. In order to save teachers' efforts, it is necessary to automatically generate learning resources. There are plenty of Web resources that can be obtained from authenticated Web sites and also can help students achieve their learning outcomes. We can directly use them rather than manually create learning contents. However, these Web resources are lack of correlations in between.

In order to find out their relationships and to generate a well-structured knowledge model with these Web resources, we still need to identify the attributes of each piece of learning resource including its knowledge domain, importance degree, correlation with a topic, and complexity.

(2) **Appropriate learning approaches.** The way to deliver knowledge elements indicates the way of how to learn by organizing learning activities into a learning path. Existing learning path generation methods [Chen06, Farr04, Kara05, Liu05, Lim009] mainly focus on the mechanism to produce the entire structure of a learning path. They use students' mastery of the prior knowledge and certain UOL selection constraints, such as mandatory UOLs, duration of study, or student learning preference, as the criteria to select suitable UOLs. Pedagogically, existing learning path generation methods only cope with part of learning needs. They do not properly consider teaching approaches, which are related to the way that a UOL is delivered and the type of activity that may help a student learn a UOL effectively, and types of assessments, which are related to the skills that the student needs to acquire. These deficiencies affect the quality of the constructed learning paths in terms of the effectiveness of knowledge dissemination and the precision in assessing the student's learning performance.

Because students are assessed depending on different learning outcomes required by courses, the designing, managing, delivering, and organizing learning activities should be carried out based on the learning outcomes. Constructing learning path involves three issues: (1) setting up the learning outcomes of the learning activities in the learning path; (2) designing and managing learning activities; and (3) how to deliver or organize learning activities. In order to design and manage learning activities, existing works, such as, SCORM [Su06], IMS Learning Design (IMS-LD) [Hern06, Amor06], and Learning Object Meta-data (LOM) [Neve02, Chan04], generate the whole structure of learning activities which are designed in terms of specific different learning contents or teaching approaches, rather than being designed in terms of the learning outcomes that are independent of subjects. And also, these specifications fail to involve a feasible assessment that can apply to different subjects and different forms of learning activities. In order to deliver learning activities, technologies like [Kazi04, Su06] come with a hierarchical structure, and require teachers to pre-define rules to control the sequence, selection, or prerequisite of learning activities. Technologies acting like containers to define how different types of information, such as learning outcome, activities, resources, can be put together and control the workflow of their delivery. However, they do not provide facilities helping teachers work out how the students can be assessed in terms of learning outcomes, and how a teacher delivers a course in terms of teaching approaches.

(3) **Guarantee student learning quality.** In order to measure student learning progress, other existing work usually identifies student learning progress by scoring subject specific attributes or by determining status about task completion, which are too simple to suggest how teaching and learning approaches can be adjusted for improving student learning performance. As there are too many student attributes, it is impossible to consider all of them, and it is not practical to integrate all attributes to fit any kind of progress analysis. Designers can set some learning outcomes in each learning activity for students to achieve and gain knowledge and skills. However, it is not easy to automatically generate the test to evaluate students' understanding according to their tailored learning resources, which can make sure students master the knowledge or skills during the process.

1.5. Research Objectives

In order to address the challenges discussed above, we need to achieve the following research objectives. In this thesis, we focus on constructing the representation of learning path as well as its generation to assess, guide, and analyze students learning progress, which shows them what to learn and how to learn. We show our research objectives as follows.

- To design the learning activities based on learning outcomes as the UOLs of a learning path, to evaluate student learning performance by both subject-specific and generic skills, in this way we can provide more comprehensive guidance of student progress. Also, to explicitly formulate the setting of pedagogy and learning outcomes, so that the learning activities are adjustable, fine-grained, and can adapt to different teaching approaches, and also offer a formal definition of the way to deliver learning activities.

- To select the most appropriate learning resources for personalized learning path, and show the way of how to learn these learning resources in a proper sequence, so that we can meet the needs of different types of students according to their learning preferences, learning abilities, and knowledge backgrounds, etc. Especially, to adaptively update the learning path, we also need a test generation scheme to automatically generate tests according to the contents of learning resources, so that we can evaluate students' learning performance and deliver them with the best learning resources that fit their learning abilities.
- To monitor student learning progress on various aspects including performance and non-performance related aspects, analyze the causal relationships of these aspects and how these attributes affect student learning performance, so that we can easily manage student learning progress, help teachers modify teaching approaches, and help students improve their learning qualities. And also, we need to evaluate students' achievements to see if they can have a balanced development on all required student attributes.

1.6. Contributions

In brief, I have made three major contributions in this thesis in order to achieve these research objectives.

- In order to find out the learning approaches and answer the research question of how to learn, we have developed a fine-grained outcome-based learning path model that allows learning activities and the assessment criteria of their learning outcomes to be explicitly formulated by the Bloom's Taxonomy [Bloo56, Bloom]. Hence, provided with different forms of learning activities, pedagogy can be explicitly defined and reused. Our model can also support the assessment of learning outcomes related to both subject-specific and generic skills, providing more comprehensive student learning progress guidance and evaluation.

- In order to find out the appropriate learning resources to construct the learning path, loosely connected Web resources obtained from the Web have been formed to well-structured learning resources based on Association Links Network (ALN) to construct a teacher knowledge model (TKM) [Mish06] for a course and generate the personalized learning path to help students achieve higher master level of knowledge. Our model automatically constructs the learning path in three different abstraction levels of ALNs, i.e. topic, keyword, and learning resource ALNs, which allows students to understand the relationships between learning resources through the three abstraction levels, and helps students minimize their cognitive workloads. On the basis of a learning resource retrieved from the TKM, we automatically construct a test to assess students' understanding based on a test generation scheme which saves teachers a lot of efforts.
- In order to answer the research question of how well students have learned, we propose a set of Fuzzy Cognitive Map-based student progress indicators. We can monitor student learning performance and analyze the factors that affect student learning performance and comprehensively describe student learning progress on various aspects together with their causal relationship. Our model is based on student learning performance related attributes (PAs) as well as non-performance related attributes (NPAs) to model student learning performance and their potentialities to make progress.

1.7. Organization

The rest of the thesis is structured as follows: Chapter 2 introduces how the existing works address current problems related to learning path construction and student progress measurement. Chapter 3 introduces the methodologies that we applied in the research. Chapter 4-6 describe the main approaches carried out in this research study: Chapter 4 describes the method of how we design the fine-grained learning outcome based learning path; Chapter 5 describes the ALN-based Learning path generation method; Chapter 6 describes the method of how we measure student learning progress and how teachers and students can apply it to aid the teaching and learning. And finally, chapter 7 is the conclusion of this research study and states the future work.

Chapter 2

2.Background

This chapter presents the background of this research. Recently, various work [Farr04, Liu05, Chen06, Hern06, Lim009] have been conducted to study learning path construction. In their formulations, they generally use lecture type of UOLs to form the knowledge elements of a learning path, where student learning performance is assessed by Q&A. They also identify the relationships of these UOLs, i.e. identify the learning sequence of these UOLs. On the other hand, the learning resources decide what to learn in the learning path. It is necessary to select appropriate learning resources as well as their relationships to form the learning path. In order to update teaching approaches including the learning contents and learning sequence according to student learning performance, then we discuss how existing works monitor and analyze student learning progress. We will discuss about more specific literature research that relates to the three research challenges in section 4.2, 5.2, and 6.2, respectively.

Our research study is supported by some mathematical models and theories in Education. We discuss them in the following subsections to introduce the background of this research. Section 2.1 shows the learning theory which is the foundation of our e-Learning research. Because this research can apply to e-Learning systems, we introduce different types of learning as well as different types of e-Learning in section 2.2. Besides, what to learn is based on the learning outcomes, in section 2.3, we introduce the learning taxonomy that is the foundation of learning outcomes. Different students would have different learning preferences and learning behaviors, in section 2.4, we discuss the learning styles that explain why the differences of students are so important. Section 2.5 introduces the learning modes that show the different participant methods during the learning process. We use different assessment approaches to assess student learning performance, so we explain how student assessment carried out in previous work in section 2.6. We also measure student learning progress to control the learning process, and section 2.7 discusses how to show student learning progress using performance inference algorithm. As we apply Association Link Network to construct learning resources, section 2.8 introduces the Association Link Network which is used to semantically construct the knowledge structure. Section 2.9 introduces all the platforms, libraries, and implementations that are used to design the software in this research. And section 2.10 summarizes the background of this research.

2.1. Learning Theory

Learning theory [Band77] is the foundation of this research, which supports all the learning processes, and is used to guide the design of learning systems. Learning theory describes how information is absorbed, processed, and retained during the learning process. There are three main categories of learning theory including behaviorism, cognitivism, and constructivism. Behaviorism focuses on achieving the objectively observable behavior by repetition of desired actions. Cognitivism looks beyond behavior to explain how the learning happened in our brain. Constructivism views learning as a process in which a student actively constructs or builds new ideas or concepts. Our research is developed based on the constructivism learning theory. Constructivism learning theory [Coop04, Fran06] requires students to construct knowledge in their own meaning, to build up knowledge concepts based on prior knowledge and their experience, to enhance their learning through social interaction, and to develop learning through authentic tasks. During Constructivism learning, students achieve learning outcomes by attempting to address problems when they find their expectations are not met, so they need to resolve the discrepancy between what they expected and what they encountered [Lefo98].

In the learning theory of constructivism, each student is considered as an unique individual with personalized needs, learning styles, learning preferences, knowledge levels and knowledge backgrounds, which is complexity and multi-dimensional. During a typical constructivist session [Coop04], students work on problems, and teachers only intervenes them to guide them in the right direction. Students could provide different responses to learning, e.g. they are involved in an active learning process, they are using critical thinking to challenge, judge knowledge, and learn from it. Under the learning theory, teaching approaches are designed according to these learning outcomes. With the help of techniques in e-Learning, the learning process, which emphasizes that knowledge is shared between teachers and students, does not focus on the teacher-centered learning environment, but put more emphasizes on self-paced learning by providing access to education at any time, any place and taking into account students' differences.

2.2. e-Learning

This research of Learning path construction and the analysis of student learning progress are concerned with learning using electronic devices and Web. We discuss different types of learning and different types of e-Learning systems in this section to help reader better understand how the learning is carrying out, and more specifically, how the e-Learning is carrying out.

2.2.1. Types of Learning

Learning has gone through several stages where learning is traditionally supported by face-to-face teaching, and now with the help of communication and information technologies, new forms of learning, such as Web-based learning, have been developed. However, traditional learning does not allow students to learn at any time and at any place, and web-based learning lacks of interaction between teachers and students. Blended learning is developed by combining the traditional learning and web-based learning to provide a better learning approach. Our research can be applied to both web-based learning and blended learning by providing a user-friendly intelligent tutoring system to construct learning path as well as to analyze student learning progress.

Traditional learning

Traditional learning is teacher-centered learning, where teachers interact with students face-to-face in classroom. Traditional learning focuses on teaching, not learning. The knowledge taught in traditional education can be used in instructional design, but cannot be used in complex problem solving practices. It simply assumes that what a student has learned is what a teacher has taught, which is not correct in most cases.

Web-based learning

Web-based learning is self-paced learning, which requires students to access Internet via devices like computers. The learning is beyond traditional learning methodology. Instead of asking students to attending courses and reading printed learning materials, students can acquire knowledge and skills through an environment which makes learning more convenient without spatial and temporal requirements. Web-based learning applications consider the integration of user interface design with instructional design and also the development of the evaluation to improve the overall quality of Web-based learning environment [Chan07]. Web-based learning is different from the term of Computer-based learning, which also uses devices like computers, but does not have to require students to access to Internet during the learning process.

Blended learning

Blended learning combines traditional learning with computer-based learning, which creates a more integrated e-Learning approach for both teachers and students. The aim of blending learning is to provide practical opportunities for students and teachers to make learning independent as well as sustainable. There are 3 parameters should be considered in a blended learning course, which are *the analysis of the competencies*, *the nature and location of the students*, and *the learning resources*. Also, blended learning can be applied to the integration of e-Learning with a Learning Management System using computers in a traditional classroom with face-to-face instruction.

2.2.2.Types of e-Learning

With the help of technologies and electronic media, e-Learning makes the teaching and learning more effectively. Teaching and learning could be approached at any time and any place. e-Learning systems have actually been well developed and have different types including traditional e-Learning system, Adaptive e-Learning system, intelligent tutoring system, and service-oriented e-Learning system. Traditional e-Learning [Dagg07] has simplex design which fails to provide more flexible ways of learning, such as personalized learning, active learning, and online interactions between teachers and students. Adaptive e-Learning [Shut03] focuses on student characteristics, such learning style, knowledge background, learning preferences, etc., which makes the learning to be applied to different teaching approaches for different types of students. Instructional design system [Gust02] contains 5 phases of *Analyze, Design, Develop, Implement,* and *Evaluate*, which aims to determine student learning states, define learning outcomes, and provide teaching strategies. Intelligent tutoring system [Murr03] does not only focus on the sequencing mechanisms of curriculum delivery, so that students know how to learn rather than just what to learn, but also applies AI to customize teaching approaches according to student's needs in order to optimize learning of domain concepts and problem solving skill. Service oriented e-Learning [Jamu09, Su07] provides with different Web services, so that both teachers and students can access the e-Learning system and use different functionalities. We briefly introduce them as follows.

Traditional e-Learning System

Traditional e-Learning separates teachers from students and also separates students from students, the teaching and learning carry out over the Internet or through computer-based technologies [Stiu10]. Traditional e-Learning cannot provide adaptive learning technologies, which needs a team that has advanced skills, such as programming, graphic design, or instructional design to improve the learning system, and requires course creator to create graphics, simulations, and animations. Teacher also needs to design learning contents for constructing courses. Learning management system (LMS) [Brus04] is an integrated traditional e-Learning system that supports a number of learning activities performed by teachers and students during the e-Learning process. LMS aims to deliver online courses to students, and try to keep students' learning progress on the right track, but LMS is not used to create learning contents. Students can use it for learning, communication and collaboration.

Adaptive e-Learning System

Students have different knowledge backgrounds, knowledge levels, learning styles, learning preferences, and also different misunderstandings and learning outcomes, etc. It will become a very huge work for teachers to design the learning contents and the learning activities, and to provide with different teaching approaches and different feedbacks. The e-Learning system is considered adaptive [Jere10] if it follows student behaviors as well as interprets them, makes conclusions about students' requirements and their similarities, adequately represents them, and finally impacts students with the available knowledge and dynamically manage the learning process. Adaptive e-Learning system has the adaptability towards students' needs, the reusability of learning activities, and effective design of learning contents. Our research can be applied to adaptive e-Learning system as our research also constructs learning resources for different types of students, and designs learning paths to support different teaching approaches.

Instructional Design System

Instructional design system is a system of determining student learning state, defining the learning outcomes, and also providing teaching strategies for knowledge transition, which aims to improve learning performance [Reis01]. Instructional design is learner-centered which focuses on current learning states, needs, and learning outcomes of students. The learning outcomes of instructional design reflect students' expectations for the learning, which expect students having the ability of applying knowledge or skill in some learning environments.

The procedure of developing instructional materials provides us the guidance and requirements of designing a qualified e-Learning system. The typical instructional design system [Gust02] includes five phases including *Analyze, Design, Develop, Implement,* and *Evaluate*. *Analyze* phase requires teachers to collect information about students, learning tasks, and learning outcomes, and then classify the information to make learning contents more applicable. *Design* phase composes the expected learning outcomes and corresponding tests through learning tasks. *Develop* phase generates learning contents based on the learning outcomes. *Implement* phase refers to how to deliver the instructions for students to learn. *Evaluate* phase ensures that the learning contents can achieve the learning outcomes through both summative and formative assessments.

Intelligent Tutoring System

Intelligent e-Learning system brings the artificial intelligence (AI) technology to the current e-Learning system together and products a personalized, adaptive, and intelligent service to both teachers and students. Intelligent tutoring systems (ITS) use AI to customize teaching approaches according to student's needs, which is trying to optimize learning of domain concepts and problem solving skill. Our research can also be applied to ITS, because the proposed work provides adaptive teaching approaches, personalized learning resources, and intelligent student progress indicators. ITS [Murr03] are computer-based instructional systems, with instructional contents organized in the form of learning activities that specify *what to teach*, and teaching approaches that specify *how to teach*. They make inferences on student learning progress and offer instructional contents and styles of instruction adaptively. Instructional contents can be broadly categorized into two main types [Bigg07]: declarative knowledge, i.e., facts or concepts, and functioning (procedural) knowledge, i.e., how something works. Early ITSs, such as SCHOLAR [Carb70a], focus only on the modeling of declarative knowledge, and cannot properly support the training of procedural and problem solving skills. Newer ITSs, such as DNA [Shut98], incorporate the modeling of functioning knowledge to address this issue.

To identify a suitable teaching approach, an ITS should understand the learning progress of a student and, more ideally, consider student learning styles [Feld88, Li10] as well. In existing ITSs, such student information is commonly maintained as a *student model* [Elso93, Brus07] and updated by some *inference algorithms* [Cona02, Chen06]. Traditionally, the student model is typically formulated in the form of a *knowledge model* [Carb70b, Brow78] to maintain the set of learning activities that a student studies. Student learning progress is then evaluated by checking the portion of expert knowledge that a student has acquired. However, this model fails to formulate errors or misunderstandings made by the student. To address this problem, the bug-based model [Brow78] is proposed, which applies rules to determine the difference between the expected and the actual ways to be used for problem solving when studying a piece of knowledge. This model essentially evaluates the problems in understanding made by a student. On top of the student model, inference algorithms are applied to determine or predict the student learning performance over a course of study based on some probability information. Popular choices of inference algorithms are the *Bayesian networks* [Cona02], which perform inferences based on some pre-condition information, particularly the previous learning performance of students, and the *item response theory* [Chen06], which performs inferences based on the probability information of the responses made by students when conducting certain assessments.

Service-oriented e-Learning System

Service-Oriented system for e-Learning describes a concept of e-Learning framework which supports e-Learning applications, platforms, or other service-oriented architectures. Service-oriented e-Learning system [Jamu09, Su07] provides web services, such as assessment, grading, marking, course management, metadata, registration, and reporting, etc., in order to produce more functionalities for the e-Learning system. It aims to produce reliable Web services that can be applied to different operation systems. Users can access these services through the Web. While our research supports such an e-Learning platform where teachers can design and manage adaptive learning paths, personalized learning resources can be generated for each student, and also student progress can be graphically presented.

2.3. Learning Taxonomy

Learning taxonomy provides the criteria of assessing student learning performance to see if students can achieve their learning outcomes. Learning outcomes are learning objectives that students are expected to achieve at the end of learning, which could be cognitive, skill-based, and affective learning outcomes. Learning taxonomy [Full07] includes three domains, *cognitive, affective,* and *psychomotor*, where each domain evaluates learning outcomes in several levels. Learning taxonomy guides teachers to design courses on the basis of achieving these learning outcomes as well. The most common learning taxonomy is Bloom's Taxonomy which we have applied in this thesis. Because it can assess knowledge, attitude, and skills, it can be applied to all disciplines. There are also some other learning taxonomies slightly different from it, such as Gagne's taxonomy, SOLO taxonomy, and Finks taxonomy. Gagen's taxonomy does not only covers the 3 categories of Bloom's taxonomy, but also involve another 2 categories of verbal information, intellectual skills. SOLO taxonomy divides learning outcomes by 5 learning stages rather than independent categories. And Finks taxonomy considers learning as a cycle consisted of 6 aspects. We introduce each of them as follows.

2.3.1. Bloom's Taxonomy

Bloom's Taxonomy [Benj56] provides the criteria for assessments of learning outcomes which could be classified into three domains of knowledge, attitude, and skills, in this way it could be applied to all kinds of subjects. A learning activity should have its own learning outcomes, such as the knowledge level, etc. Students can develop their knowledge and intellect in Cognitive Domain, attitudes and beliefs in Affective Domain, and the abilities to put physical and bodily skills to act in Psychomotor Domain.

The *Cognitive* domain refers to intellectual capability, such as knowledge, or think, which has 6 levels from easy to difficulty including Recall data, Understand, Apply, Analyze, Synthesize, and Evaluation. The *Affective* domain refers to students' feelings, emotions, and behavior, such as attitude or feel, which has 5 levels from easy to difficulty including Receive, Responding, Value, Organization, and Internalize. The *Psychomotor* domain also has 5 levels from easy to difficulty including Imitation, Manipulation, Develop Precision, Articulation, and Naturalization. The Psychomotor domain refers to manual and physical skills, such as skills or do, which was ostensibly established to address skills development relating to manual tasks and physical movement. However, it also concerns and covers business and social skills such as communications and operation IT equipment, for example, public speaking. Thus, Psychomotor extends beyond the originally traditionally imagined manual and physical skills.

2.3.2.Gagne's Taxonomy

The learning outcomes of Gagne's taxonomy [Gagn72] is similar to Bloom's taxonomy. However Gagne's taxonomy divides learning outcomes into five categories, which are verbal information, intellectual skills, cognitive strategies, attitudes, and motor skill. Verbal information is the organized knowledge including *labels and facts* and *bodies of knowledge*. Intellectual skills refer to knowing how to do something including discrimination, concrete concept, rule using, and problem solving. Cognitive strategy is the approach where students control their own ways of thinking and learning. Attitude is an internal state which affects an individual's choice of action in terms of a certain object, person, or event. Motor skills refer to bodily movements involving muscular activity, including the learning outcome to make precise, smooth, and accurately performances with muscle movements. The learning outcomes are normally dependent on each other. There are always combined learning outcomes selected for completing a task.

2.3.3. SOLO Taxonomy

The SOLO taxonomy [Bigg07] stands for Structure of Observed Learning Outcomes, which describes the level of a student's understanding of a subject through five stages, and it is able to be used to any subject area. The first stage is *Pre-structure* where students just acquire no structured information. The second stage is *Uni-structural* where students capture simple and obvious aspects of the subject, but they still have not understood significant aspects. The third stage is *Multi-structural* where students make a number of relevant independent aspects but cannot connect them. The fourth stage is *Relational* where students are able to identify the most important parts of the whole structure. The fifth stage is *Extended Abstract* where students can generalize another new application based on the structure constructed in the *Relational* stage. The SOLO taxonomy is similar to the cognitive domain in the Bloom's taxonomy, which can be used not only in the assessment, but also in designing the curriculum in terms of the learning outcomes.

2.3.4. Finks Taxonomy

Finks Taxonomy [Fink03, Fink09] is different from Bloom's Taxonomy and SOLO Taxonomy, which taxonomy is not hierarchical. It covers broader cross-domains, which emphasizes on learning how to learn and includes more affective aspects. The learning process has 6 aspects in a cycle including foundation knowledge, application, integration, human dimensions, caring, and learning how to learn. In the aspect of foundational knowledge, students understand and remember knowledge. In the aspect of application, students train up skills of critical thinking, creative and practical thinking, and problem solving skill. In the aspect of integration, students make connections among ideas, subjects, and facts. In the aspect of human dimensions, students learn and change themselves, understand and interact with others. In the aspect of caring, students identify and change their feelings, interests, and values. In the aspect of learning to learn, students learn how to ask and answer questions, and become self-directed students.

2.3.5.Subsection Summary

We apply Bloom's taxonomy as the learning outcomes in our research. There are also a lot of works on Bloom's taxonomy. [Naps02] applies Bloom's taxonomy [Benj56] as well as other factors: student learning progress, drop-out rate, learning time and student satisfaction. [Lim009] only chooses three out of the six levels: knowledge, application and evaluation, as the evaluation criteria. However, these evaluation methods still could not instantly tell students how to improve. Also, some works [Chen05, Dolo08, Yuen05, Yuan05, and Con005] consider student's ability as performance evaluation. [Chen05] evaluates student abilities based on the student's response to the recommended learning activity and modifies the difficulty levels of all learning activities which are considered as index to rank learning activities in order to update learning paths. However, a student's ability is just given by a single value. In [Dolo08], a student's abilities just limits to programming in Java or .NET, which cannot be applied to all situations. According to the research [Yuen05] on learning abilities for evaluating student learning performance, it classifies these learning abilities into eight aspects: leadership, critical thinking, value-based decision making, logical reasoning, problem solving, oral communication skills, written communication skills, and lifelong learning. Each aspect contains several sub-aspects and making 74 sub-aspects in total. However, according to the research of Psychology [Bart32], human abilities are divided into three groups: language, action and thought with 22 sub-attributes in total. We found that there are some attributes that [Yuan05] does not consider about, such as imagination, while there are some attributes in Psychology are not suitable to apply to general e-Learning, such as speed, strength of power in the action group. Besides, [Con005] also distributes different ability requirements to learning tasks including too many skills (38 skills) without classification, and some of them are overlapped.

2.4.Learning Styles

Our work has developed learning progress indicators which addressed the needs of students with different learning styles. When we assess student learning progress, we expect students to handle different learning environments. If students can well perform different learning activities, they have the ability to handle different learning environments and have a balanced development. A learning style model classifies students according to their behaviour patterns of receiving and processing information. Teaching style model classifies instructional methods according to how well they address the proposed learning style components.

According to the research of [Feld88], learning style contains five aspects. From the viewpoint of which type of information students prefer to perceive, there are sensors who prefer to solve problems using standard methods rather than unconventional methods, and intuitors who prefer to use innovated methods rather than repetition. From the viewpoint of through which sensory channel external information most effectively perceived is, there are visual students who are sensitive to diagrams and graphs, and auditory students who are sensitive to words and sounds. From the viewpoint of which information organization students are most comfortable with, there are inductive students who are sensitive when given facts and observations, and underlying principles are inferred. Deductive students are sensitive when given principles and consequences and applications are deduced. From the point of view that how students prefer to process information, there are active students who prefer engagement in physical activity or discussion, or reflective students who prefer introspection. From the point of view that how students progress toward understanding, there are sequential students who learn in continual steps, and global students who learn gradually from the whole knowledge structure to more detailed concepts.

2.5. Learning Modes

In this thesis, we use different learning modes to design teaching approaches for different aims of training students. The learning has various forms, which does not only support individual learning but also support collaborative learning. In our research, we also need to use different forms of learning to construct different teaching approaches. Individual learning help students train them to solve problems on their own, and collaborative learning help students train them teamwork spirit. The most commonly way of learning is work individually. Students have to work on their own to solve problems and reach the learning outcomes. Collaborative learning is a type of learning in which two or more people learn something together, where students can make use of peer's learning resources and skills. Collaborative learning includes collaborative writing, group projects, joint problem solving, debates, study teams, and other learning activities. Collaborative learning uses technology to define rules and roles, construct learning tasks, control and monitor the learning process, and support group interactions in a collaborative learning environment.

2.6. Student Assessment

As the aim of learning is to achieve learning outcomes, the learning path is constructed based on learning outcomes. In order to determine if students have achieved their learning outcomes, we need to assess their learning performance. Student assessment measures the level of student achievement on knowledge and abilities. The form of student assessment can be summative or formative [Osca11]. Information about student learning progress needs to be collected before, during and after learning some learning activities [Feng09, Osca11]. Student learning progress can be expressed as growth rate [Stec08, Bete09] and overall improvement [Pets11]. In addition, prediction on student's future learning performance [Hanu05, Wiel10] can also be done. A teacher may review and enhance teaching approaches based on student learning progress [Stec05, Stec08].

By tracking student learning progress and evaluating student learning performance, we can guide students to approach the most appropriate learning activities as well as to help them improve their learning performance, and reach the learning outcomes in the end. Based on previous work, learning outcomes are given by ranks [Good09, Ma00], scores [Yang05, Liu05, and Kwas08], or feedback [Leuon07, Guzm07], according to different criteria, such as the levels of acquired knowledge [Good09, Leun07], the spending time and efforts [Good09], the number of correct questions [Chen08] with tests or questionnaires, or learning abilities of students [Dolo08, Leun07, Chen05].

Although [Leuon07] can provide an instant feedback on student learning performance, the feedback can only tell if we should provide students the optional materials. In [Huan07], a student knows his/her misconceptions in solving a problem and the student's weak learning activities from a global test. However, this information is not enough to know the student's learning progress and cannot help the student improve his/her learning performance. In [Ma00], the evaluation results would always be divided to several fuzzy grades from the "best" grade to the "worst" grade, and examples of fuzzy grades include "good", "pass", "fail", etc. Even if a student performs better than the course expectation, the student would still fail as long as the student is worse than the majority of students. In [Chen05], the evaluation tests student's satisfaction on the learning path. However, this work cannot promise the student to reach the learning outcome. [Guzm07] provides a self-assessment test which can rectify misconceptions and enhance acquired knowledge. With a student's knowledge distribution model, the selected evaluation criteria determines questions and computes the expected variance of the student's posterior knowledge distribution. The test results provide an estimation of the student's knowledge level which is the minimum expected posterior variance. As they need to calculate the correct possibility and the incorrect possibility of a question, the answer has to be either true or false, but these results are too limited for the most types of questions. In short, these methods only consider if students can correctly understand knowledge in one way or another, but they ignore the assessment of balanced developments of students' knowledge and learning abilities.

Existing works [Huan07, Chen08, and Cola10] have developed ways to collectively model the students' understanding on knowledge. [Huan07] requires teachers to manually plan two formative assessments for each UOL, and a summative assessment in the end of a learning path. The two formative assessments cover the same knowledge using different questions. The 1st formative assessment calculates students' scores and analyzes their learning situations. The 2nd formative assessment ensures students understanding the concepts rather than memorizing the answers. In [Chen08], questions are manually designed by teachers based on the course materials and stored in the question database. Questions are randomly selected from the database to generate a pre-test. The incorrect test results are used to select suitable courseware to plan the learning path. However, these methods require teachers to manually design the test, then [Cola10] provides an automatic method to measure student learning performance by the Bayesian approach which selects a set of questions associated with every network node to identify if a student can correctly form the knowledge concepts. However, these questions just focus on each single node, which cannot reflect if students can correctly build up the relationships between them.

2.7. Performance Inference Algorithms

As we need to analyze student learning progress by inferring how the learning progress is changing over particular aspect(s) of student attributes, we can find out the reason how to help students improve efficiently. Previous works [Chen05, Lynn09, Gres10, and Feng09] have qualified student learning performance with different inference algorithms. Normally, people assess students with a set of questions, then the performance is the evaluation results on these questions. But the difference is that they focus on different aspects to evaluate student learning performance. Item Response Theory (IRT) [Chen05] is the function of student ability based on major fields and subjects, which gives the probability that a student would have correct answers with a given ability level. Goal Attainment Scale (GAS) [Lynn09] is the function of a combination of attained goals and involves the expected correlation of the goal scales to make it adjustable. Change-Sensitive Rating Scale (CSRS) [Gres10] evaluates student learning progress with a rating scale on a set of social behaviors including social skills (e.g. cooperate with peers) and competing problem behaviors (e.g. disruptive classroom behaviors). It focuses on computing the mean changes of student behaviors from the initial learning performance to post-treatment. An item is change-sensitive when the magnitude of change is larger than a threshold. [Feng09] presents that an individual student learning progress on subject related skills changes over time with a linear mixed-effect logistic regression model. This model is to compute the probability that an individual student gives a correct answer at an opportunity of answering a question. It is the linear function of the effects caused by two learning parameters: one is how good the student's initial knowledge is, the other is the student's change rate of his/her learning progress.

Because the performance on some concepts/attributes may depend on the performance of some other concepts/attributes, more intelligent algorithms are required to represent the causal relationships among those concepts/attributes and find out the main attributes that affect the learning progress. Which concepts or attributes are chosen for evaluation depends on the types of learning outcomes defined in the work. If the learning outcomes are just to achieve more knowledge, they may need to infer the causal relationships of concepts. If the learning outcomes are to achieve some student attributes, such as some kinds of learning abilities, then they need to infer the causal relationships of attributes. There are six popular algorithms that can structure the concepts/attributes in a graph:

- The *expert system* [Stud98, Hatz10] represents relationships between concepts in a tree structure where the top node of the tree indicates the goal knowledge, and the nodes on leaves indicate the rules. Goal knowledge is then inferred after several rule decisions.

- The *Bayesian Network model* [Dieg00, Garc07, Cola10] organizes the knowledge representations in a directed acyclic graphical, and the nodes in the model are conditional dependencies. They normally consider knowledge nodes or questions as the network nodes, and then infer the causal relationship among them. [Cola10] applies *Bayesian network* to infer student learning performance, where questions are treated as the network nodes. *Bayesian analysis* measures the percentage of correct answers as well as incorrect answers in a subject, which supports for the measurement of crossentropy to quantify the dependency weight between the questions. Although Bayesian network can infer the casual relationship among knowledge nodes, the inferred knowledge node cannot reflect back to previous knowledge nodes. They cannot be formed in a cyclic structure.

- The *Markov random field* [Zhu02] represents the structure of knowledge nodes within an undirected graph which supports both cyclic and acyclic graphs, but does not support induced dependencies. And also, Non-adjacent nodes and neighbor nodes need to be conditionally independent.

- *Neural network* [Hayk99, Hatz10] infers causal relationships within a multi-layer structure, but does not support induced independence among concept nodes.

- The *Concept Maps* [Chen01, Zapa02] are connected with labeled arrows in a downward-branching hierarchical structure, which is an acyclic structure. The relationships between concepts show relationship like 'results in', "contributes to", or "is required by", etc.

- *Fuzzy Cognitive Map (FCM):* As the structure is expected to reflect the causal relationships among knowledge nodes, the structure should be directed because one node is likely to affect other nodes or being affected by other nodes. On the other hand, the structure should be cyclic because some nodes may form a cycle. However, the above structures do not meet these requirements, but *Fuzzy Cognitive Map* (FCM) [Liu99, Luo10] can represent such causal connections among knowledge nodes in a directed cyclic structure. FCM is a tool to represent social scientific knowledge. It computes the impact of the nodes and describes the nodes and the relations between these nodes, in order to analyze the mutual dependencies between nodes.

FCM method has been well developed and widely used to different areas including social science, economics, robotics, computer assistant learning, etc. Some works [Tzen10, Cai06, Geor04, and Geor08] applied FCM to e-Learning in order to infer the casual relationship among a set of factors. One example is to use the criteria for decision making as the concept nodes in FCM, such as [Tzen10]. It can be used as the reasoning tool to select the goal of what to achieve and the actions of how to achieve [Cai06]. Also, some works [Geor04, Geor08] infer student learning styles through FCM, where the learning styles reflect how students conceive information and also conceive which kind of information. To connect one attribute to another, FCM needs to compute the impact between two related attributes, which can be considered as the weights of the FCM. Basically FCM methods have gone through three stages.

(1) The basic FCM [Tabe91, Geor08, Tzen10] pre-defines the weights with consistent values before applying FCM matrix to analyze the relationships among these knowledge nodes. [Geor08] asks experts to describe the causal weights among the attributes every time. Also [Tzen10] always uses a pre-defined weight matrix, while the attribute values update according to their last statuses during iteration.

(2) Also, the weights could change under different concept models, as the dependences among concepts are different. A better method that is proposed to constrain the weights is the rule based FCM [Peña07]. It uses fuzzy "If-then" rule to increase or decrease the causal weights by a fuzzy interval.

(3) Later, an automatic scheme [Luo10] has been proposed to calculate the casual weights. [Luo10] applies FCM to build up a learning guidance model for students. It combines unsupervised learning and supervised learning to iteratively acquire new knowledge from data, but it still needs initial human intervention.

Although these current works monitor student learning progress and provide assessment results, they just focus on setting the evaluation criteria and more accurate grading scheme. There is still no such a tool could analyze student learning progress, find out the relations between different attributes, and see how these attributes affect the learning progress. Actually, FCM supports such an inference scheme that can infer student learning progress about how an attribute affects the others. All possible attributes could be considered as the nodes, and the effect of one attribute on one another would be the inferred causal relationships. So that both teachers and students would not only know whether the student makes progress, but also know what can force the student to make progress. However, student attributes appear to have various changes for different students, different learning activities, or different subjects, etc. In order to come out the inner relationships among these student attributes, it is not enough to infer them by only using FCM. It is necessary to integrate some similarity and differences measurements to measure related comparison targets.

2.8. Association Link Network

In our research, we need to find out the relationships of learning resources to form the knowledge structure model which is used to support the construction of learning path. However, the relationships of learning resources depend on the semantic features of learning resources. Our work is based on Association Link Network to identify these relationships. Association Link Network (ALN) [Luo08A] is a kind of semantic link network, which is designed to establish associated relations among various resources (e.g., Web pages or documents in digital library) aiming at extending the loosely connected network (e.g., the Web) to an association-rich network. Since the theory of cognitive science considers that the associated relations can make one resource more comprehensive to users, the motivation of ALN is to organize the associated resources that are loosely distributed in the Web for effectively supporting the Web intelligent activities such as browsing, knowledge discovery and publishing, etc.

ALN using association rules between concepts to organize the resource since the term *association* is used in a very particular sense in the psycholinguistic literature. However, most subjects cannot distinguish the exact semantic relations. The associated relations between resources in ALN are implicit rather than explicit, which make ALN more appropriate for incrementally building up. The challenge of building up ALN is about how to efficiently and exactly perform the association weights of the new coming Web resources.

ALN is composed of associated links between nodes. It can be denoted by $\text{ALN} = \langle N, L \rangle$ where N is a set of Web resources (e.g., keywords, Web pages, and Web topics). *L* is a set of weighted semantic links. As a data model, ALN has the following characteristics.

1) **Associated relation-based link**. *Association relation-based link* is used in a very particular sense in the psycholinguistic literature. For example, the subjects respond more quickly than usual to the word *nurse* if it follows a highly associated word such as *doctor*. WWW uses hyperlink to interconnect Web resources for users freely browsing rather than for effective associated link. How to organize Web resources with associated relations to effectively support the Web intelligence activities becomes a challenge. ALN uses associated relations between Web resources to solve this problem.

2) **Automatic construction**. Given a huge number of resources in the Web, it is unrealistic to manually build a network. Actually, ALN is automatically built up, which makes it suitable to represent the huge number of resources.

3) **Virtualness**. ALN can be regarded as a virtual layer of Web resources, which is invisible to users. The operation of Web intelligence activities is implemented on this layer. Virtualness ensures the cross-media implementation of intelligent browsing, which clears the difficulty brought by different physical types of resources.

4) **Rich Semantics**. Each piece of Web resource is represented by E-FCM with rich semantics. The links with weights between nodes represent the associated relations between Web resources.

5) **Structuring**. By semantic computing, the disordered resources on physical Web layer are mapped to the well-structured ALN.

2.9. System Development Tools of the Research

We implement the learning path system, automatic learning resource generation system, and student performance evaluation system to demonstrate the valid of our work. To implement them, we have applied a lot of tools of programming languages, Web service, and database. For the learning path system, we use Jgraph, Ext Js, PHP, MySQL, and Apache to implement the prototype. For the automatic learning resources generation system, we use Tomcat, Web Services, and JSP to implement the prototype. And for the student performance evaluation system, we use Excel to analyze data and generate graphs. We brief introduce how we apply each of them as follows.

Jgraph

We use Jgraph to design the learning path graphs of the learning path system including its learning activities and the links between the learning activities. Jgraph (www.jgraph.com) is an open resource, Swing compatible graphics component based on MVC architecture, and written in the Java programming language. It is the component designed for graphs, which is mainly applied to applications that need to express the graphs structure, such as flow chart, network, traffic path, etc.

Ext JS

We use Ext JS (http://www.sencha.com/) to design the interface of the learning path system. Ext JS is a AJAX application written in Javascript, which is used to create interactive web applications rather than the AJAX framework. It can be applied to any application written by Java, .Net, or PHP.

PHP

In this thesis, the editing functions of each learning activity are written by PHP in the learning path system. PHP is a widely used server-side scripting language that is normally used to Web development and can be embedded into HTML. Generally, PHP run on the Web server, and generate user browsed web pages through running the PHP program. PHP can be deployed on many different servers (Apache, IIS, etc.), operation systems, and platforms (Window, Linux, Unix, etc.), and also can support many database systems, such as MySQL, Oracle, etc.

MySQL

We use MySQL to keep data of learning tasks, learning activities, learning stages, and learning path, and their relationships in the database, so that we can call them when create/change/delete them. MySQL is a database server, which supports standard SQL and can compile on a number of platforms. It is especially popularly used in web applications. Especially, phpMyAdmin is the MySQL database system management program written by PHP, which allows administrator manage MySQL database through Web port.

Apache

We use Apache as the local server to run the PHP programs in the learning path system. Apache is a C implementation of HTTP web server. Apache is the most widely used Web server software, which is an open source application and can run on all kinds of computer platforms, because of its security and cross platform. Apache also supports a lot of features, such as server-side programming language support (such as Perl, PHP, Python, etc.) and authentication schemes.

Tomcat

We use Tomcat to run the JSP program as the Web server for the learning resource generation system. Tomcat is a free open source Web application server, which provides software applications with services, such as security, data services, transaction support, load balancing, etc. It is widely used to small system where users is not too many, which is also the best selection for developing and compiling JSP program.

Different from Apache, Tomcat is an extension of Apache, which is a Java implementation of HTTP web server, and it is actually run JSP pages and Servlet. Tomcat is popular used because it takes a little system resource when running, has good augmentability, and supports the very common development and application system functions, such as the load balancing and email service, etc.

Web Services

We use Web services to connect our application program and the Web application, so that we can create a web service from the application. Web services are application components, which communicate using open protocols. The basic Web service platform is XML plus HTTP. Web service use XML to code and decode data, and use open protocols such as SOAP (Service Object Access Protocol) to transport data. Web services can convert applications to Web applications, so that we can publish, find, and use services or provide some functions all over the world through the Web.

JSP

We program the learning resource generation system by JSP (Java Server Pages) which is a kind of dynamic web page technique standard. The aim of JSP is to separate presentation logic from Servlet. JSP embeds Java servlets and JSP tag in the traditional Web page of HTML files, and forms the JSP files. The web application developed by JSP is cross-platform, which can run on different operation systems. JSP is normally executed on the server-side, and returns a HTML file to the client-side, so that client-side can browse the file with only a browser.

Excel

We use Microsoft Excel to generate all of these learning progress graphs to evaluate student learning performance. Excel is a spreadsheet application developed by Microsoft. There are plenty functions can be used to execute computation, analyze information and manage electronic grid or the data information in the web pages. It also has very powerful graphic feature. It can display data as line graphs, histograms, charts, and also 3-D graphs, etc. Given the statistic data, it can analyze them and dynamically generate intuitive graphs.

2.10. Summary

This chapter describes the literature review that we used in this thesis. Especially, because we use the learning theory to support the construction of learning path in e-learning for different types of students using different types of teaching approaches, and also the generation of the learning resources as the learning contents. We assess student learning progress to determine their learning qualities. The literature involves the introduction of learning theory to support our research, e-Learning to introduce the research application in this area, learning taxonomy as the criteria of learning outcomes, learning styles for different types of students, learning modes for different types of learning approaches, student assessments for different approaches to evaluate student learning performance, Association Link Network to introduce how learning resources relate to each other, and system development tools of the research to introduce the used programming techniques. Given this information, readers can have a better knowledge background before starting to understand the main research of learning path construction in e-Learning and the analysis of student learning progress.

Chapter 3

3.Research Methodology

3.1.Introduction

In this research, we firstly construct a fine-grained outcome-based learning path model which can design and manage the components and learning outcomes of a learning path. Secondly, we generate a learning path based on Association Link Networks which can automatically construct personalized learning path from Web resources. Thirdly, we design Fuzzy Cognitive Map based student progress indicators to analyze student learning progress.

The research methodology we have applied includes both qualitative method and quantitative method, which is used to verify if teachers and students are satisfied with our research work as well as to verify if our research work can provide with better teaching approaches. Research methodology also explains the methods that we use to collect quantitative data or/and qualitative data. The quantitative data is collected to measure variables and verify existing theories or hypotheses. The collected data is used to generate new hypotheses based on the results of different variables. Normally, questionnaires are applied to gather these statistic data. On the other hand, qualitative research is carried out to find out subjective assessment of attitudes, opinions and behavior, such as to understand meanings, experiences, ideas, and values, etc. Normally, interviews are applied to describe and understand subjectively certain approaches. In this chapter, the section of Research Design introduces how we design and arrange the research study in general. The section of Instrument introduces the methods we are going to use to prove our proposed model is correct. The section of Participates introduces how we chose participates in the research. The section of Study variables introduces the variables used in the experiment, and the possible effect that these variables have on the research. The section of Proposed Data Analysis introduces the statistic methods that we use to analyze the collected data. The section of Research ethics states that this research obeys ethical principles during scientific research. The section of Summary summarizes what we have found.

3.2. Research Design

This research work contains three major parts to answer the three research questions, in which we use different research methods to verify our research work. To answer the first research question of how to learn, which requires finding out the teaching approaches and the sequence of learning, we have proposed a fine-grained outcome-based learning path model. In order to verify this method, we have implemented a prototype of this model. Next, we conduct a user study, in which we have invited teachers to try out our prototype and evaluate it as well as give us feedbacks in terms of their user experiences. This user study is mainly carried out through 3 parts including an introduction on the system, user interaction with the prototype, and evaluation questionnaires. We then collected teachers' feedback on the questionnaires, and use one-way ANOVA to analyze the collected data. During the one-way ANOVA analysis, we group teachers according to their teaching experiences and knowledge backgrounds, respectively, so that we can determine if teachers with different teaching experiences or different knowledge backgrounds would have different evaluation results on our system.

To answer the second research question of what to learn, which requires finding out the learning outcomes that students are going to achieve and the learning resources that help students achieve the learning outcomes, we have proposed a learning path construction method based on Association Link Network. This method can construct personalized learning path from well-structured learning resources. In order to verify this method, we have implemented a prototype system of this model as well. Next, we have conducted two experiments to show the advantages of the system recommended ones. One is to compare the quality of manually selected LPs with system recommended LP, and the other is to compare student learning performance after using manually selected LP and system recommended LP. In the second experiment, as we have two groups of data, so we applied two sample T-tests to analyze the differences between the learning performance of the two groups of students.

To answer the third research question of how well students have learned, which requires finding out student learning progress, learning qualities, and student potential to maker further improvements, we have proposed Fuzzy Cognitive Map based student progress indicators. In order to verify this method, we have collected academic data of high school students and applied our student progress indicators to the analysis of their learning progress. And also, we designed questionnaires for both teachers and students by providing them the learning progress analysis results and ask if they understand and agree with the learning progress results.

3.3. Instrument

In this research, I have applied different methods to address different research questions, including Implementation of prototypes, User study, Questionnaires, and Comparison study. This research study uses both qualitative and quantitative approaches for data collection and data analysis. Qualitative approaches help us make general conclusion and research propositions, and quantitative approaches verify the correctness of our proposed. The following description introduces these research instruments used for each research question respectively.

3.3.1. A Fine-grained Outcome-based Learning Path Model

In order to verify our work, I implemented the prototype of the fine-grained outcome-based learning path model, so that we can ask teachers to evaluate our method through a user study.

Implementation

This prototype provides teachers the basic functionality of designing learning path, where teachers can create or delete learning activities, learning tasks, as well as adjust their settings and teacher can create and manipulate learning path components graphically. And also, this prototype provides the corresponding learning path of student learning performance. The prototype implementation help teachers better understand how they can manage and design the learning path for different types of students. I have applied Jgraph, Ext JS, PHP, MySQL, and Apache, etc. to implement the prototype. The implementation details are explained in section 2.9.

User Study

We also conducted a user study for teachers to evaluate our work, which includes three parts, an introduction on the system, user interaction with the prototype, and evaluation questionnaires. Teachers are firstly invited to experience this prototype. They can ask questions about it to help them understand how to manage it. Afterwards, they are given a questionnaire to collect their evaluations of this learning path model. The whole questionnaire (Appendix A) contains 19 questions, where the first 6 questions collect information about teachers' personal teaching information, and the rest questions can be divided into three major questions: (1) Can the new model provide a more systematic and intuitive way for teachers to construct learning paths? (2) Does it produce learning paths that address the diverse needs of different courses? (3) Do teachers think that it is easier to set out criteria to assess student learning outcomes through the new model? Teachers are expected to scale each of these questions using 5-point likert scale to indicate their satisfaction on our work. With these statistic data, we can analyze if teachers satisfy with our work.

3.3.2. Learning Path Construction based on Association Link Network

In order to verify this work, we implemented a prototype of learning path construction system, with which we can ask both teachers and students to evaluate the system through a comparison study.

Implementation

To evaluate the performance of the learning path that is constructed based on Association Link Network, the implemented prototype of the learning path construction system graphically shows how learning resources are related to each other as well as support the editing of teacher knowledge model. Teachers can adjust the structure of teacher knowledge model. And students can learn tailored learning resources through associations of these learning resources in the keyword, concept, and learning resource ALNs, respectively. I have applied Tomcat, Web Services, and JSP, etc. to implement the prototype. The implementation details are explained in section 2.9.

Comparison Study

We then conduct a comparison study to evaluate the method in two aspects. One is to compare the importance of system recommended learning path with the manually selected learning paths, the other is to compare student performance between students who use this system and the students who do not use the system.

In the first experiment, importance of LP is evaluated by summing up the importance of the nodes that constitute a LP. Teachers are asked to manually construct LPs according to the topic ALN. Such a construction should fulfill two requirements: 1) the selected topics should connect with each other; 2) the selected topics should be important to students. Such requirements also govern how the recommended LP generated by our system.

To determine whether the comprehensiveness of the ALN structures will affect the quality of LP generation, we conduct experiments using three different abstraction levels of TKM by changing the number of association links constituted the topic ALN. Particularly, we use topic ALNs that have 196 links, 271 links and 360 links, corresponding to 20%, 50%, and 80% of the total association links, to form the low, middle and high resolutions of TKM, respectively.

In the second experiment, we randomly divide students into two even groups. The 1st group of students perform learning based on the teacher constructed LPs, while the 2nd group of students learn by the system recommended LP. All students are given 50 minutes for studying the learning resources in the LPs, and take the same examination with 25 questions to assess their understanding. Given their answers of these questions, we can compare their performance, and also compare if their performance is stable.

3.3.3. Fuzzy Cognitive Map based Student Progress Indicators

Questionnaires

To verify this research work, we evaluate if the proposed Fuzzy Cognitive Map based student progress indicators can help both teachers and students to better understand student progress and provide them more information to manage the teaching and learning process. This research work collects feedbacks from teachers and students using questionnaires and generates graphs to visually describe student progress.

These graphs present student progress in different learning stages, show how the performance on an attribute affects the performance of the other attributes, compare the performance among different groups of students, and also indicate the potential of students making progress in the future.

We designed two kinds of questionnaires for teachers (Appendix B) and students (Appendix C), respectively. Both of them contain six questions which evaluate the visualized learning progress in six aspects that covers different stages of learning from Early stage, Interim stage, to Mature stage. These questions aim to collect if teachers and students can better understand student progress and make the learning process more efficient.

3.4. Participants

3.4.1. A Fine-grained Outcome-based Learning Path Model

We evaluate the fine-grained outcome-based learning path model by testing if teachers with different teaching experience or knowledge backgrounds would have different evaluation results on our model. We invited 15 teachers who all have different teaching experience and from different subject disciplines. These teachers are from Durham University and some local high schools. And they all have experience of using e-Learning systems, so that they can provide more professional feedbacks.

3.4.2. Learning Path Construction based on Association Link Network

To complete the evaluation of the learning path construction based on Association Link Network, we have invited both teachers and students to help us complete the comparison study. The 10 teachers are invited from Computer Sciences Department to manually select learning paths which are used to make comparison with system recommended learning path. We also invited 10 postgraduate students from Computer Science Department, but they have different learning abilities, i.e. they perform differently when studying the same LR. We randomly divide them into two even groups. The 1st group of students learn by the manually selected LP, while the 2nd group of students learn by the system recommended LP.

3.4.3. Fuzzy Cognitive Map based Student Progress Indicators

In order to analyze student learning progress with our Fuzzy Cognitive Map based student progress indicator, we need teachers' help to set the learning outcomes for each subject, and also we need to collect student learning performance according to their learning outcomes. We ask 6 teachers in 6 subjects to set learning outcomes in terms of the performance related attributes and non-performance related attributes. And also, we have collected academic data of 60 students from No. 83 High school of Xi'an, China. The same teachers and students are required to evaluate our work by determine if the student progress analysis results can help them better understand student learning progress and make further improvements.

3.5. Study Variables

Variables are the values that change within a certain scope. Their changes may cause changes on the experiment results. On the other hand, they also could be changed because of the changes of some other variables. They also could remain the same no matter how the experiment conditions change. We applied some variables to control our experiments, and see if they would cause changes to the experiment results. We also applied some variables, which can be obtained from our experiments, as the criteria to evaluate our work. We explain them as follows.

3.5.1. A Fine-grained Outcome-based Learning Path Model

The experiment of evaluating the fine-grained outcome-based learning path model has applied the following variables that would take effect on teachers' evaluation results.

Teachers' teaching experience

In this study, teaching experience refers to how long a teacher has been a teacher. We consider it as a variable because teachers have different teaching experience may have different evaluation results about our prototype according to their teaching experience.

Teachers' knowledge discipline

Teachers' knowledge discipline refers to teachers' knowledge backgrounds, i.e. which subjects they teach. Also, teachers from different knowledge disciplines may use different teaching approaches. We consider it as a variable that may cause changes to their evaluation results.

Teachers' satisfaction score

In order to evaluate teachers' feedbacks from the questionnaire (Appendix A), we use teachers' satisfaction score to indicate their overall satisfaction on our outcome-based learning path model. Questions include if they are satisfied with the functionalities of the model, if the model can be easily understood, if it is easy to manage the model, etc. The answers of these questions are quantified by the 5-point likert scale, then we can calculate the overall teacher's satisfaction score by the sum of all these questions.

3.5.2. Learning Path Construction based on Association Link Network

The experiment of evaluating the work of learning path construction based on Association Link Network has applied the following variables as the criteria to evaluate if our work is good enough.

Importance of a learning path

The learning path construction method based on Association Link Network can automatically construct personalized learning path. However, in order to evaluate if the system recommended learning path is good enough, we consider the importance of the learning path as a variable, which is calculated by the sum of importance of each topic in the learning path. We can compare the importance of system recommend learning path and that of manually selected learning paths to see which one is better.

Learning performance on a learning path

Learning performance indicates students learning quality, which we can use to determine if the system recommended learning path could contribute to student learning, and if the system recommended learning path is superior to manually selected learning path. We ask students, who use our system and who do not use our system, to do the same test. The learning performance is the overall score in the test.

Stability of learning performance

Considering that these participated students have different learning abilities, and also the learning resources have different complexities, the students may have similar performance on simple learning resources, because in which case, all students can provide correct answers. Or they may have similar performance on very complex learning resources, because none of them can provide correct answers. On the other hand, they may have quite different performance on the medium difficulty level of learning resource, because only students with higher learning abilities may provide correct answers. We use stability of learning performance to indicate if different students can have stable performance on the same learning resource. If we can improve the stability of learning performance, then it means that we can better help low learning ability students improve their learning performance, so that they can have the similar learning ability with high learning ability students. The variable is collected from all students' learning performance on each piece of learning resource, more details about the formulation of this variable can be found in section 5.6.2.

3.5.3. Fuzzy Cognitive Map based Student Progress Indicators

The experiment of evaluating the work of Fuzzy Cognitive Map based student progress indicators has applied the following variables as the criteria to verify our work from the aspects of student learning performance, student development balance degree, and the state value of a student attribute. We explain each of each as follows.

Student learning performance

Student learning performance refers to the performance on performance related attributes. We use it to monitor student learning performance changing over different attributes in the same stage of learning. Given the learning performance on different performance related attributes and which attribute will cause the changes of the student learning performance, both teachers and students can know students' strength as well as weakness and help them improve correspondingly.

Student development balance degree

We would like to find out if students have the potential to make further improvements. Teacher can decide to go on providing them corresponding learning resources if they have the potential. During the development of student learning ability, there are many non-performance related attribute. Student development balance degree indicates how well a student can handle different learning environments which require the student to have different non-performance related attributes. If a student has a balanced development on all non-performance related attributes, for example, the student is good at learning both concrete examples and abstract concepts, or the student has no difficulty in learning knowledge presented in the form of either verbal, visual information or context, then the student can perform better under different learning environments. We consider the development balance degree as a variable to indicate student progress potential to achieve more in the future.

State value of a student attribute

We have applied two types of attributes to describe the characteristics of student learning, which include performance related attributes and non-performance related attributes. However, the performance of an attribute may cause effect on the performance of the other attributes. For example, if a student has good performance on the 'Responding' attribute, then the student probably prefers the learning style of 'Active' (Ref. Section 2.4) when the student processes information. In order to calculate the overall strength of impact of an attribute on all the others, we use the 'state value' of the attribute to measure the impact. Each state is actually the value of a node in the Fuzzy Cognitive Map, which represents the causal relationships between these nodes and how they affect each other.

3.6. Proposed Data Analysis

In this research study, we have applied different methods to analyze the data that are collected from different research instruments, including a fine-grained outcome-based learning path model, learning path construction based on Association Link Network, and Fuzzy Cognitive Map based student progress indicators. We introduce the proposed data analysis method for each of these methods.

3.6.1. A Fine-grained Outcome-based Learning Path Model

As we use questionnaires as the research instrument to collect teachers' evaluation results on our work, where we have scaled these questions with 5-point likert scale, so that we can quantify teachers' evaluation results and provide numerical analysis using statistic method like one-way ANOVA.

Likert Scale: In the questionnaire, each question for evaluating our model has 5 options (Totally Agree=5, Agree=4, Neutral=3, Not Quite Agree=2 and Disagree=1), teachers can select the options that best fits their decisions. The quantified answers help us measure teachers' overall satisfaction on our model.

One-way ANOVA: In the study, we analyze if teachers' teaching experience and knowledge backgrounds will affect their evaluation results. We divide teachers into several groups according to their teaching experience and knowledge backgrounds to compare if their evaluation results are similar or not. Because one-way ANOVA is used to compare the similarity between data in two or more groups, but the size of these groups does not need to have exactly the same number, we can apply one-way ANOVA to compare the results. After we obtain teachers' evaluation results by the likert scale measurement, we can use the 'one-way ANOVA' functionality of 'Data analysis' provided by Microsoft Excel software to automatically calculate if the evaluation results among different groups are similar or not.

3.6.2. Learning Path Construction based on Association Link Network

We conducted two comparison studies to evaluate the work of learning path construct. Firstly, we applied the ratio of system recommended learning path and manually selected learning paths, in order to verify that our work can provide a learning path with higher importance degree in terms of covered knowledge concepts. Secondly, we used independent two-sample T-tests to compare the learning performance of two groups students who used our method and who did not use our method.

Ratio: Ratio is a type of measurement of scale. In the first comparison study, the ratio is made of the importance degree between system recommended learning path and manually selected learning paths. It measures the differences between the two paths and shows how their differences change over when the size of teacher knowledge model is different.

Independent Two-sample T-tests: When the number of groups for comparison is two and the size of each group is the same, then ANOVA turns to be the independent two-sample T-tests. In order to verify that students using system recommended learning path have better learning performance, we use the independent two-sample T-tests to compare the differences of student learning performance variances between the group of students who use our Association Link Network based learning path construction model and the group of students who do not use our model.

3.6.3. Fuzzy Cognitive Map based Student Progress Indicators

When teachers and students try to understand student progress, it is greatly straightforward to let them visualize the learning progress. If analysis results can be presented in the form of graphs, we can design a visual questionnaire and use quantitative answers to respectively collect evaluation results from teachers and students.

Graph Comparison: We have collected a great number of data about student learning progress, including the values of performance-related attributes and non-performance related attributes at different learning stages, the performance and development balance degree on a variety of subjects for different groups of students, students' potential for making progress, the changes of students' performance over different tests, and the impacts of attributes on the performance of other attributes. It is not sufficient to use only numeric analysis to present the comparison of learning progress that changes with different attributes, different learning stages, different groups of students, and different tests. We used graphs to present the comparisons of all of them in order to help both teachers and students better understand students' learning progress.

Likert Scale: we also collected both teachers' and students' evaluation results regarding the analyzed student progress via questionnaires. To quantify their evaluation results, we applied 5-point likert scale to collect data. Similarly, each question has 5 options (Totally Agree=5, Agree=4, Neutral=3, Not Quite Agree=2 and Disagree=1).

3.7. Research Ethics

All questionnaires were collected anonymously. No age, sexuality or any other private information was collected for research either. When participates used with our prototype, they were not required to provide any private information either. All data are promised to use for research only, and will not be open to public. All participates are requested to attend to the experiment voluntarily, anyone who do not like to share their ideas or spend their time can refuse to take part in the study.

3.8. Summary

This chapter describes the issues related to the research methodology. It explains how we designed the research study, which methods we used to prove our proposed method is correct, how participates took part in the research, which kinds of variable we considered to measure our proposed model, which statistic methods we used to analyze the collected data, and the ethic issue. However, as the number of participates in each study was not plenty enough, it may cause some errors to the analysis results. That is the limitation of this study.

Chapter 4

4. Method for constructing a Fine-Grained Outcome-based Learning Path Model

Recently methods have been developed to design learning paths based on attributes that describe learning contents and student characteristics, helping students learn effectively. A learning path (or curriculum sequence) comprises steps for guiding a student to effectively build up knowledge and skills. Assessment is usually incorporated at each step for evaluating student learning progress. Although existing standards, such as SCORM and IMS-LD, provide data structures to support systematic learning path construction and IMS-LD even includes the concept of learning activity, they do not provide any facilities to help define the semantics in order for pedagogy to be formulated properly. On the other hand, most existing work on learning path generation is content-based. They only focus on what learning content is to be delivered at each learning path step, and pedagogy is not incorporated. Such a modeling approach limits student learning outcome to be assessed only by the mastery level of learning content, without supporting other forms of assessments, such as generic skills. In this chapter, we propose a fine-grained outcome-based learning path model to allow learning activities and their assessment criteria to be formulated by the Bloom's Taxonomy. Therefore, pedagogy can be explicitly defined and reused. Our model also supports the assessment of both subject content and generic skills related learning outcomes, providing more comprehensive student progress guidance and evaluation.

4.1. Introduction

Learning path defines how a course of study is proceeded. It comprises steps for a student to go through in order to conduct learning. At each step, the student studies certain learning content (i.e., what to learn), which should be disseminated through suitable pedagogy (i.e., learning and teaching approaches). Student assessment should also be included for evaluating student learning progress. Practically, a student is expected to achieve various learning outcomes, which are broadly categorized into subject-specific knowledge and skills, and generic skills. Specifically, subject-specific knowledge refers to facts and concepts within a subject domain. Subject-specific skill refers to the learning outcome of formulating, evaluating and synthesizing matters within a subject. Such skill may share among subjects of similar nature. Generic skill refers to the learning outcome that can be applied to various subject domains and student future development.

Pedagogy formulation and student assessment are main challenges for learning path construction. Consider practical situations, we use the teaching unit COMP2161 Computer Systems II in our school as an example. We specify "To gain detailed understanding of the difficulties encountered with setting up large computer networks" as a subject-specific knowledge, "To be able to implement and work with different types of computer systems" as a subject-specific skill, and "To be able to communicate technical information in a scientific fashion" as a generic skill, to evaluate part of the student learning outcomes. Subject lecturers are required to design suitable learning activities (i.e., how to learn) helping students achieve these outcomes, and proper assessment methods to evaluate student learning progress.

In terms of pedagogy, we offer two main types of learning activities: *lecture* and *practical*, where their pedagogies are "learn by perceiving oral presentation" and "learn by experimenting", respectively. Although lecturers can implement more fine-grained pedagogies or even other types, such pedagogies are hard to be formally formulated and reused. In terms of student assessment, defining and assessing subject-specific knowledge is easy, as it is directly tied with the design of teaching subjects. However, subject-specific and generic skills are usually left as written documentation rather than really used for assessing student achievement, since they may require evaluating student learning outcomes achieved from a set of relevant or even all subjects, which is not trivial for implementation.

Existing work on learning path generation for e-learning [Chen08, Kara05, Lim009] are generally content-based without modeling pedagogy or learning activity. Students are usually only assessed by the mastery level of the learning content in each learning path step. As subject-specific and generic skills are learning activities dependent, therefore such skills cannot be properly assessed.

SCORM [SCORM] and IMS-LD [IMSLD] are popular standards defining data structures for learning paths. SCORM follows the content-based approach without supporting the assessments of generic skills. Although IMS-LD includes learning activity in their data structure, it only provides a container to hold learning activities without offering any facility to help define their semantics. As a result, teachers are responsible for manually specifying such definitions, which may be hard to reuse.

In this research, we propose a fine-grained outcome-based learning path model for teachers to formulate a course of study as a sequence of learning activities. This allows pedagogy to be explicitly formulated. We also introduce a two-level learning path modeling to facilitate the assessments of different forms of student learning outcomes, including subject-specific knowledge and skills, and generic skills. Our work does not deal with the problem of adaptive learning. Our contributions are:

- **Pedagogical support:** We model a learning activity as a composition of learning tasks enabling teachers to construct the learning and teaching approaches in explicit forms. We also model learning tasks to tie with learning outcomes based upon the Bloom's Taxonomy [Bloo56, Krat73, Simp72], such that teachers may be able to formulate comprehensive assessment criteria, as they do in a conventional classroom teaching environments.

- **Student assessment**: We introduce a two-level learning path modeling, allowing teachers to assess collective student learning outcomes generated from individual learning activities or a specific type of learning outcome generated dispersedly from a set of relevant learning activities.
- **Reusability**: Our model allows teachers to reuse their teaching and assessment approaches. It is done by applying a designed learning activity structure to govern the dissemination of another set of learning contents. Given that we formulate pedagogy through a mathematical model, the weight associated with each learning task becomes an intuitive manipulator for teachers to adjust their teaching and assessment approaches for the new learning activity.

The rest of this chapter is organized as follows. Section 4.2 summarizes existing works. Section 4.3 presents our new learning path model. Section 4.4 discusses the implementation of the prototype system. Section 4.5 presents and analyzes our experiment results. Finally, Section 4.6 concludes the work presented in this chapter.

4.2. Related Work

A learning path is the implementation of a curriculum design. It comprises elements forming steps for students to go through for acquiring knowledge and skills. In existing work, learning outcome assessment is generally tied up with these steps. In this section, we examine how existing approaches define learning paths and assess learning outcomes. The discussion includes conventional classroom teaching, learning path generation systems and de facto standards that define learning paths.

4.2.1. Conventional Classroom Teaching

Under the conventional classroom setting, students usually share a common learning path due to the one-size-fit-all teaching approaches. This learning path is typically pre-defined and mostly static, as teaching resources or constraints, such as teaching staff, classrooms and the period of study, are usually fixed. Although subject-specific knowledge and skills, and generic skills are generally specified in the syllabus as learning outcomes, not all of them can be assessed explicitly. In general, subject-specific knowledge can be assessed by subject coursework or written examinations where assessment criteria are usually well-defined. In contrast, subject-specific and generic skills are acquired more broadly across closely related subjects and even subjects without trivial relations. They require methods for evaluating how part of a subject can help train up students with certain skills and linking up learning outcomes from corresponding subjects. However, such methods are usually not available in practice.

4.2.2.Learning Path Generation System

Learning path generation systems construct adaptive learning paths by arranging selected learning contents in a proper sequence for students to study, aiming at improving student learning effectiveness. [Kara05] initially generates a set of learning paths by matching the educational characteristics of learning contents (i.e., subject-specific knowledge / skills and generic skills) with student characteristics and preferences (i.e., students' learning styles, working memory capacity, etc.). The suitability of each piece of learning content, which constitutes a learning path, is then calculated as a weight by a decision-making function. Based on a shortest path algorithm, the most suitable learning path can be chosen. Student assessment results are not involved in the method. Instead, [Chen08] involves a pre-test to assess students and capture their incorrect responses, forming the inputs to a genetic algorithm, which is driven by learning content difficulty level and concept continuity, to generate an optimal learning path. LS-Plan [Lim009] characterizes learning contents by learning styles [Feld88, Li10] and difficulty levels (based on the Bloom's Taxonomy). The system requires a student to conduct a test (if existed) after finishing each learning path step in order to examine the student's mastery level of certain learning content and verify the student's learning style. The next learning path step can then be determined based on the test result. The above methods are content-based without incorporating pedagogy (i.e., learning and teaching approaches). Also, learning outcome assessment is confined to the mastery level of learning content.

For implementing pedagogy, LAMS [Dalz03] provides an interactive user interface allowing teachers to define a learning path based on a set of predefined learning activities, such as read notice board, chatting, and small group debate, for individuals or a group of students. It also models student assessment as a learning activity. A designed learning path can be reused for teaching different subjects by replacing the learning contents associated with its learning activities. However, it cannot assess students based on a composition of multiple learning outcomes or a learning outcome that is dispersedly acquired from multiple learning activities. A comprehensive learning activity model was proposed in [Cono05]. It defines a learning activity as a composition of learning content, learning outcomes, teaching approaches and tasks. However, the correspondences among the components have not been modeled, i.e. it cannot formulate student learning outcome assessment if a learning activity involves several tasks.

4.2.3.Designing and Managing Learning Activities

There are also standards for defining learning paths. SCORM [SCORM] defines an interface between learning contents and a learning management system (LMS) and supports exchanging learning contents among different LMSs. It models learning contents with a hierarchical activity tree. A learning objective is defined at each activity of the tree to form the criteria for assessing student learning outcome. Some of these learning objectives are globally shared among certain activities or some are formed by the weighted sum of the learning objectives of the child activities. There are also rules for controlling the sequence of learning content delivery. However, SCORM only addresses the needs of a single student, and does not model pedagogy as it is content-based. IMS-LD [LD] is a meta-language that is divided into 3 parts: Level A defines activities and roles for delivering learning content, Level B adds properties and conditions to Level A to describe student learning outcomes and govern learning content delivery, and Level C adds notification to Level B to define events that trigger activities. Unlike SCORM, IMS-LD supports the concept of learning activities where their workflow and dependency are modeled. It also supports collaborative learning activities. However, the learning activity modeling is still like a container, where teachers need to manually define and interpret the semantics, making it difficult for reuse. On the other hand, IMS-SS [SIMSEQ] offers a standard for controlling the flow of learning activities through pre-defined rules, branching definitions and learning outcomes of student interactions with learning contents. This standard is also content-based without modeling pedagogy.

4.3. The Fine-grained Outcome-based Learning Path Model

In this chapter, we propose a fine-grained outcome-based learning path model. The model is defined mathematically such that the setting of pedagogy and student learning outcome assessment can be explicitly formulated and reused. Considering the fact that a learning path has two functionalities, specifying a student learning process and connecting student learning outcomes for evaluating student progress, this chapter defines learning paths with two levels, namely learning activity (LA) and learning task (LT) levels (Ref. Section 4.3.2), such that student achievement in both LA-specific and different types of learning outcomes can be comprehensively revealed.

4.3.1. Overview of the Learning Path Model

Existing learning path generation methods are usually content-based. As illustrated in Fig. 4. 1 (a) and Fig. 4. 1 (b), they construct learning paths based on knowledge elements (KEs), which are delivered through lecturing and assessed by question-answering (Q&A). However, pedagogy is generally not included in their methods. Assessment of different forms of learning outcomes, such as generic skills, is also not properly supported. Such deficiencies impose significant restrictions on these methods for modeling how students are being trained or assessed, and rely on teachers to work out these by themselves. Such burden partly explains why learning path generation systems are not widely adopted for learning and teaching in practice.

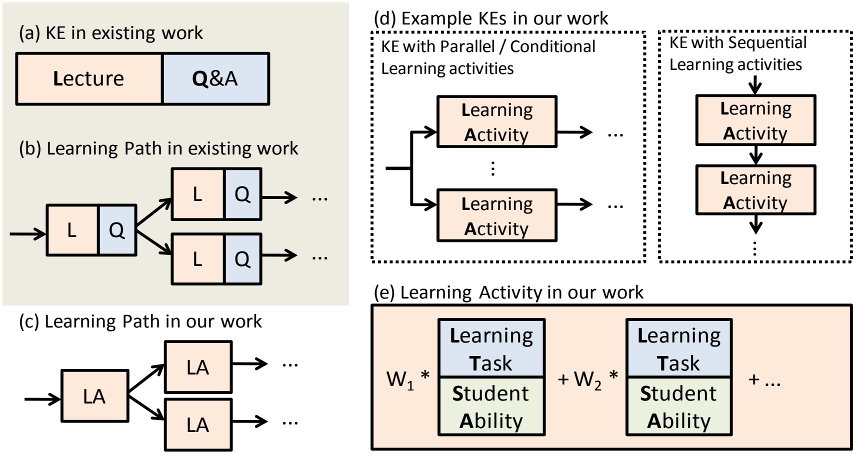


Fig. 4. 1 The learning path formulation in existing work and in our work.

To model the student learning process, we propose using *learning activities* (*LAs*) [Con005] instead of KEs to form the building blocks of a learning path as shown in Fig. 4. 1 (c), and model each KE as a set of *LAs*. As shown in Fig. 4. 1 (d), this formulation allows a teacher to govern KE delivery by setting up flow-controls to *LAs*, including sequential, parallel and conditional. The introduction of *LAs* facilitates teachers to define their teaching strategies, i.e., how they disseminate a KE. Learning contents associated with each *LA* can be obtained from the Web or created by teachers.

To support modeling pedagogy of a *LA*, as illustrated in Fig. 4. 1 (e), we define a *LA* to comprise a set of *learning tasks (LTs)*, where a *LT* is designed to train and assess a specific type of *Learning outcome (LO)*. We associate a weight, w_i (ranging between [0,1] and $\sum w_i = 1$), to each *LT* indicating its importance in a *LA*, which implicitly defines the amount of time spending on the learning task and the weighting of its assessment. Pedagogy of a *LA* can be adjusted by changing LTs and their weights.

To model *LO* requirement of a *LA*, each *LT* in the *LA* is required to assign with a *SA* as the assessment criteria. Note that two different *LTs* are not restricted to be assessed by different types of LOs. The student learning outcome from a *LA* is then defined as a weighted composition of the *SAs*. With the two-level learning path modeling, student assessment can be conducted at each *LA* or by a specific learning outcome. The *LA* level learning path helps assess student learning progress made from a series of *LAs*, while a *LT* level learning path connects corresponding *LTs* from relevant *LAs* to help evaluate student learning outcomes or skill specific learning progress.

To support time management in the learning process, we also divide the time span of a *LA* level learning path into a finite sequence of time slots, and refer to each time slot as a *learning stage (LS)*, where a *LA* may be taken place in a designed *LS* or span over a number of *LSs*. Based on this definition of *LS*, we define a student's *learning progress* as the accumulated learning outcome over some consecutive *LSs*.

In contrast to [Con005], our model explicitly defines the relationship among learning tasks; formulates their assessments by Bloom's taxonomy and defines how such assessments are combined to form the learning outcome of a learning activity. We also uniquely support student learning outcomes specific assessment across a series of learning activities. Table 4. 1 summarizes the major elements of our learning path model. We will elaborate their details in the following sub-sections.

4.3.2.Formal Definitions

Student Learning Outcome: *Student learning outcome* refers to a set of attributes describing if a student has acquired them after studying something. These attributes may indicate whether the student can only recall the subject content or may apply subject knowledge to solve problems in unseen situations, for instance. In practice, it is a popular approach to assess learning outcomes as a composition of different levels of learning outcomes. For example, a teacher may set different types of question in an examination paper to assess different learning outcomes. Research on learning outcomes was first conducted systemically by a group of educators led by Benjamin Bloom

Table 4. 1 Definition of major elements

Abbr.	Key Element	Definition
SA	Student Ability	Set of attributes indicates how a student makes progress in learning.
LT	Learning Task	A fine-grained type of training helps a student achieve a specific ability.
LA	Learning Activity	A training unit comprises a set of LTs to define its teaching and learning approach.
LA^C	Collaborative Learning Activity	A specific type of LA designed for students to learn under a group setting.
LP	Learning Path	Sequence of steps for a student to go through and build up knowledge & skills.
LS	Learning Stage	Finite period of time defined within the time span of a learning path.

[Bloo56]. They produced the Bloom's Taxonomy to classify thinking behaviors to six cognitive levels of complexity. This taxonomy has been extended to cover three domains: *cognitive* (knowledge based), *affective* (attitudinal based) [Krat73] and *psychomotor* (skills based) [Simp72]. It forms a comprehensive checklist guiding a teacher to ensure that a course design can help train up students with all necessary abilities. Table 4. 2 summarizes the Bloom's Taxonomy by listing the main characteristics of different learning outcomes according to the Bloom's domains (columns) and their corresponding levels of complexity (rows).

To help formulate the assessment criteria of student learning, we propose using student outcomes from the Bloom's Taxonomy as the basis for assessment since they can comprehensively quantify the levels and the types of student achievement. To define the criteria, a teacher needs to identify a set of Student Learning Outcomes used for assessment and puts them into a *Student Learning Outcomes Table (SLOT)*, which is defined as follows:

$$SLOT = \{A_1, \cdots, A_2, \cdots, A_{|SLOT|}\} \text{ for } \quad 1 \le i \le |SLOT| \tag{4.1}$$

Table 4. 2 A summary of the Bloom's taxonomy.

Level of Complexity	Cognitive (Knowledge)	Affective (Attitude)	Psychomotor (Skill)
1	Knowledge	Receiving	Imitation
2	Comprehension	Responding	Manipulation
3	Application	Valuing	Precision
4	Analysis	Organizing	Articulation
5	Synthesis	Characterizing by value or value concept	Naturalization
6	Evaluation		

the cardinality of *SLOT*. To facilitate the learning outcome assessment, for each learning outcome, two Bloom's Taxonomy related functions $B_c(A_i)$ and $B_d(A_i)$ are set up for retrieving the *level of complexity* and the *Bloom's taxonomy domain*, respectively. For example, the learning outcome of 'Comprehension' has the complexity level of 2 in the 'Cognitive' domain, i.e., $B_c(A_i) = 2$ and $B_d(A_i)$ = Cognitive. To gain a better idea on how a suitable set of learning outcomes can be defined in terms of $B_c(A_i)$ and $B_d(A_i)$, the reader may refer to the Bloom's taxonomy [Bloo56, Krat73] or some quick references available on the Web, such as [Bloom].

Although Bloom's Taxonomy covers a comprehensive list of learning outcomes, which can maximize the benefits of our model, we expect that some teachers may prefer using a simpler learning outcome model or even define their own lists. This will not affect any functionality of our model. In this sense, new versions of the Bloom's Taxonomy are also applicable to our model.

Learning Task: To allow a fine-grained formulation of the learning process of KEs, we introduce the idea of *learning task*, which is designed for training up a student with an outcome-specific learning outcome. By putting together a set of learning tasks, a *learning activity* is formed. Similar to the selection of learning outcomes, a teacher also sets up a *learning task table*

(*LTT*), which comprises a list of learning tasks for constructing learning activities as follows:

$$LTT = \{T_1, \cdots, T_i, \cdots, T_{|LTT|}\} \text{ for } \quad 1 \le i \le |LTT| \tag{4.2}$$

where T_i is a learning task and $|LTT|$ is the cardinality of *LTT*. A function $S_a(T_i)$ is associated with each learning task T_i to return a student's level of achievement. The mapping from *LTT* to *SLOT* is surjective, i.e., a teacher can design different types of learning tasks to train up students with the same type of learning outcome.

The design of learning tasks is typically course dependent. As we do not expect teachers having comprehensive knowledge in the Bloom's taxonomy due to its complexity, to help teachers proceed with the design systematically and in an easier way, we suggest that a teacher may optionally consider whether a learning task is set up for teaching declarative or functioning knowledge [Bigg07]. Declarative knowledge relates to the study of factual information, while functioning knowledge relates to the study of how something works. For example, to design learning tasks for teaching declarative knowledge, reading can be included to help assess learning outcome in memorization, while an in-class quiz can be set out to assess student understanding. Table 4. 3 shows some sample learning tasks along with the corresponding types of knowledge, learning outcomes for assessment, and the Bloom's domains and levels of complexity.

Learning Activity: When designing a course, a teacher typical establishes a set of *learning activities*, such as lecture, tutorial or practical, for students to learn KEs through different ways. In our formulation, a *learning activity* (*LA*) is formed by a row vector of learning tasks, $[T_1 \quad \cdots \quad T_i \quad \cdots \quad T_{|LA|}]$, such that:

$$LA = [w_1 \quad \cdots \quad w_i \quad \cdots \quad w_{|LA|}]\ [T_1 \quad \cdots \quad T_i \quad \cdots \quad T_{|LA|}]^{\mathrm{T}} \text{ for } \ 1 \le i \le |LA| \tag{4.3}$$

where $[\cdot]^{\mathrm{T}}$ is a transpose function, w_i is a weight to indicate the importance of

Table 4. 3 **Examples of learning tasks.**

Type of Knowledge	**Learning Task**	**Student learning outcomes for Assessment**	**Bloom's Taxonomy Correspondence**
Declarative	Reading	Memorization	Cognitive, Level 1
	In-class Quiz	Understanding	Cognitive, Level 2
	Peer-Teaching	Understanding	Cognitive, Level 2
Functioning	Case Presentation	Understanding	Cognitive, Level 2
	Performing a Case	Application	Cognitive, Level 3
	Computer Program Design	Synthesis	Cognitive, Level 5

learning task T_i, $\sum w_i = 1$ and $|LA|$ is the cardinality of LA. The weights associated with these learning tasks will be added up to 1 or 100%, meaning that if the weight of a learning outcome (which is associated with one of the learning tasks) has been increased, the rest of the learning outcomes will be decreased in its contribution to this 100%, and vice versa. Specifically, if the weight of a learning outcome $\boldsymbol{w}$ has been adjusted to become $\boldsymbol{w'}$, the contribution of the rest of the learning outcomes will become $\mathbf{(1 - \boldsymbol{w'}) / (1 - \boldsymbol{w})}$. Therefore, the weight of any of the rest of the learning outcomes $\boldsymbol{wr}$ will be adjusted to become $\boldsymbol{wr} \cdot \mathbf{(1 - \boldsymbol{w'}) / (1 - \boldsymbol{w})}$. The *learning outcome* (*LO*) of a *learning activity* (*LA*) can then be assessed by:

$$LO = \left[w_1 \cdots w_i \cdots w_{|LA|}\right] \left[f_1\big(S_a(T_1)\big) \cdots f_i\big(S_a(T_i)\big) \cdots f_{|LA|}\left(S_a\big(T_{|LA|}\big)\right)\right]^T \quad (4.4)$$

where $f_i()$ is a function to evaluate the student's level of achievement in a given learning outcome. The weights used in both (4.3) and (4.4) are the same ones, as the weight associated with a learning task also defines the importance of the associated learning outcome of the learning task. Note that we refer T_i as a symbol representing learning task rather than treating it as a mathematical scalar for computation, although in implementation, T_i may be a scalar for storing the ID of a learning task.

Instead of asking teachers to create new evaluation functions, they may reuse existing ones, such as simple marking (quantitative assessment), grading (qualitative assessment) or performing evaluation through the item response theory [Chen06], if they are applicable to the types of learning outcome. As such, our learning path model can fit different types of assessment methods and inference algorithms, which could be subject-specific or a combination of methods for performance evaluation. Note that within a learning activity, each learning task is typically designed for training students up with a different type of student learning outcome.

In fact, modeling a *LA* is not straightforward. Given that different teachers may adopt different teaching approaches, and different students may have different learning styles, the actual tasks used even in the same type of *LA*, e.g., a lecture, can be very different. Such a difference also appears in certain type of *LA* at different subject disciplines. This suggests that we need a more fine-grained model to formulate *LAs* to cope with practical needs. Therefore, we propose to formulate a *LA* as a set of learning tasks. It offers course designers or teachers a way to properly define teaching approaches for delivering KEs. While a *LT* is an implementation of a low-level teaching technique that focuses on training up and assessing students with certain learning outcome, such as an *informal in-class quiz and feedback*, a *LA* is an implementation of a high-level teaching strategy that course designers or teachers use to approach a KE for training up students with a composition of knowledge and skills.

Our model offers a more accurate modeling of learning activities in terms of learning process and learning outcome requirements. Particularly, we formulate a learning activity as a container of a suitable set of learning tasks, such that it can be easily customized by altering its learning tasks to fit a certain subject discipline or the student's learning characteristics. This feature helps accelerate the process of producing new learning activities from existing ones. It is also critical to our previous work on adaptive course generation [Li10], which applies filtering technique to arrange tailor-made learning content for different students at different learning stages, extending it to further support teaching and learning approach adaptation.

Collaborative Learning Activity: A *collaborative learning activity* (LA^C) is a specific *LA* designed for students learn together in a group setting. In a normal *LA*, its learning tasks and assessments are designed for an individual student. In contrast, a collaborative learning activity comprises two parts: one for an individual student in the group and the other one for the whole group. They apply to both learning tasks and their assessments. Specifically, this kind of learning activity comprises two types of learning tasks, a single set of collaborative learning tasks ψ_C and multiple sets of individual learning tasks ψ_i for $1 \leq i \ll |S|$, where $|S|$ is the number of students participating in the group. Mathematically, ψ_C and ψ_i are one-dimensional vectors of learning tasks (as Eq. 4.5.1) designed to be performed by a group of students together and by an individual student S_i within the group, respectively. To facilitate the assessment of learning outcomes, Ξ_C and Ξ_i are one-dimensional vectors of weights (as Eq. 4.5.2) used to indicate the importance of learning tasks in ψ_C and ψ_i, respectively. Hence, a collaborative learning activity, LA_i^C, designed for a student S_i is defined as:

$$LA_i^C = \begin{bmatrix} \Xi_C {\Psi_C}^{\mathrm{T}} \\ \Xi_i {\Psi_i}^{\mathrm{T}} \end{bmatrix} \tag{4.5}$$

$$\Psi_C = [{T_1}^C, \cdots, {T_{|C|}}^C] \text{ and } \Psi_i = [{T_1}^i, \cdots, {T_{|i|}}^i] \tag{4.5.1}$$

$$\Xi_C = \left[{w_1}^C, \cdots, {w_{|C|}}^C\right] \text{ and } \Xi_i = \left[{w_1}^i, \cdots, {w_{|i|}}^i\right] \tag{4.5.2}$$

where all elements in both Ξ_C and Ξ_i sum up to 1. ${T_1}^C, \cdots, {T_{|C|}}^C$ are the set of learning tasks needed to be completed collaboratively, and ${T_1}^i, \cdots, {T_{|i|}}^i$ are the set of learning tasks needed to be completed individually. ${w_1}^C, \cdots, {w_{|C|}}^C$ and ${w_1}^i, \cdots, {w_{|i|}}^i$ are the correspondent weights of importance for collaborative learning tasks and individual learning tasks, respectively. Mathematically, the definitions of both $\Xi_C {\Psi_C}^{\mathrm{T}}$ and $\Xi_i {\Psi_i}^{\mathrm{T}}$ are equivalent to Eq. 4.3, and therefore the student learning outcome can thus be evaluated by Eq. 4.4 when proper learning outcome evaluation functions are in place. We refer collaborative learning tasks in Eq.4.5 as symbols rather than treating them as mathematical scalars for computation. From the teacher's perspective, the entire collaborative learning activity in a group setting is represented as:

$$LA^C = \begin{bmatrix} \Xi_C {\Psi_C}^{\mathrm{T}} \\ \Xi_1 {\Psi_1}^{\mathrm{T}} \\ \vdots \\ \Xi_{|S|} {\Psi_{|S|}}^{\mathrm{T}} \end{bmatrix} \tag{4.6}$$

Note that the learning outcome of a student can be evaluated in the same way regardless whether a collaborative learning activity exists, since collaborative learning activity only introduces certain learning tasks having their assessment results shared by some students, the assessment results collected from such learning tasks can still be processed in the same way as those collected from learning tasks conducted by individual students.

Learning Path: *Learning path* (*LP*) is for specifying a student learning steps and linking student learning outcomes for progress evaluation. We define a *LA* level and a *LT* level of learning paths. The *LA* level *learning path* (*LP*) is made up of an organized set of learning activities. It is modeled as a directed graph, *LP* = (*V*, *E*), defining the course of study for a student. It also links the learning outcomes of *LAs* to facilitate student learning progress evaluation. Specifically, *E* is the set of edges while *V* is defined as:

$$V = \{LA_1, \cdots, LA_i, \cdots, LA_{|V|}\} \text{ for } 1 \le i \le |V| \tag{4.7}$$

where LA_i is a learning activity and $|V|$ is the cardinality of *V*. If two learning activities have a prerequisite relation, they will be connected by an edge in *E*. Our formulation is backward-compatible with KE based learning path models. Specifically, as illustrated in Fig. 4. 1 (d), we can group relevant *LAs* together with their flow-control structures to form a KE, turning our learning path model to become KE based. Therefore, it is possible to integrate existing learning path generation system [Chen08, Kara05, Lim009] with our learning path model. Particularly, as we offer a fine-grained modeling on student assessment, this makes more comprehensive student progress information available and that learning path generation results can be enhanced when student learning progress information is considered [Chen06, Lim009]. On the other hand, a *LT* level learning path is designed to link certain learning tasks defined in relevant learning activities, where those learning tasks are designed to collectively train up and assess a specific type of learning outcome. In terms of the structure, similar to the *LA* level of learning path, a *LT* level learning path is also a directed graph, but its elements are *LTs* rather than *LAs*. As an illustration, examples of a *LA* "Computer Organization (LT)" and its *LTs* are shown in Fig. 4. 4 (a) and Fig. 4. 4 (b), respectively. An example of a *LA* level of learning path is shown in Fig. 4. 2. Based on this learning path, two sample *LT* level learning paths, which assess communication skill and writing skill of a student, respectively, are shown in Fig. 4. 6 and Fig. 4. 7.

Learning Stage: To provide teachers a metric to control the number of learning activities taking place at any period of time and to schedule learning activities properly, we divide the time span of a learning path into a finite sequence of time slots, and refer to each time slot as a *learning stage* (*LS*). A learning activity may take place in a designated learning stage or may span over a number of learning stages. The definition of learning stage well matches the timetabling concept well in practice, where a teacher may divide an entire course taking place with a finite sequence of time slots, such as teaching weeks or semesters, and assign a proper number of learning activities to each time slot. During each learning stage, a student only needs to study a subset of KEs through designated learning activities. To indicate the *starting learning stage* (*sLS*) and *ending learning stage* (*eLS*) of a *LA*, we set up two functions, $LS_s()$ and $LS_e()$, respectively, as follows:

$$sLS = LS_s(LA) \tag{4.8}$$

$$eLS = LS_e(LA) \tag{4.9}$$

To govern the student learning process, *time constraints* and *dependencies* are often set up among the learning activities. The time constraint is defined based on the concept of *learning stages*. If two learning activities, LA_j and LA_k, are specified to start at the same learning stage, then they are satisfied with the following constraint:

$$LS_s(LA_j) = LS_s(LA_k) \quad (4.10)$$

We may also set up some rules using $LS_s()$ and $LS_e()$ to verify if LA_j and LA_k overlap each other at some learning stages. These time constraints are useful for verifying the *coexistence dependency* of LA_j and LA_k. We need these rules particularly when we need to make sure that a set of chosen learning activities are conducted in parallel at some point. On the other hand, if LA_j is designed to complete before LA_k starts, then we have:

$$LS_e(LA_j) < LS_s(LA_k) \quad (4.11)$$

This time constraint can be applied as a rule to ensure the *prerequisite* relation between LA_j and LA_k.

Student learning progress: Learning progress describes how much knowledge or skill that a student has acquired from a course over certain learning stages. With Eq.4.4, learning outcome can be evaluated as a weighted composition of learning outcomes achieved from a learning activity. Therefore, student learning progress can be computed as an accumulated learning outcome over certain consecutive learning stages, by following the *LA* level learning path based on a selected group of *learning activities* for assessing *subject-related outcomes*. Alternatively, we may evaluate a student's learning progress on a specific learning outcome based on a *LT* level learning path. This allows assessing the *generic outcomes or transferable skills* [Dodr99], which are typically related to personal effectiveness, e.g. communication and teamwork skills. This feature generally cannot be achieved in existing methods as they use KEs to construct learning paths.

4.3.3.Discussions

The new model facilitates the implementation of generic and practical systems for learning path generation. For KE delivery, we can model each KE to comprise different types of learning activities. This matches very well with practical needs, where some learning activities, such as lectures, practical sessions and tutorial classes, can be run concurrently within a learning stage (e.g., a semester) to offer various types of training. In addition, as we allow the construction of a flow-control structure to govern the delivery of the learning activities that constitute a KE, our model potentially enables the construction of adaptive KEs to support students with different learning styles. However, adaptive learning path generation is out of the scope of this research. We consider it as a future work.

For KE assessment, since we model each learning activity as a composition of some learning tasks and assess each learning task based on certain learning outcome, the new model is more generic. It supports different types of learning activities and student learning styles. For example, to encourage student participation and provide a fair/open environment for assessment, [Ma00] proposes to allow both teachers and students to collaboratively set up assessment criteria for assessing learning outcomes across the domains of knowledge, attitude and skill, rather than simply using a standard Q&A assessment. On the other hand, [Kore08] has found that student performance in a virtual laboratory (a "practical" learning activity) can be evaluated by assessing learning outcomes through different levels of cognition, particularly those higher ones, including analysis, synthesis and evaluation [Bloo56]. These two examples illustrate that traditional Q&A assessment is insufficient to address some practical or advanced needs in student learning, and that their proposed models can well address the needs.

4.4. Implementation

To evaluate our work, we have implemented a prototype system based on our fine-grained outcome-based learning path model. We use PHP and Javascript as the server-side scripting language, Apache as the Web server, MySQL as the database, and Windows as the operation system to implement this prototype, and use the graph visualization library JGraph to generate diagrams. The prototype comes with a drag-and-drop graphical user interface assisting teachers to create and manipulate learning path components graphically. The

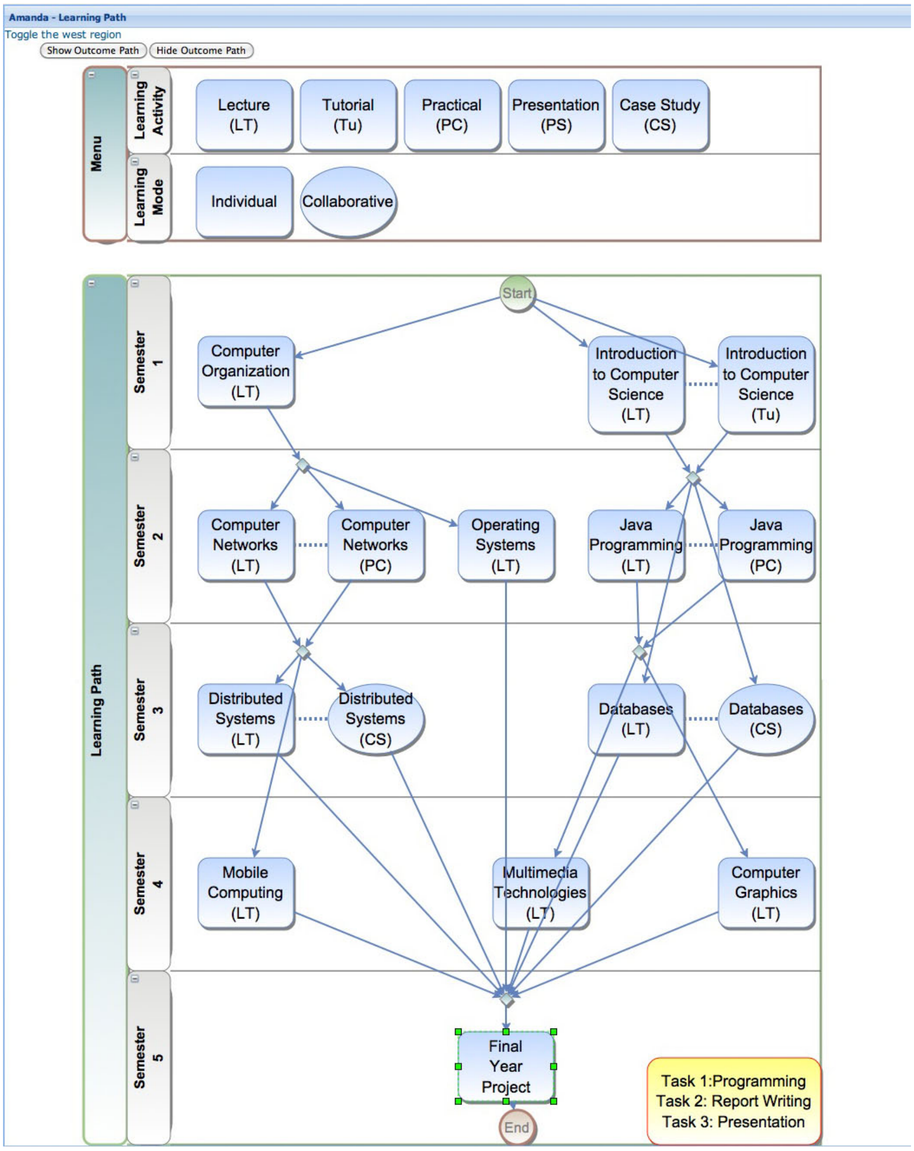
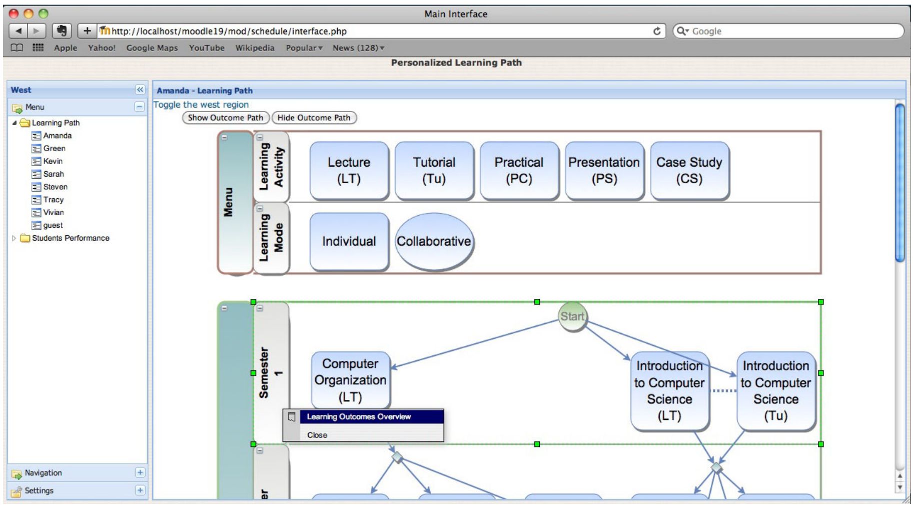


Fig. 4. 2 A screen shot of our prototype.

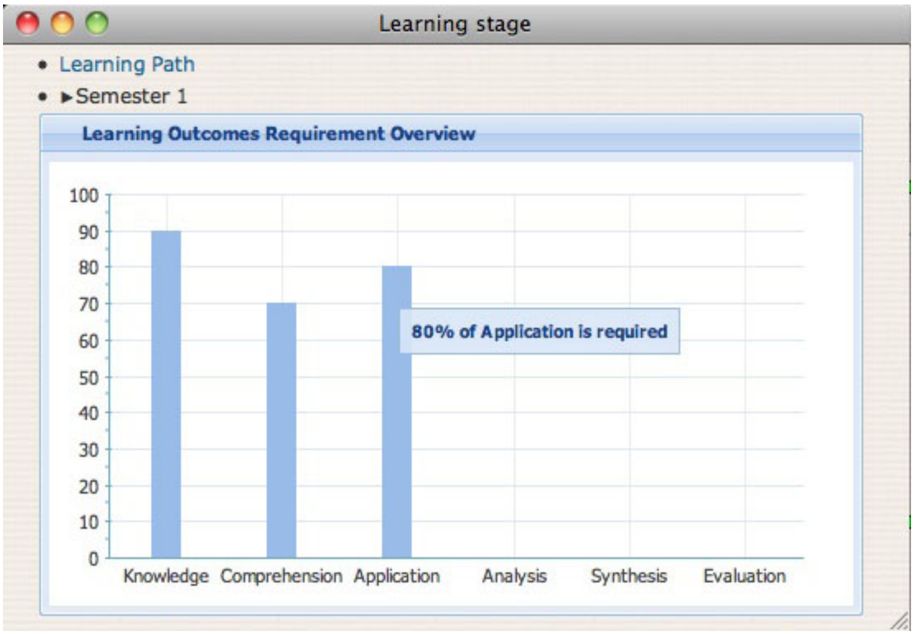
prototype is not currently a functioning learning management system, where content management was not implemented. Fig. 4. 2 shows a screen shot of our prototype where a teacher is working on a *LA* level learning path that comprises learning activities for all students in a computer science program. As shown at the upper part of Fig. 4. 2, there is a menu providing some predefined learning activities for the teacher to construct learning paths. Under the menu, there is an area for learning path construction. Each of the test users was invited to attend a personal introductory session, which lasted for about an hour. Each session started with a briefing on the proposed learning path construction model. They can ask questions during the briefing if they have anything confused. The test user then had a chance to use the prototype to construct learning paths and was required to answer a questionnaire to comment on the prototype. The questionnaire contains questions to collect teachers' background information as well as to collect teachers' evaluation results on our prototype from both choice questions and written form. More details about the research questions and collected results of the questionnaire can be found in section 4.5. And the whole questionnaire is listed in Appendix A.

Fig. 4. 2 shows a sample learning path constructed by a teacher. As an example, a "Lecture" type of learning activity – "Computer Networks (*LT*)" is constructed in Semester 2, which can be further customized by modifying its learning tasks and their associated weights. For instance, *LA* "Final Year Project" is selected to reveal its learning tasks, which are shown in the yellow box located at its right hand side. Teacher can overview the learning tasks contained in the learning activity before he/she decides to change the task arrangement of the learning activity by opening another window. In addition to "Computer Networks (*LT*)", a "Practical" type of learning activity – "Computer Networks (PC)" is constructed. These two learning activities come together forming a KE, which is indicated by a dashed-line connection. This KE formulation allows students to follow multiple approaches when learning a subject and achieve more learning outcomes.

A student may conduct a learning activity if he/she has passed all pre-requisite(s). Note that arrows indicate pre-requisites, while rhombuses indicate multiple learning activities sharing the same pre-requisites or learning activities having multiple pre-requisites, e.g., "Distributed Systems" has both "Computer Networks (*LT*)" and "Computer Networks (PC)" as pre-requisites. Optionally, a learning path can be turned into an adaptive one if suitable types of learning activities can be set up for each student. Despite this feature surpasses existing KE-based methods where they do not support the modeling of pedagogy and certain forms of learning outcomes. However, further techniques should be developed to avoid teachers manually producing all settings.



(a)

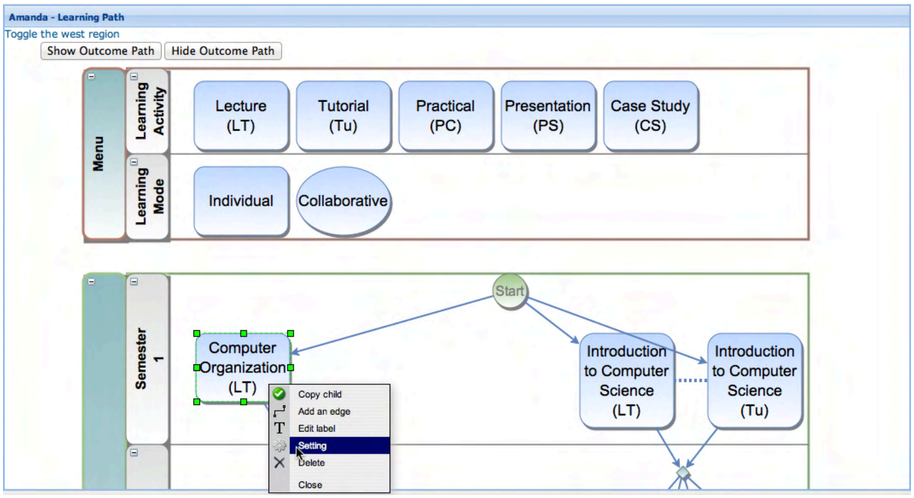


(b)

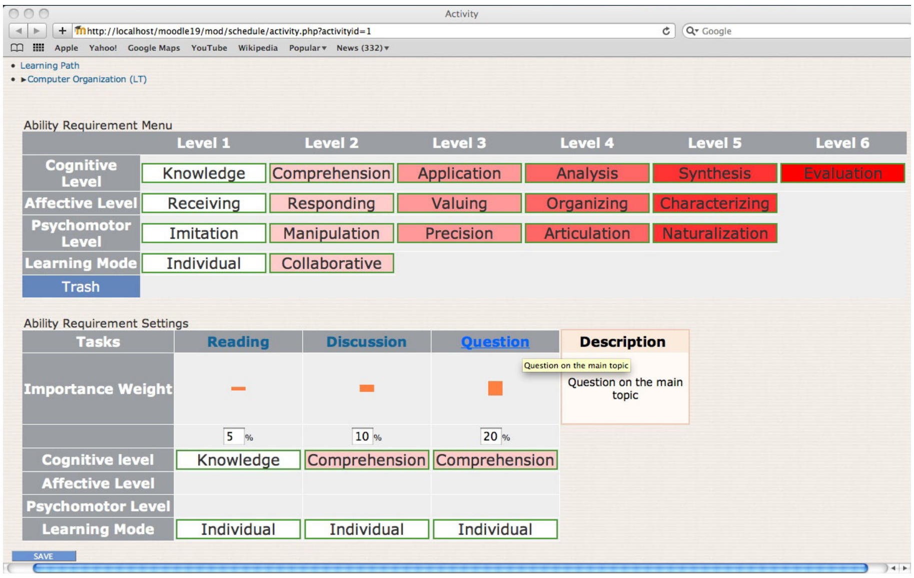
Fig. 4. 3 Viewing the learning outcome setting at the learning stage level.

Teachers then proceed with more fine-grained settings. Our prototype provides interfaces for teachers to define and review learning outcome settings at both learning stage and learning activity levels. Fig. 4. 3 (a) shows a learning stage – "Semester 1" is selected. Its learning outcome settings show in Fig. 4. 3 (b), indicating Semester 1 assesses student learning outcomes based on *knowledge*, *comprehension* and *application* levels under the cognitive domain of Bloom's Taxonomy. The chart also shows the total percentage of each learning outcome collected from all learning activities within the learning stage to indicate its importance. Such weights cannot be adjusted.

We also ask teachers to work on individual learning activity. Fig. 4. 4 (a) shows that learning activity "Computer Organization (*LT*)" in Semester 1 is



(a)



(b)

Fig. 4. 4 Manipulating the learning outcome setting at the learning activity level.

selected for editing. The lower part of Fig. 4. 4 (b) shows its settings with editable learning tasks, i.e., *Reading*, *Discussion* and *Question*. The prototype can automatically normalize the weights of all learning tasks based on the weight adjustment mechanism described in the sub-section of "Learning

Activity" under section 4.3.2. This feature is handy, allowing a teacher to focus on the relative importance of learning tasks rather than the actual values of the weights. In addition, a teacher can change the learning outcome setting of a learning task by dragging-and-dropping learning outcomes from the learning outcome requirement menu, as shown in the upper part of Fig. 4. 4 (b).

For demonstration purpose, our prototype also supports basic learning progress evaluation. We classify a student's learning outcome of a learning activity with a few grade levels, ranging from "Fail" to "Excellent". As shown at the top of Fig. 4. 5, they are represented by different colors. Fig. 4. 5 shows that a student has just completed Semester 1, and has received a "Good" learning grade in "Computer Organization (*LT*)" but failed in both the "LT" and "Tu" learning activities of "Introduction to Computer Science"(in pink color). Based on the setting of our prototype, this student needs to retake these failed learning activities before starting Semester 2.

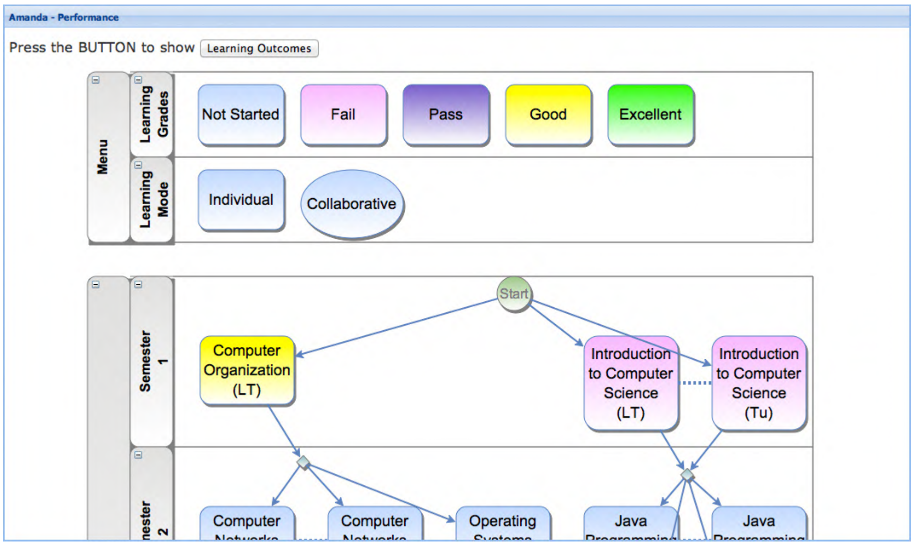


Fig. 4. 5 A screen shot showing the progress of a student.

Our prototype also supports the construction of the *LT* level learning paths to indicate how a student is being trained in terms of a specific type of student learning outcome. This function can be activated by pressing the "Show Outcome Path" button at the top-left side of the user interface shown Fig. 4. 4 (a). Fig. 4. 6 shows the *LT* level learning path for communication skill while Fig. 4. 7

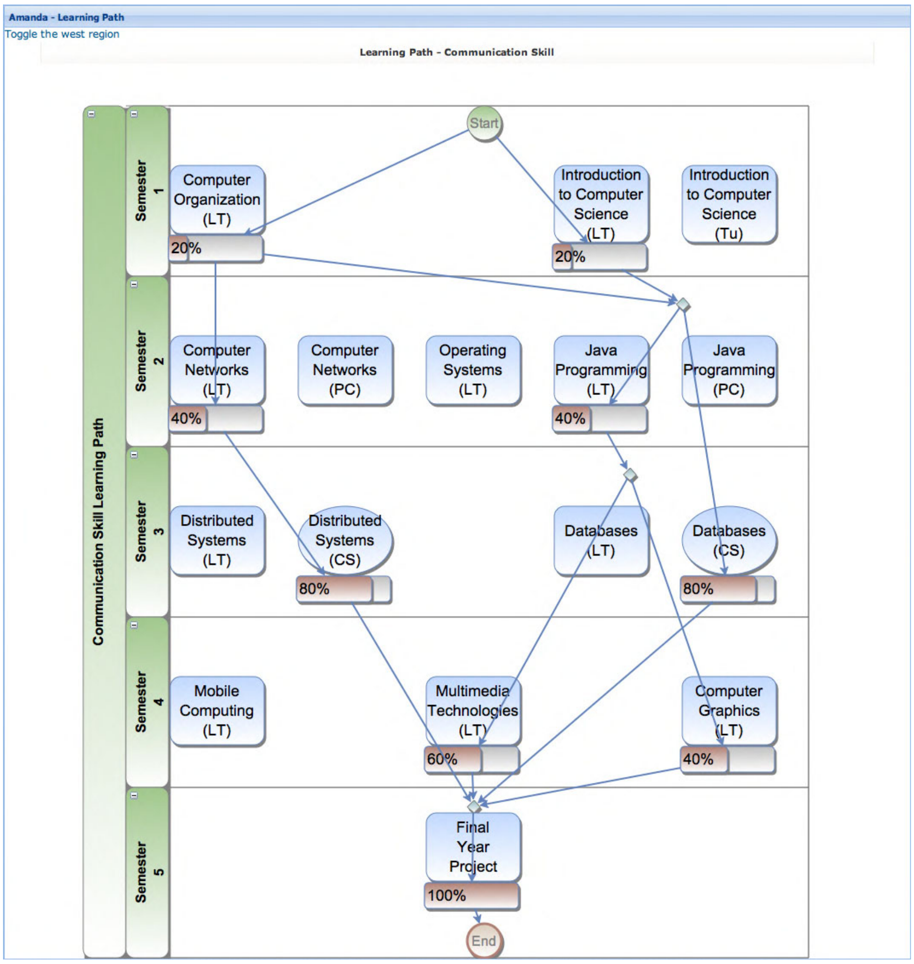


Fig. 4. 6 Learning path for communication skill.

shows the path for writing skill. To illustrate the assessment of learning outcome, we use a percentage value to show the difficulty level of certain learning outcome required at a *LA*. If the student can pass the assessment associated with the corresponding *LT*, it means that the student has made the prescribed level of achievement in that particular learning outcome. Using Fig. 4. 6 as an example, at the beginning, two *LAs* are involved in Semester 1 to train up a student's communication skill. The difficulty levels of both are set to 20%. As a student proceeds with the course of study, the student may gain a higher level of achievement in communication skills. This is shown by the increase in the difficulty level associated with the communication skill along the learning path. Finally, after the student has gone through the entire course of study, the student is expected to have gained very mature communication skill with the 100% of difficulty level, if the student can pass the assessment of the corresponding *LT* set in the “Final Year Project” learning activity in

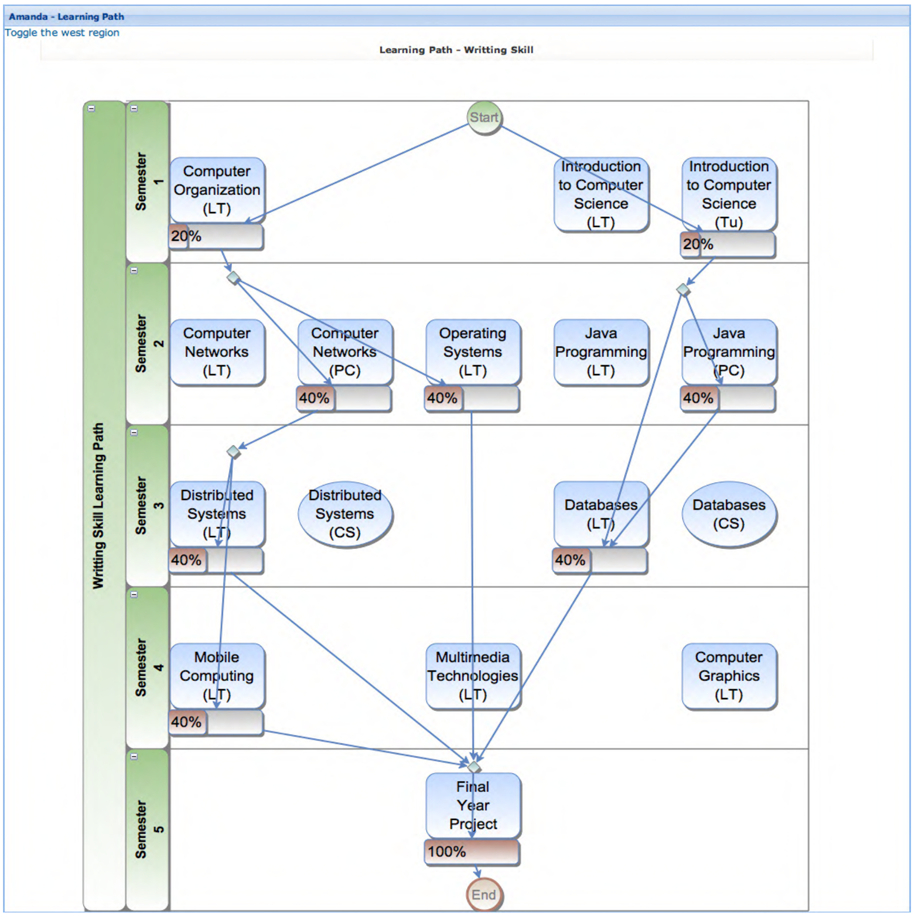


Fig. 4. 7 Learning path for writing skill.

Semester 5. In general, the *LT* level learning paths help students learn more effectively by letting them understand how well they have achieved in certain learning outcome. In case if a student fails in certain learning outcome, the student can be supported by re-doing only the relevant learning tasks in order to fix such a learning problem. This fine-grained arrangement can enhance the learning effectiveness as it avoids the students re-doing the entire learning activities or KEs.

4.5. User Study Results and Analysis

Following the case study as depicted in section 4.4, we have delivered a questionnaire to collect teachers’ feedback on the proposed learning path model. The evaluation model and the results are shown as follows:

Research question: We tested whether teachers of different 1) knowledge background or 2) teaching experience will find our model providing a good way for constructing learning paths and assessing student learning outcome. Our prototype is designed to let teachers visualize and try out our model. We do not evaluate the user interface design of the prototype, as it is out of the scope of this research. We invited teachers from Durham University and some local high schools to try out our prototype and give us feedback of their satisfaction on our learning path model by using 13 questions to access the following research questions:

- **RQ1:** Can the new model provide a more systematic and intuitive way for teachers to construct learning paths?
- **RQ2:** Does it produce learning paths that address the diverse needs of different courses?
- **RQ3:** Do teachers think that it is easier to set out criteria to assess student learning outcomes through the new model?

The questions provide proper coverage for evaluating both the LA and LT levels of learning path construction. Teachers were required to provide feedback on the 13 questions based on a 5-point likert scale (Totally Agree=5, Agree=4, Neutral=3, Not Quite Agree=2 and Disagree=1). As we use continuous and ordered rating scales, where they are assumed to have equal intervals and implicitly approximate interval data, they are quantitative and allow us to use ANOVA [Kirk95] for analysis. We also have another 5 questions collecting personal information of a teacher, including teaching experience, teaching discipline, e-learning tools experience, and teaching approaches and styles.

Sample building: 15 teachers were involved in the experiment. The independent variables are 1) knowledge background (KB) and 2) teaching experience (TE), where each of them is classified into groups of samples as follows for analysis.

- **Groups under KB:** Science (7 teachers), Engineering (6 teachers) and Arts (7 teachers).
- **Groups under TE:** 0-1 year (6 teachers), 1-4 years (4 teachers), 5-9 years (5 teachers), and 10 years or above (5 teachers).

Note that we did not use a control group as all the teachers in our experiment have experience in using e-learning tools, such as Wimba Create, Blackboard, Learning Object Creator and Web tools. Some of them have even involved in designing or modifying teaching activities. This indicates most of our test users have a good understanding in difficulties and important factors of learning path design. Therefore, besides the ANOVA analysis, we also collect opinions from the teachers regarding their experience with our model.

Statistical model: We employ one-way ANOVA [11] to analyze each of the independent variables because both variables comprise more than two groups. Methods that can analyze only two groups, such as Wilcoxon test, are not applicable.

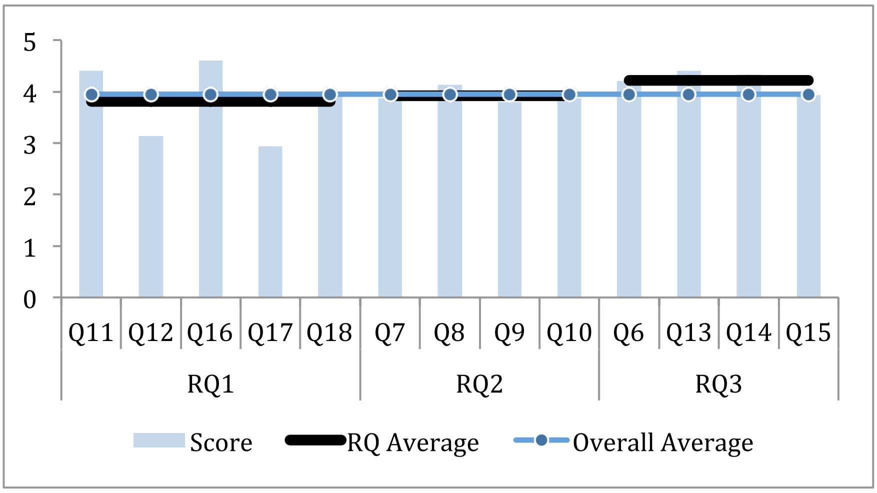


Fig. 4. 8 Summary of scores from the questionnaire.

Statistical results and conclusions: As shown in Fig. 4. 8, the teachers have rated an overall average score of 3.95 out of 5 with the 13 questions, meaning that they have a very good satisfaction of using our model across different aspects of learning path construction. More specifically, the average scores of individual group of questions are 3.81 (RQ1), 3.92 (RQ2) and 4.22 (RQ3). While teachers have a very good satisfaction on our model regarding intuitiveness and meeting diverse needs, they rate much higher on our model in terms of assessing student learning outcomes. Note that the scores of Q12 and Q17 are rated lower than the other questions. They asked feedback on whether the prototype can clearly show the relationship among LAs and the design of a LP, respectively. The lower scores are related to the user interface design of the prototype. Although this issue is out of the scope of this research, we believe this is an important issue to work on for our future work, particularly it relates to how we can avoid putting burden on teachers to work out mathematics for setting up learning paths and learning activities.

In general, the teachers agree that incorporating learning outcomes from the Bloom's Taxonomy is useful, and they feel that the introduction of *learning task* is good as it allows a teacher to focus on designing simple tasks to train up students with a specific learning outcome. They are in favor of the idea of *learning activity*, which comprises learning tasks, as it is more intuitive for teachers to create and organize learning activities. According to the results of one-way ANOVA, no statistically significant differences in teacher evaluations were found due to knowledge background or teaching experience.

We set p-value to 0.05, meaning that our test is based on the assumption that the probability of getting statistically significant results simply by chance is less than 5%. As shown in Table 4. 4, when performing AVONA test on teacher's knowledge background, F-value is 0.8999 and p-value is 0.4163 when df_1 between the 3 groups is 2 and df_2 within the groups is 33. As F-value is close to 1 and p-value is much greater than 0.05, there is not a statistically significant difference between the means of all groups, and the difference in teaching experience is not statistically significant to the teachers' evaluation. Similarly, the same conclusion can be drawn when we perform AVONA test on teacher's teaching experience, as F-value is 1.1627 and p-value is 0.3347 when df_1 between the 4 groups is 3 and df_2 within the groups is 44.

Analytical Comparison: To depict the differences between our model and existing methods [Chen08, Cono05, Dalz03, Kara05, Lim009]. We examine the nature of the constructed learning path (LP) and the nature, the number and the sequence of the learning objects (LOs) used to build a learning path from different methods. Table 4. 5 summarizes the comparison. The most significant difference of our model is that it offers multiple learning

Table 4. 4 Results of one-way ANOVA analysis.

ANOVA Single factor: Knowledge background

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	0.670139	2	0.335069	0.899926	0.416344	3.284918
Within Groups	12.28688	33	0.37233			
Total	12.95702	35				

ANOVA Single factor: Teaching Experience

Source of Variation	SS	df	MS	F	P-value	F critical
Between Groups	1.353611	3	0.451204	1.162679	0.334742	2.816466
Within Groups	17.07519	44	0.388072			
Total	18.4288	47				

Table 4. 5 Comparison between our model and existing methods.

Comparison Criteria	**Methods**		
	Our Model	**Chen et al. [5], Karampiperis et al. [10], LS-Plan [14]**	**LAMS [6, 7]**
Constructed LP(s)	Multiple LPs with 2 Levels: LA & LT based (Support fine-grained pedagogy)	Single LP: KE Based (Pedagogy is not supported)	Single LP: LA Based (Support coarse-grained pedagogy)
Nature of LOs	Formed by LAs or by LTs (Relevant LAs can form a KE)	Formed by KE	Formed by LA (No explicit LA and KE mapping)
Number of LOs	Determined by number of LAs or by number of LTs	Determined by number of KEs	Determined by number of LAs
Sequence of LOs	Ordered by LAs or by LTs	Ordered by KEs	Ordered by LAs

paths to support various forms of student learning outcomes assessment on top of the traditional functionality of a learning path, which models the steps of a course of study. In contrast, existing methods only support the traditional functionality and offer a single learning path. As a result, student learning outcome assessment is only a consequence of such a modeling, and that various types of student learning outcomes assessment are hard to be supported. Regarding learning objects, existing work use a KE or a LA to form a LO, and that they determine the number and the sequence of LOs. In contrast, we model a LO with two levels: LA or LT based, which leads to two different types of LO sequences.

4.6.Summary

In this chapter, we have presented a novel learning path model based on learning activities, which supports the assessment of various types of knowledge and skills to describe the student learning progress. We have mathematically defined the model, its components, and the relations and constraints among the components, allowing course designers or teachers to explicitly formulate and reuse the learning and teaching approaches. Our work may also open up new research and development on more advanced adaptive e-Learning systems that can incorporate precise teaching approaches to match with different student learning styles. We have implemented a prototype and conducted a user study to verify if the proposed model can match with the teachers' needs well. Results show that our model is favorable and most of the teachers participated in the user study indicated that they would like to use it in their course design.

Our work may open up new research and development on more advanced adaptive e-Learning systems that incorporate precise teaching approaches to match with different student learning styles. We believe that while an automatic learning path generation method is desired, teachers may still want to have the flexibility for manually customizing a learning path. In our opinion, a sensible solution should aim at avoiding teachers to spend time explicitly setting up a lot of mathematical parameters for students with different learning styles. In this sense, we determine user interface design and setting up templates for learning paths and their components could be two possible directions for future work. For user interface design, similar to our prototype, we should work out visual aids and manipulators for teachers to adjust and visualize the importance of each learning path component. As a complement, techniques should be developed for producing templates for learning paths and their components. We may also extend existing work on adaptive learning path generation, such as [Li10, Ullr09], to work with the template based idea to produce adaptive fine-grained learning paths.

Chapter 5

5. Learning Path Construction based on Association Link Network

In the last chapter, we mainly formulate learning activities to construct the learning path based on learning outcomes in terms of how to learn. We still need to design learning resources forming the learning contents that are used in a learning path to define what to learn. Manually designing the learning resources is a huge work to teachers and quite time consuming. To solve this problem, we can make use of the Web resources by turning them into well-structured learning resources for students with different knowledge backgrounds and knowledge levels. So the key problem of constructing personalized learning path is to generate learning resources by identifying the knowledge structure and attributes of these Web resources, and to correctly deliver them to students. In this chapter, we show how we construct well-structured learning resources from loosely connected Web resources by constructing a set of three different networks to formulate topics, keywords and the actual learning resources. Such formulation is used to generate learning paths with different abstractions of knowledge, helping students better understand the knowledge covered by the learning resources.

Nowadays the Internet virtually serves as a library for people to quickly retrieve information (Web resources) on what they want to learn. Reusing Web resources to form learning resources offers a way for rapid construction of self-paced or even formal courses. This requires identifying suitable Web resources and organizing such resources into proper sequence for delivery. However, getting these done is challenging, as they need to determine a set of Web resources properties, including the relevance, importance and complexity of Web resources to students as well as the relationships among Web resources, which are not trivial to be done automatically. Particularly each student has different needs. To address the above problems, we present a learning path generation method based on the Association Link Network (ALN), which works out Web resources properties by exploiting the associations among Web resources. Our experiments show that the proposed method can generate high quality learning paths and help improve student learning.

5.1. Introduction

Learning resources (LRs) refer to materials that help students learn and understand certain knowledge. Such LRs can be constructed by different types of media, including text, audio, and video. Typically, producing LRs is very time consuming. With the availability of the Internet, such situation may be improved, as information covering a huge variety of ready-made knowledge, namely Web resources, is made available. Examples of Web resources include materials from Wikipedia, BBC, Reuters, etc. Reusing such resources may help teachers significantly reduce their time on producing LRs and may also facilitate the generation of self-paced courses. However, Web resources may be loosely connected without any well-defined structure or relationship, and may also be redundant. It is not trivial to transform Web resources into LRs, as relationships among LRs are required to be well defined and LRs should be arranged to deliver in a proper order for a particular student to study.

Identifying relevant LRs is essential to learning path generation. Existing works determine such a relevancy by matching student specific requirements, including topics to learn, learning preferences or constraints [Farr04, Dolo08] against the characteristics of LRs, which can be maintained by a list of attributes, such as related topic and difficulty level, or additionally by a structure that defines how LRs are related among each other [Meli09]. Learning path generation methods aim at arranging selected LRs into a proper sequence for delivering to students, so that they can learn effectively in terms of minimizing the cognitive workload. Basic work [Farr04] only consider attributes associated with each LR, such as its related topic. More advanced works [Kara05, Chen08] consider the structure among LRs which facilitates them to model the cognitive relationships among LRs. Such relationships are fundamental to learning effectiveness. However, structures among LRs are not trivial to build. Existing work considers using pre-defined structures [Kara05] or generating LR structures based on pre-test results [Chen08], which involves significant human efforts.

We present a learning path (LP) generation method based on the Association Link Network (ALN) [Luo08A, Luo11], which discovers knowledge structure among Web resources based on association. This allows teachers to reuse Web resources forming LRs, where relationships among LRs are automatically constructed. The main contributions of our research study in this chapter include:

- We apply ALN to transform Web resources into well-structured LRs, where the pedagogical attributes of LRs, including their knowledge domain, importance and complexity, can be automatically determined. This allows us to construct a teacher knowledge model (TKM) for a course, and generate adaptive learning path to each student. We also maintain a student knowledge model (SKM) to monitor student learning progress.
- We model the TKM as well as the LP by 3 ALNs, namely LR, topic and keyword based ALNs. This modeling allows students to perceive the relationships among LRs through different abstraction levels, which can help students minimize their cognitive workload during the learning process.
- We construct a test generation scheme to automatically assess student understanding against a LR within a UOL. We use the associations between topics or keywords as the rules to test if students can build up the correct association between major concepts. This automatic scheme saves

a lot of efforts to manually design tests.

In this chapter, we organize the structure as follows. Section5.2 explains the construction of the teacher knowledge model (TKM). Section 5.3 presents the generation of adaptive learning paths. Section 5.4 shows some results and Section 5.5 concludes this chapter.

5.2. Related Work

5.2.1. Learning Resources Construction

To support students learning effectively, relevant LRs should be identified and delivered in a proper sequence based on student needs and knowledge backgrounds. [Farr04] proposes using Web resources as LRs without requiring teachers to create LRs. Suitable Web resources are selected based on certain student specific criteria, including topics to study, learning preferences and learning constraints, e.g. available study time. [Dolo08] also allows students to search LRs for learning. However, the method in addition performs a query rewriting based on student profiles, which describe student learning preferences and learning performance (which indicates student knowledge level), so that students only need to focus on what they want to learn and the system will take care of the suitability of every LR, which matches the student searching criteria. [Meli09] proposes a more comprehensive modeling of LRs, where each of them is designed to associate with a concept, a knowledge type (verbal information or intellectual skills), and a knowledge level. LRs are connected based on concept relationships, where teachers manually define prerequisite among concepts. However, such relationships are not fine enough to support the arrangement of individual LRs in a proper sequence for delivery. [Acam11] characterizes LRs based on subjects and organizes LRs by ontology-based subject relations, including part of, prerequisite, and weaker prerequisite relations. They form the basis for both determining the delivery sequence of LRs and selecting suitable LRs according to the student preferred subjects. However, subject information is too coarse that each subject is associated with many LRs, making precise learning path hard to be generated.

5.2.2. Learning Path Generation Algorithm

Given that LRs are properly modeled, a learning path generation algorithm can be used to deliver LRs for students to learn. [Farr04] allows students to submit queries selecting suitable LRs. The selected LRs will then be ordered by the topics and the instructional methods that they belong to, respectively. As structures of LRs and relationships among LRs, which are critical to the control of student cognitive workload in learning, are not considered, learning effectiveness cannot be guaranteed. [Kara05] models the structure among LRs based on a hierarchy of topics, which are defined by the ACM Computing Curricula 2001 for Computer Science. The method initially generates all possible learning paths that match the student goal. It then selects the most suitable one for a student to follow by considering the student cognitive characteristics and learning preferences. Although the relationship among LRs is essentially constructed manually, learning effectiveness is better addressed. [Chen08] models the relationships among LRs based on an ontology-based concept map, which is generated by running a genetic algorithm on a set of student pre-test results. The method successfully works out the prior and posterior knowledge relationships of LRs, so that LRs can be delivered based on their difficulty levels and concept relations to reduce student cognitive workloads during the learning process. However, the relations of LRs are provided by the concept relations. In this way, they can only make sure the concepts in the learning path are continual, but the LRs may be not continual. It is necessary to provide students continual LRs through the learning path.

5.3. The Teacher Knowledge Model

The Association Link Network (ALN) [Luo08A, Luo11] is designed to automatically establish relations among Web resources, which may be loosely connected without well-defined relations. ALN defines relations among Web resources by analyzing the keywords contained in Web resources. Such relations are referred as associations, which link up Web resources and ALN to describe the semantic relationships of Web resources, and turn Web resources into LRs. In our work, we further exploit such associations to automatically formulate some key attributes of LRs, including their importance and complexity, which are fundamental to LP generation. The LPs comprise a set of sub-ALNs, which are parts of the whole set of ALNs respectively, namely LR, topic and keyword, to help students perceive LRs together with their multiple levels of relationships. By following such learning paths, the cognitive workload of the student on learning can be greatly reduced. To set up a measure for evaluating student learning progress, we define the set of ALNs that link up all available LRs of a course as the teacher knowledge model (TKM). We also maintain a student knowledge model (SKM) (Ref. Section 5.3) to describe student learning progress. SKM comprises the system recommended LP and the part of the LP that a student has finished studying, together with all relevant LRs. SKM also comprises a student profile, indicating the student's knowledge levels and preferred topics.

Technically, the foundation of ALN is the association of keywords, where there exists an association link between two keywords appear in the same paragraph. To facilitate the formulation of LRs and the learning paths, we extract the most important keywords identified from a set of LRs as topics, where the association link between two topics are inherited from that between the corresponding keywords. The topics are used as a means to determine whether any two knowledge concepts are related. In contrast to a topic, a keyword only indicates a certain aspect of a piece of knowledge concept. On the other hand, there exists an association link between two LRs if some keywords contained in the two LRs are associated with each other. As an ALN represents the network of a set of nodes $\{c_1, c_2, \cdots, c_n\}$ by their association, where n is the number of nodes. Mathematically, an ALN is represented by a matrix of association weights aw_{mn}, where each formulates the association relation between a cause node c_m and an effect node c_n. It is defined as in Eq. 5.1:

$$ALN = \begin{pmatrix} aw_{11} & \cdots & aw_{1n} \\ \vdots & \ddots & \vdots \\ aw_{m1} & \cdots & aw_{mn} \end{pmatrix} \tag{5.1}$$

Particularly, LRs, topics and keywords are all modeled by ALNs. An ALN can be automatically and incrementally constructed by adding or removing nodes. When a new node is added to an ALN, we need to check such a node against all existing nodes in the ALN, identifying whether the nodes are relevant and computing the association weights between the newly added node and each of the relevant existing nodes in the ALN. When removing a node, all association links induced by the node will be removed. This incremental property makes adding new Web resources to form new LRs or removing LRs to from a course easily. We now depict the details of the construction of the three different ALNs in our system.

To turn a set of Web resources into learning resources, we initially extract their keywords and construct the association links among the keywords by Eq. 5.2.

$$aw_{ij} = P(k_j|k_i) = \sum_{k=1}^{n} b_{ir}/n \tag{5.2}$$

where aw_{ij} is the association weight from cause keyword k_i to effect keyword k_j, k_i is associated to k_j when they exist in the same paragraph p_m [Luo08A]. An association weight, which is also the $P(k_j|k_i)$, indicates the probability that the occurrence of cause keyword k_i leads to effect keyword k_j in the same paragraph at the same time. b_{ir} is the probability that the occurrence of cause keyword k_i in the r^{th} sentence leads to the occurrence of effect keyword k_j in the same sentence. n is the number of sentences in the paragraph p_m. We apply TFIDF Direct Document Frequency of Domain (TDDF) [Luo08B] to extract domain keywords from a set of Web resources, where keywords are texts that appear in a good number of Web resources, i.e. the document frequency is higher than a threshold. The associated relation is determined by $A \xrightarrow{\alpha} B$, meaning that if node A is chosen from an ALN, node B will also be chosen with the probability α.

We then extract and link up topics from the LRs. Topics refer to the most important keywords, which have the highest numbers of association links than the other keywords, meaning that they can represent the most important information of a set of LRs. In our experiments, we select the top 20% of keywords forming the topics. Pedagogically, topics model the knowledge concepts covered by the LRs, while keywords are associated to a topic as the topic's key attributes, which help explain why certain knowledge concepts are related to some others. This modeling is much comprehensive than existing work, as they only associate LRs based on topics.

To construct LRs for a course, we follow the knowledge domain (i.e. a set of topics) of the course and select relevant Web resources that match the knowledge domain, turning such resources into LRs. We have conducted experiments on our method using 1085 Web resources about health information from www.reuters.com/news/health. We do not create LRs for similar Web resources in order to avoid students spending time on learning similar contents repeatedly. We check Web resource similarity based on their keywords and association links. In the implementation, we pick the first selected item of such Web resources to create a LR and stop creating further LRs for any Web resource that has a high similarity. Fig.5.1 shows part of the keyword ALN that we have created, where each node represents a keyword, and each edge, namely an association link, represents the existence of an association between two nodes. Actually, in Fig.5.1, each edge has its value of association weight in the matrix of ALN, indicating the association degree between the two keywords that connected by the edge. The importance of a node is directly proportional to the number of association links connecting to it. Note that the edges showing in the figure do not imply any association weight.

TKM formulates the overall knowledge structure of a course based on topic, keyword and LR ALNs. Research [Shaw10] shows that formulating concepts into a knowledge map, which is a graph having concepts as nodes and they are connected by links that model the relationships between two concepts, can significantly improve student understanding, particularly when

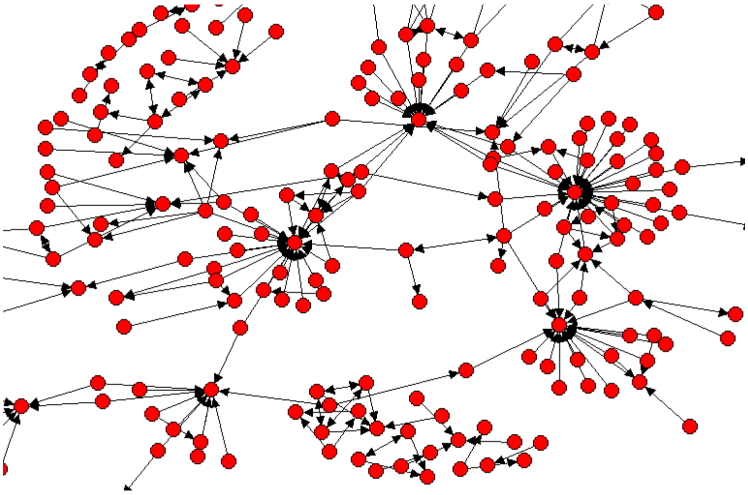


Fig.5.1 An illustration of a keyword-based ALN.

comparing with studying through LRs collated by a simple Webpage browse-based structure. Our ALN based knowledge structure is similar to a knowledge map. Instead of having freestyle labeling to formulate the relationship (i.e. the link) between two concepts, we use association weight to model quantifiable relationships among concepts. In addition, we have three different types of ALNs representing different abstraction levels of a set of concepts, i.e. topic, keyword and LR ALNs, where the relationships among such ALNs are also explicitly defined, i.e. given a node in an ALN, the corresponding nodes in the other two ALNs are well-defined. This implies that it is easy to retrieve LRs based on student-preferred topics and the knowledge structure for a set of LRs.

The ALN structure also allows us to automatically compute the complexity and the importance of each LR, avoiding instructors or course designers to manually define such attributes, which is extremely time consuming when there are a massive number of LRs to deal with. More specifically:

- We compute the complexity of a LR, which can be used to match student knowledge level, based on the algebraic complexity of human cognition that associates with the complexity of both keywords and association links of the LR X as in Eq. 5.3.

$$\lambda_X^T = \sum_{K=0}^{D-1} W_k \cdot \lambda_X^k \tag{5.3}$$

where λ_X^T is the text complexity of LR X in terms of keywords, D is the number of keywords in LR X. λ_X^k is the number of degree-k association, i.e. the number of keywords having k association links connected to LR X, which indicates the complexity of association link. W_k is the number of keywords having degree-k association, which indicates the complexity of keywords. A LR is low in complexity if it has low number of association links while such links are of low degrees.

- The number of association links indicates the number of relationships existing between a node and its connected nodes. The association weight indicates how strong a node is related to another one. We therefore use the association weight and the number of association links to indicate the importance of a node.

5.4. Student Knowledge Model and Personalized Learning Path

Student knowledge model (SKM) formulates student learning progress. It comprises a dynamical generated personalized LP and a set of student characteristics. A personalized LP is technically a subset of the TKM. Student characteristics that we have considered include knowledge background, knowledge level, and preferred knowledge concepts, which are learned topics, learning performance on such learned topics, and topics that a student is interested or can effectively learn, respectively. The algorithm for personalized LP generation is as follows,

(1) **Initialization:** Based on the topic ALN of TKM, we determine the starting point of a personalized LP according to the initial knowledge of a student, i.e. the topics learned. If such information does not exist, we consider the topics, where their complexity matches the student's knowledge level, and select the most important one as the starting point. This ensures the most suitable and fundamental knowledge is selected for a student to start learning. We compute the complexity of a topic by considering the average complexity of all LRs associated with the topic as follows:

$$D_T(x) = \frac{1}{N}\sum_{p=1}^{N} \lambda^T(LR_p) \tag{5.4}$$

where $D_T(x)$ represents the complexity of topic x, and $\lambda^T(LR_p)$ is the complexity of LR p (ref. Eq. 5.3).

(2) **Incremental LP Generation:** Based on the current node of a LP, we incrementally generate the next node of the LP by identifying a suitable one from the set of direct connected nodes according to the topic ALN of TKM. The selection is based on two criteria: the *complexity* and the *importance* of the topic. The complexity of the topic should match the student's knowledge level. If there are more than one node meeting the complexity criteria, we then select the node with the highest importance $I_{S_i}(x)$, which is formulated by the summation of association weights where student preference on a topic is considered as in Eq. 5.5:

$$I_{S_i}(x) = \sum_{j=1}^{n} aw_{xj}(x) \cdot P_{S_i}(x) \tag{5.5}$$

where I_{S_i} represents the importance of topic x for student i, $aw_{xj}(x)$ represents the association weight between topic x and topic j, and $P_{S_i}(x)$ represents student i's degree of preference on topic x, which could be any value from 0 to 1, and "0" indicates no preference and "1" indicates full preference.

(3) **LR Selection:** Based on the LR ALN of TKM, we select a set of LRs, where their associated topics match with the selected topic by step 2. As shown in Eq. 5.6 and 5.7, a student specific LR p will be identified by matching the complexity $\lambda^T(LR_p)$of the LR with the knowledge level KL_{S_i} of the student. We use the coefficient 0.1 to constrain the error between the complexity of LRs and the student's knowledge level, where the error should be smaller than a tenth of the students' knowledge level. We can recommend LRs that best fit the student's knowledge level.

$$LRs = \{p \mid \|\lambda^T(LR_p) - KL_{S_i}\| < 0.1 KL_{S_i}\} \tag{5.6}$$

$$D_{S_i}(x) = \lambda^T(LR_p)/P_{S_i}(x) \tag{5.7}$$

LP Progression and Alternative LP: After a student successfully studying a LR, we update the SKM by indicating the student has finished such a LR and the associated keywords. Our system will then go back to step 2 again for incremental LP generation. If a student fails the corresponding assessment, it is likely that the student lacks the knowledge of some aspects of the topic about the LR. To deal with such a learning problem, we adjust the LP by redirecting the student to learn an alternative LR, which is the most important unlearned prerequisite node of the failed LR as defined in the LR ALN of the TKM, before coming back to learn the failed LR. Such an alternation may be carried out repeatedly on the rest of the unlearned prerequisite node of the failed LR if necessary. Fig.5.2 gives an example of a recommended learning resources by the system.

(4) **Learning Performance:** A student i has finished learning a course when there is no more LR to follow. Student learning performance D_i can be computed by the difference between the real performance SKM_i (i.e. the finished LP) and the expected performance LP_i defined by the recommended LP as stored in the TKM:

$$D_i = \|SKM_i - LP_i\| \tag{5.8}$$

where D_i evaluates whether the student has a good learning performance at the end of the student's learning. The student has a better learning performance if SKM_i is closer to LP_i. Fig.5.3 shows an example of a system recommended LP formed by a set of the three abstraction levels of ALNs for a student. Fig.5.3- a depicts the topic ALN that comprises 5 topics, forming the topic level of the LP (i.e. project → president → lead →plastic → pharmacy), where the edge thickness indicates the association weight. The path starts from the most important topic "project", and then the second important one which has to connect with the first one is "president", and end with the least important one "pharmacy". All keywords that have association with the five topics are extracted from the teacher knowledge model of keyword abstraction level, together with their association links in between to form the learning path in keyword abstraction level, as shown in Fig.5.3- b. And all LRs that contain the five topics are extracted from the teacher knowledge model of LR

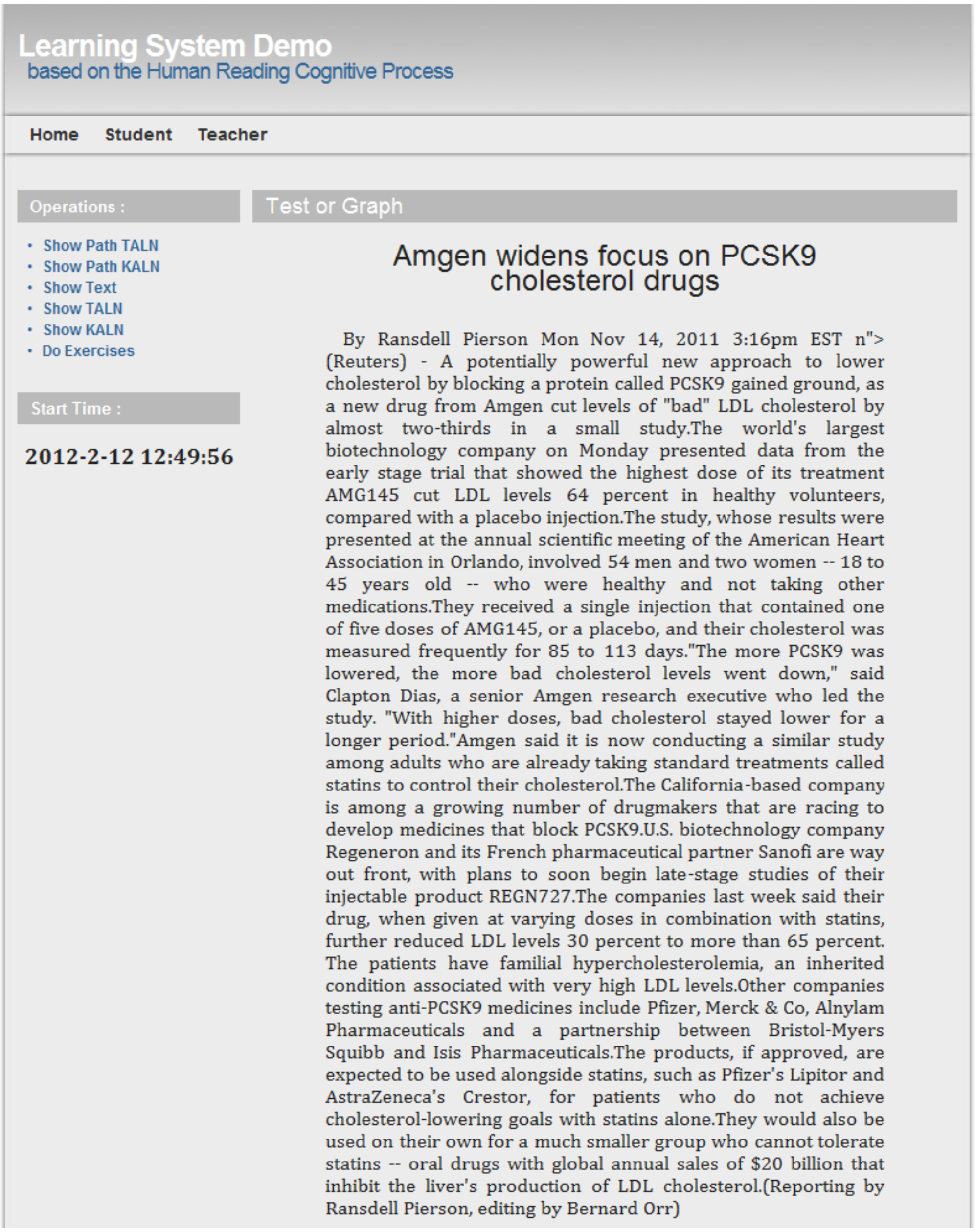


Fig.5.2 Example of a recommended learning resource.

abstraction level as well, together with the association links in between to form the learning path in the LR abstraction level, as shown in Fig.5.3- c. However, students may not have enough time to learn all these LRs, so we just recommend them the LRs that match with the student’s knowledge level. The highlighted LRs as shown in Fig.5.3- c are the recommended LRs that match the student’s knowledge level. Since there are associations among LRs through sharing keywords, a student showing interest in a LR may also

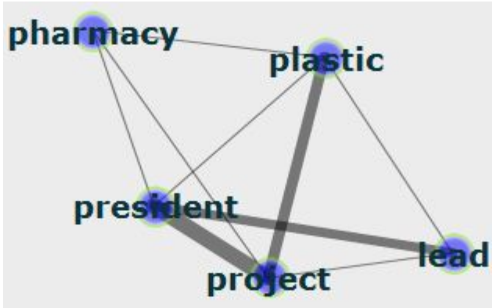


Fig.5.3- a The path automatically selected by system .

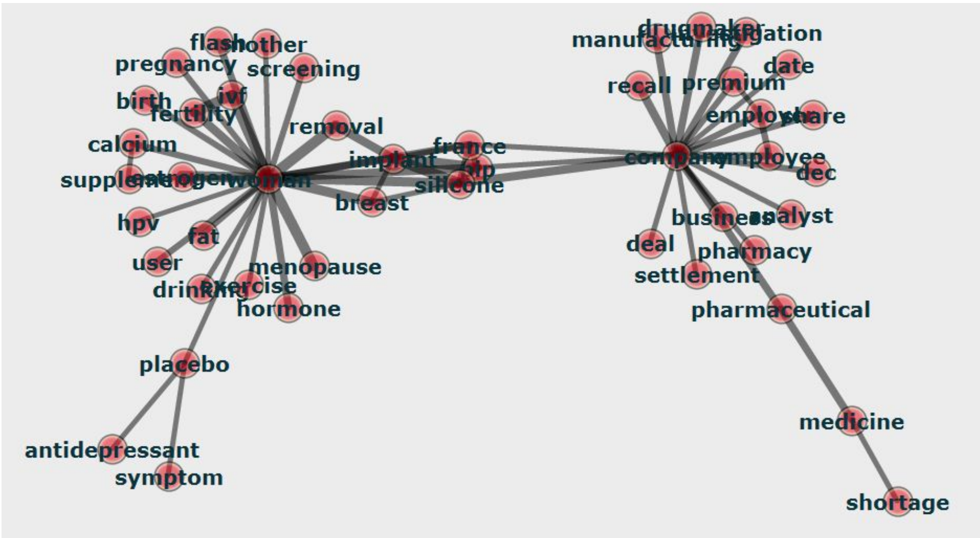


Fig.5.3- b The correspondence keyword ALN

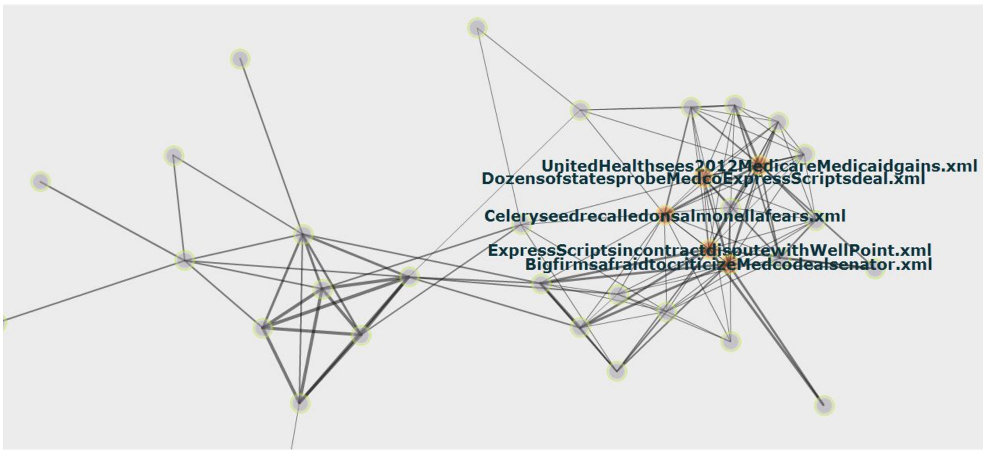


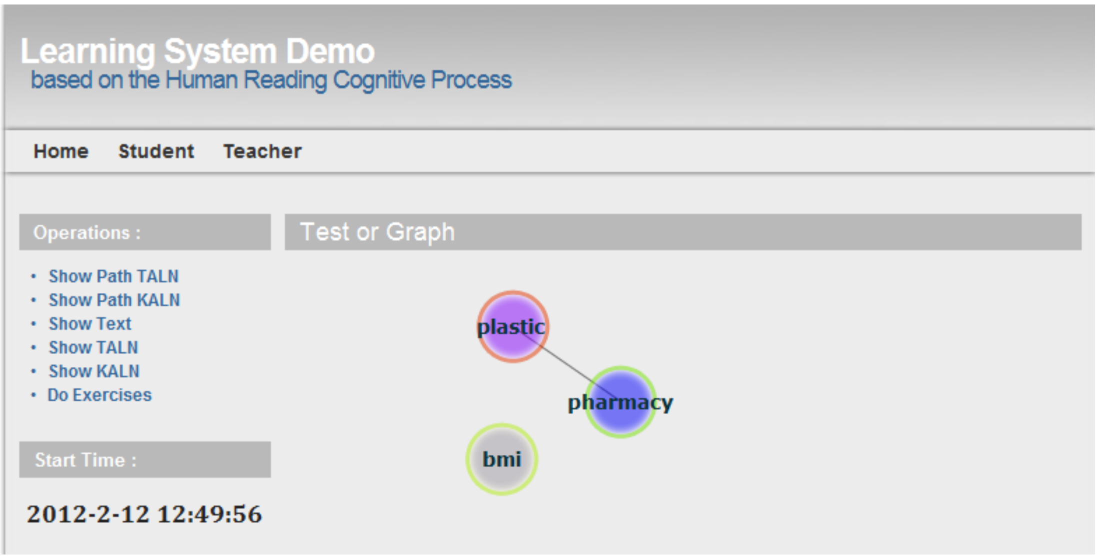
Fig.5.3- c The correspondence learning resource ALN and selected learning path of learning resources for students

Fig.5.3 System recommended learning path in 3-ALN.

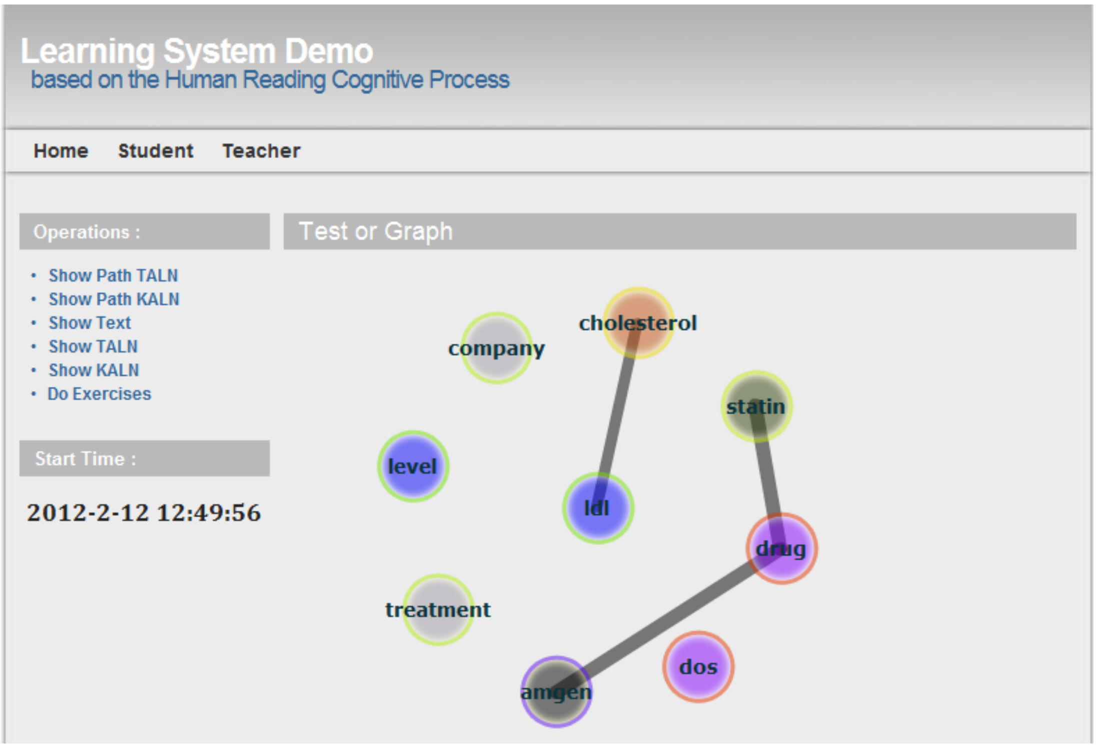
interest in its associated LR. A student can also gain understanding in a LR through its associated LRs. Our three different ALNs provide such associations and therefore help improve student learning.

5.5. Student Assessment against Learning Resources

In our method, student assessment is embedded into the learning process of each learning resource, allowing us to determine whether a student has completed learning a certain piece of knowledge with a proper level of understanding. The assessment result provides a means for updating student profiles regarding students' knowledge levels and completed knowledge concepts. In fact, learning process is a cognitive process of knowledge and behavior acquisition, which is commonly perceived as a process of association of a certain form of new concepts with existing knowledge in the memory of the brain. So in our research, as a part of the learning process, the assessment is also designed to follow the cognitive process. In cognitive science, learning is deemed as a relatively permanent change in the behavior, thought, and feelings as a consequence of prior learning experience. So we need to assess students' prior learning experience to see if they have made a relatively permanent change. In our research, both learning process and assessment construct the whole cognitive process. According to Learning Intelligent Distributed Agent (LIDA) cognitive cycle [Fran06] which is designed based on the theory of human cognitive cycle, students should go through the cognitive cycle to complete the cognitive process of learning knowledge. In the cognitive cycle, students carry out their learning in 3 states, namely understanding state, attention (consciousness) state, and action selection and learning state. We use a set of three different ALNs to help students complete the cognitive process. By considering the example of a learning resource as shown in Fig.5.2, we explain how the three states control the studying of a learning resource within the cognitive cycle by Fig.5. 4 and Fig.5. 5. In the understanding state, we highlight the major attributes (keyword ALN, Fig.5. 4-1) and knowledge concepts (topic ALN, Fig.5. 4-2) of the learning resource to help students focus on the important aspects of the learning resource. In the attention state, we present the associations among different topics and keywords by the links of keyword ALN and topic ALN to help students understand the knowledge structure. The nodes in Fig.5. 4 represent the major attributes and knowledge concepts, the links between nodes represent the associations among them, and the colors are just randomly assigned to the



(a) Topic layer of ALN that exist in the learning resource



(b) Keyword layer of ALN that exist in the learning resource

Fig.5. 4 State understanding & attention: Highlight the major attributes; Build up associations among topics and keywords.

nodes to distinguish overlapped nodes in case the nodes are too many. In the action state, we assess students if they can build up correct associations of the major attributes or the knowledge concepts using the automatically generated test as shown in Fig.5. 5 where we ask students to choose the correct associations between keywords or topics from the choice questions. However, there is no need to straightly carry out the three states one after another. Students can jump to any state during the process. If they got failed in the test, they can jump to the other state to learn again and then go back to a new test until they understand the knowledge. To evaluate student learning

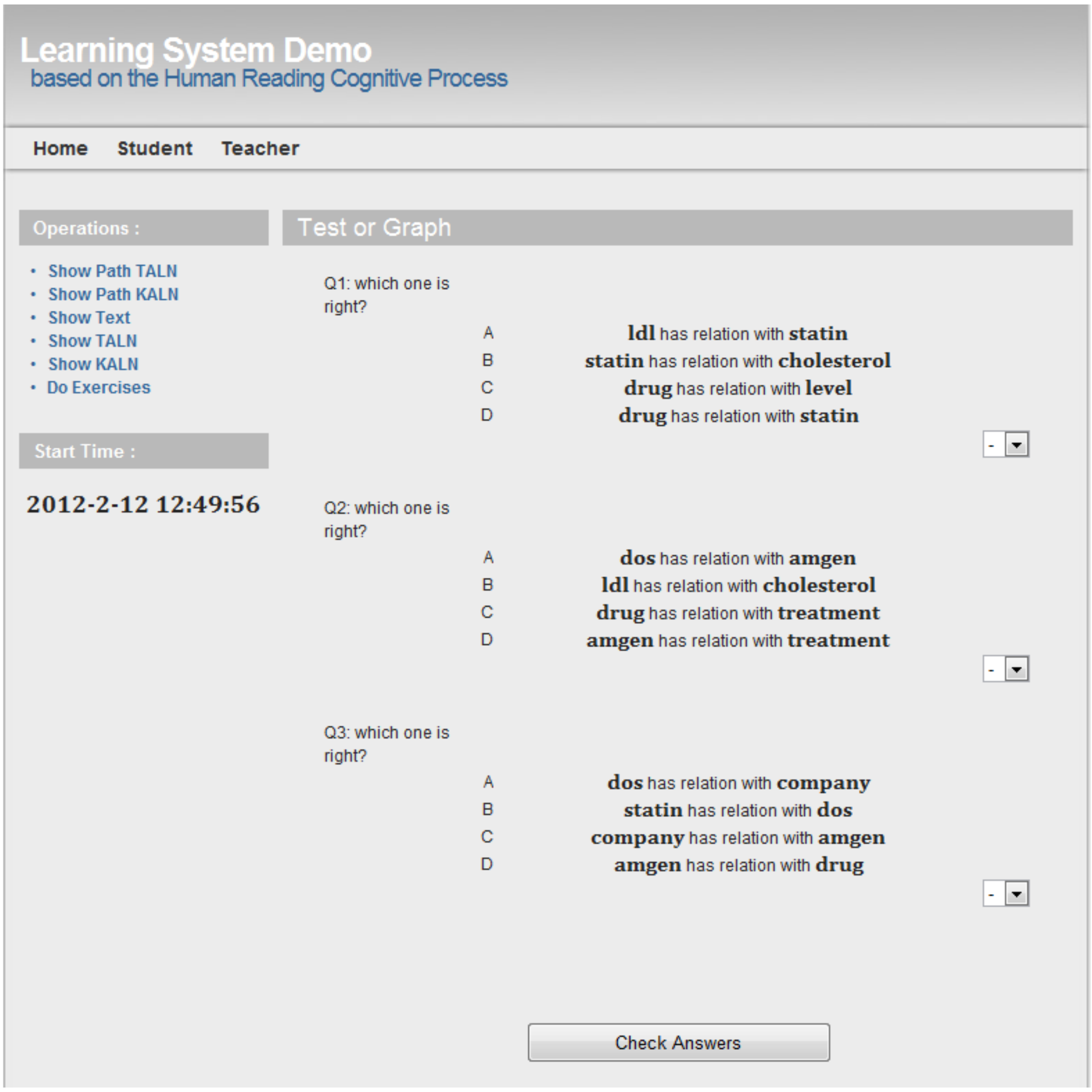


Fig.5. 5 An example of automatic generated test.

performance, we automatically generate tests using a test generation schema by the following steps,

- Step 1: Select an association link from the topic ALN (for example Fig.5. 4-1 or the keyword ALN (for example Fig.5. 4-2);
- Step 2: Determine the complexity of the selected association link λ_X^k which has been introduced in section 5.2 as the difficulty of level of the question;
- Step 3: Add natural languages in between to bridge the associated two keywords into a new sentence as the corrected option of the question;
- Step 4: Randomly select any two keywords which have no association in between, and also add natural languages in between to bridge the associated two keywords into a new sentence as the distracted options.

In this way, tests (for example Fig.5. 5) can be automatically generated without any manual effort. We can save a lot of time for teachers. In the test, all questions are presented in the way of choice-question with four options, and each option describes if two keywords have associations in between. A student selects the correct option from them. This test generation schema can be applied to any learning resource, which can automatically generate different levels of questions and help students strengthen their understanding. So it is easy to control the difficulty levels of the tests for assessing different students. In the end, each student's errors have different distribution over the TKM. If the errors concentrate on a small area, then the student has problems on related topics, so the student just needs to pay a few efforts to get improved. However, if the errors distribute over the network, then the student has problems on many different topics, so the student needs to pay huge efforts to get improved.

5.6. Evaluation Results and Analysis

In order to show the advantage of the system recommended learning path, we have conducted a quantitative analysis showing the importance of LP for both system recommended one and manually selected ones to make comparison of the two LPs. We also conduct a qualitative analysis explaining the comparison results. And also, in order to compare student learning performance based on the teacher generated learning paths and the system recommended one, we show the performance for the two groups of students by graphs, quantitatively analysis the improvement of their performance and their stability of their performance, and qualitatively explain the results.

5.6.1. Compare the Importance of Manually Selected and System Recommended Learning Paths

In this experiment, importance of LP is evaluated by summing up the importance of the nodes that constitute a LP. Ten teachers from the School of Computer Science, Shanghai University, are asked to manually construct LPs that comprise 5 nodes (i.e. topics) from the topic ALN of teacher knowledge model. They are asked to construct a LP that should fulfill two requirements: 1) the selected topics should connect with each other, and 2) should be important to students. Such requirements also govern how the recommended LP generated by our system. We can compare the learning paths selected by teachers and the learning path recommended by our system. Because we want to test if the complexity of TKM will cause any effect on teachers' decision as well as on our system recommendation results, we choose 3 topic ALNs which have different number of links. Particularly, we use topic ALNs having 196 links, 271 links and 360 links, which correspond to 20%, 50%, and 80% of the total association links, forming the low, middle and high resolutions of TKM, respectively. So teachers actually need to select 3 learning paths from each of these TKMs. Correspondingly, system recommends 3 learning paths according to the 3 resolutions of TKM. Results show that the importance of system recommended LP is higher than that of the manually selected LPs. To determine whether the comprehensiveness of the ALN structures will affect the quality of LP generation, we conduct experiments using three different resolutions of the TKM by changing the number of association links constituted the topic ALN. Table 5. 1 depicts the details of the LPs constructed by both the teachers and our system based on the middle resolution of TKM. As shown in the table, although some of the teacher selected topics are the

Table 5. 1 Topics in the selected learning path in Middle resolution

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Importance Degree
Teacher 1	FDA	Roche	Avastin	Stent	Patient	9.6
Teacher 2	Antidepressant	Vaccine	FDA	Avastin	Drug	15.2
Teacher 3	Cancer	Risk	Analyst	Company	Childhood	12.8
Teacher 4	Patient	Staff	Pneumonia	Drug	Analyst	17.0
Teacher 5	Researcher	Implant	Company	Calcium	Cancer	9.2
Teacher 6	Company	Calcium	HPY	Supplement	France	11.2
Teacher 7	FDA	Pneumonia	Dialysis	Antidepressant	treatment	12.2
Teacher 8	Cancer	Implant	Test	Screening	Prostate	7.2
Teacher 9	Analyst	Pharmaceutical	Medicine	Company	Premium	11.2
Teacher 10	**Antidepressant**	**Patent**	**Pneumonia**	**Analyst**	**Staff**	**15.8**
System	Drug	Company	Avastin	Pharmaceutical	Shortage	27.2

same as the ones recommended by our system, indicating that teachers are able to pick some important topics, the LP importance of their constructed learning paths are lower than the system recommended one.

Fig.5.6 compares the LP importance of the learning paths generated by the teachers and our system when different resolutions of the TKM are made available. In the figure, the left y-axis shows the LP importance and is referred by the histogram, while the right y-axis shows the LP importance ratio of the manually selected LPs w.r.t. the system recommended one and is referred by the polylines. We group the results by the resolutions of the TKM. It is found that no matter which resolution of the TKM is made available, our system still produces learning paths with a higher LP importance than the teacher generated ones. The upper and the lower polylines respectively show the maximum and the averages of LP importance ratios of the teacher generated learning paths. They indicate the quality of the learning paths generated by the teachers w.r.t. to the system recommended ones. On the other hand, when the resolution of the TKM increases, the generated LPs both by the teachers

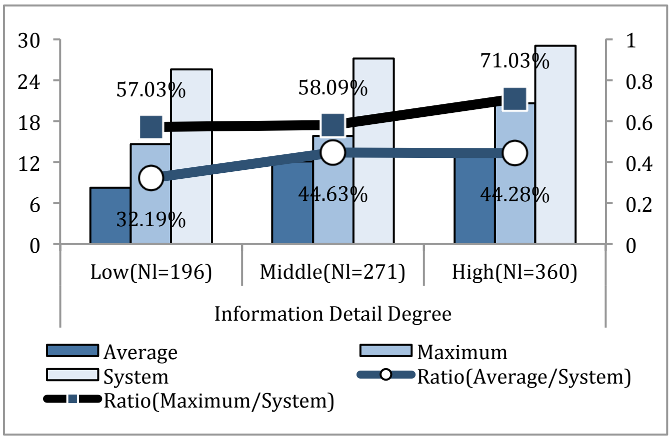


Fig.5.6 Comparison of manually selection and system recommendation results of learning path in learning resources ALN in terms of importance degree.

and our system also increase in the LP importance. It is because when richer course domain information is made available, i.e. more association links forming the TKM, a better decision can be made on the LP construction. However, as teachers are generally overwhelmed by the massive number of LRs and association links, they tend to construct learning paths based on partial information from the TKM. As a result, their produced learning paths are of lower LP importance.

5.6.2. Comparison of Performance on Two Groups of Students

We conducted experiments on comparing student learning performance based on the teacher generated learning paths and the system recommended one. We have invited 10 postgraduate students from School of Computer Science, Shanghai University, to participate the experiments. It is easier to invite students from School of Computer Science rather than students from other departments as we are in the same School, but this does not affect the experiment results, as long as these students have different learning abilities, who perform differently when studying the same LR. We randomly divide the students into two even groups. The 1st group of students perform learning based on the teacher constructed LPs, while the 2nd group of students learn by the system recommended LP. All students are given 50 minutes for studying the contents (contains 5 LRs) provided the LPs and take the same examination with 25 questions, which assess their understanding. Results show that students using the system recommended LP perform better and have more stable learning performance.

Better learning performance

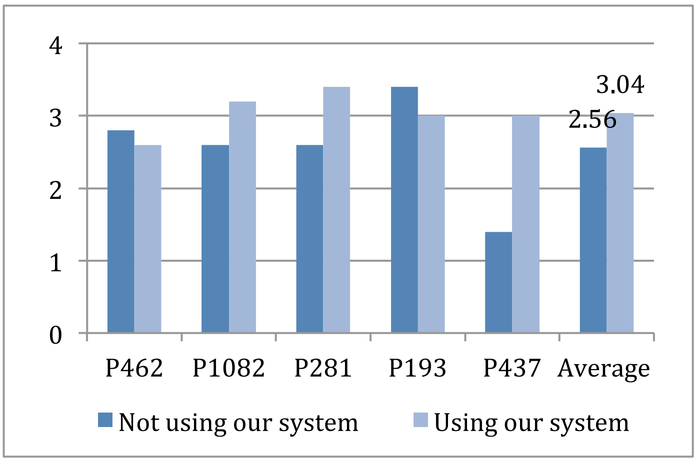


Fig.5.7 Comparison results of two types of learning

We compare the learning performance of two groups of students on the LRs using two-sample T-tests on the differences of their learning performance as in Eq. (5.9).

$$t = (\overline{x_1} - \overline{x_2}) / \left(s_{x_1 x_2} \cdot \sqrt{2/n} \right) \tag{5.9}$$

where $\overline{x_1}$ and $\overline{x_2}$ are the means of their performance within the first group and the second group respectively on n LRs, and $s_{x_1 x_2}$ is the standard deviation of the two samples. $\overline{x_1} - \overline{x_2}$ is the standard error of the difference between the two means. Assuming the null hypothesis is that the two groups of students have the same learning performance on the same LRs. The two-sample T-tests are used to determine if the two groups of data are significantly different from each other. In practice, we can directly use the function of "T-test" in Microsoft Excel software to automatically calculate the t value. Its value is 2.50411, so the corresponding p-value is 0.0367 which is smaller than the threshold of Statistical significance (0.05). It means the null hypothesis is rejected, i.e. the learning performance of the two student groups is significantly different. We then compare the detailed learning performance of the two student groups based on each LR. As shown in Fig.5.7, students studying using the system recommended LP generally perform better. In average, they got 60.8% in the examination, while the students studying through manually selected LPs got 51.2% only. Note that y-axis shows the scales of the learning performance, while x-axis shows the indices of individual LRs. Although students using the system recommended LP perform less well in LRs P462 and P193, learning performance of both student groups in such LRs are still quite similar.

Stable learning performance

We test if the students in each group can have similar learning performance σ_i^2 on the same LR i by analyzing their performance variances (ref. Eq. 5.10). The results are shown in Fig.5.8, where the y-axis indicates the performance variances.

$$\sigma_i^2 = 1/m \cdot \sum_{j=1}^{m} \left(x_{ij} - \bar{x}_i\right)^2 \tag{5.10}$$

where σ_i^2 is the performance variances of LR i, $\bar{x}_i$ is the average performance on LR i, x_{ij} is the learning performance on LR j of student x_j, and m is the number of students If different students show similar learning performance on the same LR, their learning performance variances will be low. We refer

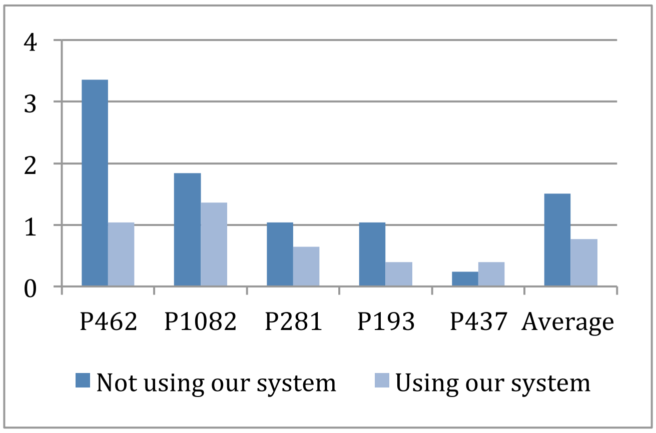


Fig.5.8 Comparison of students' stability of learning performance

this as stable learning performance. For instance, if all students have the same learning performance on the same LR, the performance variance will be equal to 0, and their learning performance is the most stable. In contrast, if half of the students got very high marks and the other half got very low marks, their learning performance is described as unstable, where the performance variance can approach to 6 according to Eq. 5.10.

As shown in Fig.5.8, although students studying through manually selected LPs (Group 1) perform slightly better on LRs P462 and P193 than those studying by the system recommended LP (Group 2), the learning performance of group 1 students is quite unstable, i.e. students perform quite differently in the same LR. Overall, group 2 students generally have more stable learning performance than group 1 students. However, for LR P437, group 1 student has more stable learning performance as they have consistently low performance in such a LR. Our experiments indicate that by using the system recommended LP, even student coming with different learning abilities can be trained to perform better in learning. In addition, the entire cohort will have a more stable learning performance.

5.7.Summary

In this chapter, we have presented an ALN-based LP construction method. We construct multi-level of abstractions of LRs through association, allowing a knowledge map like learning path to be derived. Such a learning path structure can help students learn more effectively. The ALN-based association structure also allows important parameters of LRs, such as their complexity and importance, to be derived. This offers sufficient information for automatic construction of pedagogically meaningful LPs. This feature is particularly critical when a massive amount of Web resources are considered to be transformed as LRs for students to learn.

We have implemented all the above features of the ALN-based learning path construction method in an application program programmed by Java. We kept all the data of LRs in text files which are downloaded from www.reuters.com by a Web crawler. We use JSP (JavaServer Pages) to compile the web pages. The interaction between the application program and the user interface is connected through the Web Service. We use Tomcat as the web server to run the JSP Pages. Our experiments show that our method offers better and much stable student learning performance. In practice, as Web resources obtained from different providers may have very different presentations and inconsistent contents.

Chapter 6

6. Fuzzy Cognitive Map based Student Progress Indicators

Learning path shows students what to learn and how to learn, but we still need to evaluate student learning performance and check their learning quality. This learning progress information can help teachers improve their teaching approaches and let students know if they are on the right track of progress. As there are a lot of attributes that can affect student learning quality, we have developed a method to identify the attributes that may affect certain type of students a lot or a little, and present students how their learning progress changes with these attributes.

Student learning progress is critical for determining proper learning materials and their dissemination schedules in an e-Learning system. However, existing work usually identifies student learning progress by scoring subject specific attributes or by determining status about task completion, which are too simple to suggest how teaching and learning approaches can be adjusted for improving student learning performance. To address this, we propose a set of student learning progress indicators based on the Fuzzy Cognitive Map to comprehensively describe student learning progress on various aspects together with their causal relationships. These indicators are built on top of a student attribute matrix that models both performance and non-performance based student attributes, and a progress potentiality function that evaluates student achievement and development of such attributes. We have illustrated our method by using real academic performance data collected from 60 high school students. Experimental results show that our work can offer both teachers and students a better understanding on student learning progress.

6.1. Introduction

Both teaching and learning become flexible and adaptive. Teachers often need to provide students various feedbacks, including scores and breakdowns, description on what went good/wrong, and suggestions for further improvement. Most of this information can be expressed numerically and consolidated to form inputs to the e-Learning systems [Li08] for generating adaptive courses. They may also form meaningful feedbacks to help teachers and students make various enhancements. However, existing work has not exploited such information well. This chapter addresses this issue. We present a student progress-monitoring model which forms a core component of e-Learning systems. Our model aims to generate comprehensive feedback indicators which allow students to understand their learning performance and how they can be improved, and allow teachers to adjust their teaching approaches based on student learning performance, and allow both parties to identify main parameters to affect student learning progress and their developments in different attributes. Our model based on students' performance related attributes (PAs) as well as non-performance related attributes (NPAs) to model student learning performance and their potentialities to make progress. We also infer the causal relationships among these attributes to reflect how they affect the changes of one another. They are useful to making teaching approaches to different groups of students. Hence, our work contributes to the development of adaptive e-Learning technologies. The main contributions are:

- Proposing student attribute descriptors to mathematically model the casual relationship and the changes of both performance and non-performance based attributes of students. This sets the foundation to support student learning progress analysis.

- Proposing student learning progress indicators to pedagogically depict student learning progress and development in terms of individual student and various groupings, and against teacher's expectations.

The rest of this chapter is organized as follows. Section 6.2 summarizes existing work. Section 6.3 presents our modeling on student learning progress and development. Section 6.4 presents experimental results and discussions. Section 6.5 shows an evaluation of the work on measuring student learning progress. Finally, Section 6.6 concludes this chapter.

6.2. Related Work

A learning path is the implementation of a curriculum design. It comprises elements forming steps for students to go through for acquiring knowledge and skills. In existing work, learning outcome assessment is generally tied up with these steps. In this section, we examine how existing approaches define learning paths and assess learning outcomes. The discussion includes conventional classroom teaching, learning path generation systems and de facto standards that define learning paths.

6.2.1. Student Attributes

To model student learning state, subject specific and general attributes can be considered. By considering subject specific attributes, [Chen05] evaluates how students make progress on their understanding of certain learning materials. The method runs maximum likelihood estimation on the level of understanding claimed by students against the difficulty of learning materials. [Mitr01] investigates self-assessment skills of students by identifying the reasons for a student to give up solving a problem and the ability of the student to identify the types of problems to work on. The method collects student learning progress based on mainly two attributes: the difficulty level and the type of problem. [Guzm07] studies the use of self-assessment tests to improve student's examination performance; the tests generate questions adaptively based on student's answers to each previous question. The method applies item response theory (IRT) to predict student's probability of correctly answering questions based on a student's knowledge level. A student is assessed based on the correctness of the answers and the probability distribution of these corrected answers on each knowledge level, i.e., the probability of the corresponding knowledge level, associated with each concept.

Besides subject specific attributes, there are also non-subject related attributes governing student learning progress, which are referred to general attributes. [Yang10B] studies how students learn through peer assessment. Students are asked to qualitatively assess peers based on feasibility, creativity and knowledge, where the first two are general attributes, which respectively represent the ability to identify appropriate learning materials and to come up with original ideas. [Gres10] investigates the minimal set of social behavior to be included in the brief behavior rating scale (BBRS), forming a compact progress monitoring tool for efficiently identifying the change in student's social behavior. [Lim009] shows that learning styles are critical to student learning and can help identify adaptive learning materials to students. In addition, learning styles can be evolved over time. As shown above, existing works model student learning state using a few specific types and numbers of attributes. They give students feedback on certain aspects but can hardly provide students a global picture showing how improvement can be made across different subjects or learning activities, as they do not consider that student learning progress can be governed by student learning performance and development in both subject specific and general attributes as well as the causal relationships among such attributes.

6.2.2.Student Assessment

To evaluate student learning progress, existing work has developed ways to collectively model knowledge and skill sets of students. For instance, [Chen01] uses attributed concept maps to represent both knowledge gained by a student after a learning activity and the teacher's prototypical knowledge. A fuzzy map matching process is then used to compare both maps to determine how well the student has progressed in the learning. [Feng09] proposes to use a fine-grained skill model to represent a set of skills hierarchically. A generalized linear mixed effects model is then applied to generate statistic information to describe the student progress on different skills. [Stec05] proposes curriculum-based measurements to intuitively monitor student progress. It monitors student knowledge and skills frequently and depicts the results graphically in order to show what progress a student has made globally over a period of time and locally among each piece of knowledge/skill, and whether such progress meets the teacher expectation. [Bake10] predict student performance use the contextual estimation of student guessing correctly and making errors despite knowing the skill to construct the Bayesian Knowledge Tracing to model student knowledge.

Existing work mainly identify student progress as a set of state changes made by a student regarding certain learning attributes and whether they match with the teacher expectations. However, such progress information is quite primitive. It is not sufficient to form indicators helping students and teachers make improvement on learning and teaching, unless they pay extra cognitive efforts to manually extract more comprehensive progress information from the feedback. It is because learning attributes are not independent but may have certain causal relationships among each others, which can also be dynamically changed over time. In addition, at different learning stages, student progress may be governed by a different set of learning attributes. For example, a student may be expected to mainly train up with concept memorization at an initial stage rather than focusing on the learning outcome of applying knowledge. However the situation will become in the opposite when a student is going through a mature learning stage. On the other hand, a teacher may need a higher level of student progress information, such as the performance distribution within a cohort, the portion of students meeting the teacher expectations, or whether a student or a group of students is/are developing certain learning skills, to support teaching approaches adjustment. Our work is developed to provide a comprehensive solution to address such complicated needs.

6.2.3. Student Grouping

The information about the progress of a group of students also contributes to analyze the learning characters or behavior of one type of students. Teacher can know the major character of a group of students and make teaching approaches accordingly. On the other hand, teachers compare progress individually and in a group, so that they can provide students accurate and detailed feedbacks, effective instructions. And it is also convenient for an individual student to know the student's own progress and what is the student's difference from the others.

There are many criteria for grouping students. Some works simply group students by their attribute levels. [Mart07] groups students by their knowledge levels, and then recommends different learning tasks to different levels of students. [McMa07] groups elementary student with different levels of writing skill and uses writing assessments to examine the criterion validity and the sensitivity of growth. So that to make sure that students are progressing towards writing standards, to identify those who struggle, and to inform instruction aimed at improving students' writing proficiency. [Bisw10] analyzes the student distribution of their misconceptions. A student may have a misconception when the student builds up the relationship of two knowledge concepts incorrectly. Students have the same misconception are grouped together to analyze how they understand knowledge. However, it is not enough to analyze the performance of a group of students who have only one common attribute. Sometimes, students' progress is affected only when combined attributes act together. [Brus04] groups students with similar knowledge backgrounds and also with the same knowledge level that they want to achieve, and then they could be provided with the same navigation support of learning materials. However, students with different learning abilities would still being grouped together, so the learning materials may not appropriate to everyone.

We find out that existing works just group students whose attributes are either all good or all bad, while miss the effect of the other situations.

However, they do not consider about the other patterns of attribute distribution. It is more intelligent to synthetically consider several aspects of student attributes, no matter if students are good at all of them or bad at all of them, as long as they keep the similar performance. It is not necessary to group all good students together and all bad students together. For example, according to students' performance, students with good communication skill, good listening skill and bad writing skill maybe grouped together for activity like 'debating', but students with bad communication skill, good listening skill and good writing skill would be considered as another group for activity like 'summary report'. In fact, some attributes are related to each other, and only the same attributes cannot represent student behavior patterns. Students with similar ability distribution should be the better way that is used to group the same type of student.

6.3. Mathematics Model

Analyzing student learning progress is not trivial. Different subjects (or learning activities (*LAs*) [Yang10]) have different assessment criteria, where some are subject specific but some are shared among subjects. On the other hand, student learning styles and learning modes also play significant roles on how a student perform and make development in different assessment criteria. We have developed the student attribute descriptors to provide a more complete picture on student learning progress and development.

6.3.1. Modeling of Student Attribute Descriptors

Student Attribute Matrix

We propose a student attribute model (SAM) (Eqs. 6.1-2) to incorporate both performance (PA) and non-performance (NPA) based learning attributes, forming an unified representation to support student learning progress and development analysis. SAM is the foundation of student attribute descriptors. It comprises subject-related and generic outcome attributes from Bloom's Taxonomy [Bloo56] (Table 6. 1), learning style attributes from Felder-Silverman's model [Feld88] and learning mode attributes describing whether a learning activity is an individual or a collaborative one [Gokh95] (Table 6. 2). We apply a different version of Bloom's Taxonomy from the version we applied in chapter 4, which categorizes the Psychomotor domains into 7 levels rather than 5 levels. Because we found that this way to divide Psychomotor domains is much more easier to be understood by teachers and students in the user study. We have adopted these well-established models to describe student attributes as they have been widely used and verified. In practice, teachers can use only a subset of attributes to model their teaching subjects (or *LAs*), forming a *local measurement*, and optionally annotate attributes with subject specific names if needed. Teachers can also put together local measurements to reveal a bigger picture on the all-round performance and development of a student, forming a *global measurement*.

Table 6. 1 Attributes from Bloom's Taxonomy

Level of Complexity	**Cognitive (Knowledge)**	**Affective (Attitude)**	**Psychomotor (Skill)**
1	Knowledge	Receiving	Perception
2	Comprehension	Responding	Mind Set
3	Application	Valuing	Guided Response
4	Analysis	Organizing	Mechanism
5	Synthesis	Characterizing by value or value concept	Complex Overt Response
6	Evaluation	/	Adaptation
7	/	/	Origination

Table 6. 2 Attributes regarding learning styles and learning modes.

Learning Mode	**Perception**	**Input**	**Organization**	**Processing**	**Understanding**
Collaborative	Concrete	Visual	Inductive	Active	Sequential
Individual	Abstract	Verbal	Deductive	Reflective	Global

SAM is modeled as a dot product of the attribute criteria matrix *C*, which comprises criteria for PAs (C_{PA}) and NPAs (C_{NPA}), and the score matrix, which comprises scores α_{ij}. As shown in Eq. 6.1, each criterion is modeled as a row vector A_i, which comprises a set of a_{ij} to model the different aspects of an attribute. For attributes from Bloom's Taxonomy, each aspect corresponds to a level of complexity, while for attributes regarding learning styles and learning modes, each aspect corresponds to a characteristic of each learning style or learning mode. An aspect is modeled by a real number between 0 and 1 to represent its importance in a subject (or *LA*), where an aspect is set to be 0 if it is not being assessed. *To* model student learning state and teacher's expectation of a subject (or *LA*), as shown in Eq. 6.2, we define a score matrix to comprise scores α_{ij}, where each score represents the level of achievement (or required efforts) of an aspect of a PA (or NPA). In an e-Learning system, each subject (or *LA*) will associate with a SAM to define the teacher's expectation, while each student studying the subject (or *LA*) will be assigned with a SAM that is constructed by the same *C* to maintain the student's learning state.

$$C = \begin{bmatrix} C_{PA} \\ C_{NPA} \end{bmatrix} = [A_1, \cdots, A_i, \cdots, A_n]^T = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{nPA,1} & \cdots & a_{nPA,m} \\ a_{nPA+1,1} & \cdots & a_{nPA+1,m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \tag{6.1}$$

$$\mathrm{SAM} = \left\langle \begin{bmatrix} \alpha_{11} & \cdots & \alpha_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} & \cdots & \alpha_{nm} \end{bmatrix}, C \right\rangle = \begin{bmatrix} \alpha_{11} \cdot a_{11} & \cdots & \alpha_{1m} \cdot a_{1m} \\ \vdots & \ddots & \vdots \\ \alpha_{n1} \cdot a_{n1} & \cdots & \alpha_{nm} \cdot a_{nm} \end{bmatrix} = \begin{bmatrix} sa_{11} & \cdots & sa_{1m} \\ \vdots & \ddots & \vdots \\ sa_{n1} & \cdots & sa_{nm} \end{bmatrix} \tag{6.2}$$

Because a student will perform independently among different aspects of the attributes, each aspect could then be considered as a random variable, which follows the normal distribution $sa_{ij} \sim N(\theta, \sigma^2)$ as shown in Eq. 6.3.

$$p(sa_{ij}; \theta) = 1/\sqrt{2\pi}\sigma \cdot e^{-(sa_{ij}-\theta)^2/2\sigma^2} \tag{6.3}$$

where $p(\cdot)$ is the probability distribution function of sa_{ij}; θ is the estimation value of sa_{ij}; σ^2 measures the width of the distribution. We use *Maximum Likelihood Estimation* [Kay93] to estimate θ, where the largest probability happens when sa_{ij} equals to θ, which is proved as a correct expectation of the observed data of sa_{ij}. So *SAM* could be dynamically updated by the mean value of all previous SAMs (Eq. 6.4).

$$SAM(t) = 1/t \sum_{i=1}^{t} SAM_{\mathrm{i}} \tag{6.4}$$

where SAM_i only expresses the learning state for the i^{th} LA. $SAM(t)$ records the overall learning state of a student after learning *t LAs*. Because the change between *SAM*(t) and *SAM*(t-1) may be perturbed by some uncertain factors and may not reflect the real learning performance, we consider averaging all previous learning performance to be the latest learning state of a student to reduce such an error.

Progress Potentiality Function (PPF)

To analyze the potentiality of a student for making progress in learning performance and for developing skills in non-performance based attributes, we have developed a PPF to form a student achievement descriptor (Eq. 6.5).

$$P = f(L_{PAs}, L_{NPAs}) \tag{6.5}$$

where $f(\cdot)$ is the PPF, P is the student learning progress, L_{PAs} and L_{NPAs} , as shown in Eqs. 6.6-7, are the student learning performance in *PAs* and the degree of balance of a student's development in *NPAs*, respectively. A student has a higher potentiality to achieve more if the student can perform better in PAs and/or has a more balanced development in *NPAs*.

$$L_{PAs} = \sum_{i=1}^{nPA} \sum_{j=1}^{m_i} sa_{ij} \tag{6.6}$$

$$L_{NPAs}{}^{-1} = \left(1/nNPA \times \sum_{i=1+nPA}^{n} m_i\right) \sum_{i=1+nPA}^{n} \sum_{j=1}^{m_i} \left(sa_{ij} - 1/m_i\right)^2 \tag{6.7}$$

where m_i is the number of non-zero aspects for each attribute, *nPA* is the number of *PAs*, *nNPA* is the number of *NPAs*, and n is the number of attributes. $1/m_i$ is the perfect probability if *NPAs* can be developed evenly. Eq. 6.6 reflects that students who have higher value of learning outcome, their overall student learning performance could be higher as well. And Eq. 6.7 reflects that if the different aspects of non-performance related attributes tend to be developed evenly, then the student can have a more balanced development in *NPAs*. We normalize the values of all L_{PAs} and L_{NPAs}^{-1} to be within [0, 1] to allow them to be processed in a unified way. In the end, $f(\cdot)$ is given by $P= L_{PAs}+L_{NPAs}$.

Fuzzy Cognitive Map (FCM)

Existing work evaluate student learning progress mainly by their subject performance (PAs). However, student learning is a complicated process. Student learning performance can also be affected by NPAs, e.g. an active student tends to have better communication skills than a passive student. In addition, both PAs and NPAs may affect among each others. To model such complicated relationships and infer changes among the attributes, we apply Fuzzy Cognitive Map (FCM), which is formulated by Eqs. 6.8-10, to analyze changes of SAMs and infer the causal relationship among the attributes in a SAM.

$$F_j = f\left(\sum_{\substack{i=1 \\ i\neq j}}^{n} F_i\, f_{ij}\right) \tag{6.8}$$

where F_j and F_i are the state values of a pair of a starting attribute A_j and an ending attribute A_i, respectively. There are n attributes in total. The value of state F_j indicates the existent degree of a FCM node (i.e. an attribute). In our model, F_j reflects the overall strength of impact of an attribute on all the others, which can be formulated by:

$$F_j(t) = \sum_{\substack{i=1 \\ i\neq j}}^{n} F_i(t-1)\cdot f_{ij}(t) \tag{6.9}$$

where $F_j(t)$ is the state value of attribute A_j after finished the t^{th} *LA*. It is updated by the current causal weights f_{ij} from all the other attributes to attribute A_j together with the previous status values of all the other attributes. We assume all attributes having the same impact on each other at the beginning and set their initial state values to '1'. Note that f_{ij} is represented by a real number within [-1, 1] as it reflects the fuzzy meaning showing the impact degree from a starting attribute to an ending attribute, where $f_{ij}> 0$ (or $f_{ij}< 0$) implies increasing (decreasing) in the state value of a starting attribute will lead to an increase (decrease) in the state value of ending attribute. Otherwise, $f_{ij} = 0$ implies no causal relation existing between a starting and an ending attribute. The matrix of the causal weights forming the FCM is shown as follows:

$$\mathrm{FCM} = \begin{bmatrix} 0 & f_{12} & \cdots & f_{1n} \\ f_{21} & 0 & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & 0 \end{bmatrix} \quad (6.10)$$

After a student finished the current LA, the causal relationships among attributes are re-evaluated by taking mean of the Mahalanobis distances between the current and each of all previous SAMs, which essentially captures the changes of attributes of the SAMs. Because Mahalanobis distance can measure the similarity of an unknown multivariate vector to a known one (e.g. a group of mean values), and also measure the dissimilarity between two random vectors. The larger is d, the more dissimilar of the two vectors. d is 0 when the two vectors are exactly the same. The Mahalanobis distance is defined as Eq. (6.11):

$$d(SAM_x, SAM_y) = \sqrt{(SAM_x - SAM_y)S^{-1}(SAM_x - SAM_y)^T} \quad (6.11)$$

where S is the Covariance matrix of SAM_x and SAM_y, which measures the dissimilarity of two matrixes and is defined by Eq. (6.12)

$$S = \mathrm{cov}(SAM_x, SAM_y) = E\left[(SAM_y - E[SAM_y])^{\mathrm{T}}(SAM_x - E[SAM_x])\right] \quad (6.12)$$

where $E(SAM_x)$ is the expectation value of SAM_x. If we only measure the similarity of a specific attribute A_i, then the Mahalanobis distance turns to the following form:

$$d_i(SAM_x, SAM_y) = \sqrt{(SA_{ix} - SA_{iy})S^{-1}(SA_{ix} - SA_{iy})^T} \quad (6.13)$$

where S turns to

$$S = \mathrm{cov}(SA_{ix}, SA_{iy}) = E\left[\left(SA_{iy} - E[SA_{iy}]\right)^{\mathrm{T}}(SA_{ix} - E[SA_{ix}])\right] \quad (6.14)$$

Hence, the causal weights f_{ij} of FCM can then be dynamically updated. Such calculations are shown by Eqs 6.15-17.

$$f_{ij}(t) = \begin{cases} \frac{1}{\frac{(t-1)t}{2}}\left(\frac{(t-2)(t-1)}{2} f_{ij}(t-1) + \sum_{x=1}^{t-1} y_{ij}(k,t)\right) & i \neq j \\ 0 & i = j \end{cases}$$
$$= \begin{cases} \frac{t-2}{t} f_{ij}(t-1) + \frac{2}{t(t-1)} \sum_{x=1}^{t-1} y_{ij}(k,t) & i \neq j \\ 0 & i = j \end{cases}$$

(6.15)

$$y_{ij}(k,t) = \frac{Sign_i \cdot d_i(SAM_k, SAM_t)}{Sign_j \cdot d_j(SAM_k, SAM_t)} \quad (6.16)$$

$$Sign_i = sign\left(\sum_{level=1}^{num\ of\ levels}(SA_{i,k} - SA_{i,t})\right) = \begin{cases} 1 & progress \\ -1 & regress \end{cases} \quad (6.17)$$

where $f_{ij}(t)$ expresses a causal weight after a student finished the t^{th} *LA* and $k \in [1, t-1]$ is the index of previous *t*-1 activities. Since the changes of attributes are measured between the current SAM and each of the previous SAMs, after a student finished studying a new *LA* (i.e. a new SAM is generated), there will be $(t-1)t/2$ times comparisons in total. $y_{ij}(k,t)$ models how much A_j will change relative to the change of A_i between SAMs obtained at the t^{th} and the k^{th} *LAs*, where $d_i(SAM_k, SAM_t)$ is the Mahalanobis distance of these SAMs. $Sign_i$ equals to 1 if the student makes progress, otherwise it equals to -1.

6.3.2.Student Progress Indicators

Learning Attribute and Student Groups

To analyze student learning progress and development, we need different kinds of groupings, namely *learning attribute groups* (*LAGs*) and *student groups (SGs)*. LAGs are formed to support local measurement. They comprise groups to maintain subsets of learning attributes. These groups are:

- **Subject Group:** to assess subject (or *LA*) specific knowledge or skills. In our experiments, we maintain groups for Arts, Science and all subjects.
- **Learning Stage Group:** to assess students at appropriate cognitive levels during different stages. Learning stages contain three stages to imitate students' early, interim, and mature stages respectively. The early stage assesses students' basic knowledge in cognitive levels. The interim stage assesses student learning progress potentiality in non-performance related attributes as well as attributes in Affective and Psychomotor domains to monitor if they have balance development. And the mature stage assesses students' advanced knowledge in cognitive levels.

SGs are formed to support a more holistic analysis. They can be constructed manually or automatically, which include:

- **Study Group:** to divide students based on subject of study, e.g. Arts and Sciences. We also consider individual or all students as general groups. All these groups' types are manually pre-defined.
- **Performance Group:** to divide students based on their learning performance associated to skills. Teachers are expected to apply their experience to define groups of best, good, satisfactory, below average, and disqualified students, which form *performance metrics* describing teacher's expectation on students with different learning performance.

Such metrics may also be automatically generated by applying performance information from former cohorts. Because we also define students' attribute values in a fuzzy meaning which indicates the degree of requirements for each aspect, we can apply these fuzzy values to measure the degrees of belonging to clusters. And in Fuzzy C-mean clustering method, each point has a degree of belonging to clusters, rather than belonging completely to just one cluster. Points on the edge of a cluster may have a less degree than points in the center of cluster. When analyze students' actual performance, we apply the Fuzzy C-mean clustering method [Bezd81] to divide students into groups based on their SAMs, where the student learning performance metrics defined by teachers forming the representatives of the clusters.

Formulation of Student Progress Indicators

Student learning progress indicators are functions developed to produce information for pedagogically depicting student learning progress and development. There are three indicators:

- **Knowledge Construction Indicator (KCI):** Inputs of KCI are PAs, NPAs based on selected LAGs. It produces the learning status of a student with respect to certain learning stage by evaluating the updated SAM and FCM, followed by classifying the student into a proper performance group. KCI offers comprehensive information describing how a student performs.
- **Teacher's Expectation Indicator (TEI):** Inputs of TEI are a set of KCI based on selected LAGs and SGs, i.e. collective information indicates the learning progress and development from a group of students. Based on the performance metrics, TEI produces a picture on how a selected group of students make progress against the teacher's expectation. For instance, showing whether there are too many students perform significantly better than what a teacher expected. In such a case, the teacher may conclude the course is too easy.
- **Student Growth Indicator (SGI):** Inputs of SGI are a number of sets of PAs and NPAs of a student or a group of students from certain series of learning stages, i.e. the learning progress and development made by certain student(s) over a period of time. SGI evaluates PPF based on the inputs to indicate whether certain student(s) make progress or regress over time.

According to the above description, we can provide with the Eq. 6.18 to present the whole idea of student(s) learning progress.

$$(SP, t) = f(s_1, s_2, \{LS, g\}, a) \tag{6.18}$$

where *f*(*) presents the function of *type of student(s)* (s_1), *selected subjects* (s_2), *Learning Stage* (*LS*) or the general *growth* (g)over time, and *attributes' performance* (a). The type of student(s) could be a type of student group, an individual student, or all students. And *attributes' performance* could be learning performance on *PAs,* or balance degree of *NPAs*. We can get the student(s)' *learning progress* (*SP*) and *teacher's expectation* (*t*) with *f*(*) for the *type of students* (s_1) in the corresponding *subjects* (s_2) and *attributes*, and corresponding *learning stage* (*LS*) or the general *growth* over time (g).

6.4. Experiment Results and Analysis

In order to analyze student learning progress with our Fuzzy Cognitive Map based student progress indicator, we have collected performance data of 60 high school students from No.83 Xi'an Middle School, China. These data contains their test results in both year 1 and year 2. Meanwhile, we ask 6 teachers in 6 subjects to set their learning outcomes by the PAs and NPAs. We generate questionnaires for both teachers and students by providing them the learning progress analysis results and ask if they can understand and agree with the learning progress results. In the end, we analyze the results quantitatively by showing student learning progress by graphs, and provide qualitative analysis to explain their meanings.

6.4.1. Experiment Data Collection

We conducted experiments with our method by evaluating the learning progress of 60 students from No. 83 High school of Xi'an, China. Results are collected from 4 assessments conducted on the students over last year. All students studied the same 6 subjects, including Math, English, Physics, Chemistry, Political economy, and History. Math, Physics, and Chemistry are considered as Science subjects, while the other ones are Arts subjects. Requirements of PAs and NPAs of each subject are set by the corresponding subject teachers.

6.4.2. Progress and Development in Different Stages

We select student S2 to demonstrate how we depict the learning progress and development of a student at different stages. We just need to set different parameters under different requirements, then we can view the student learning progress in different conditions. For example, during the *early stage*, S2 was assessed by the lower levels (level 1 to 3) attributes of Bloom's cognitive domain (Fig.6. 1). According to the above conditions, these parameters could be set as *s_1=individual student S2*, *s_2=All subjects*, *LS=early*

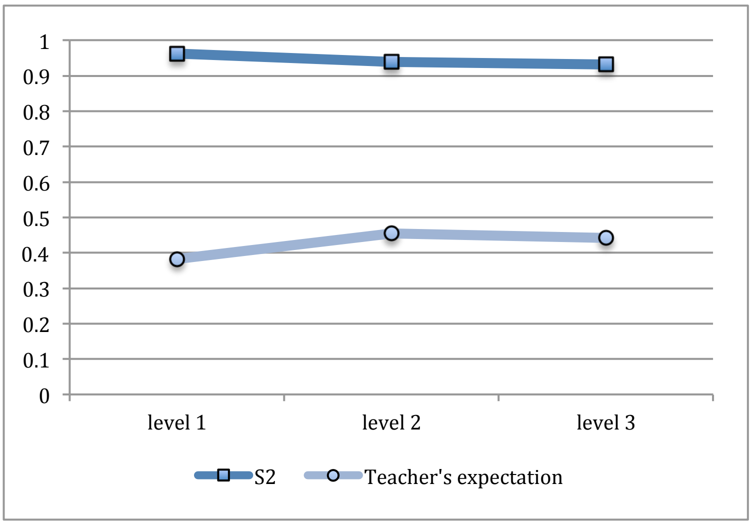


Fig.6. 1 Early stage performance of S2.

stage, p=performance on PAs. During the *interim stage*, S2 was mainly assessed by the student's progress potentiality in non-subject specific attributes with a formative assessment (Fig.6. 2). The student's performance

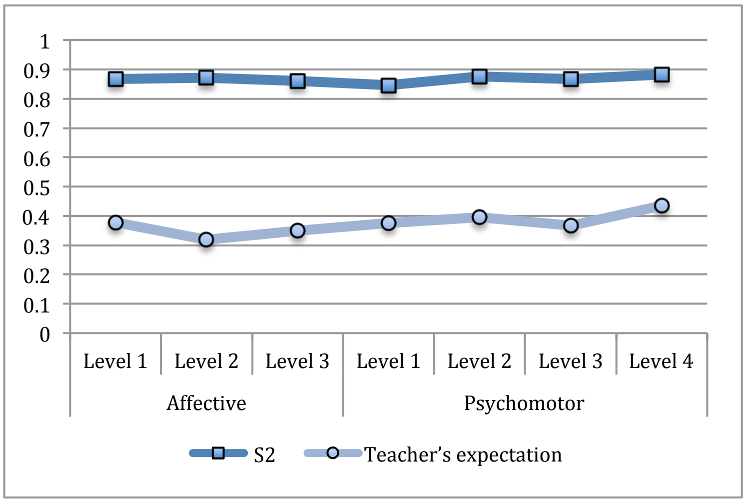


Fig.6. 2 Interim stage performance of S2.

is much higher than teacher's expectation, so the student achieves the learning outcomes required by teachers. Similarly, according to the above conditions, these parameters could be set as *s_1=individual student S2*, *s_2=All subjects*, *LS=interim stage, a=performance on PAs*. Such attributes included those of the first 3 levels of the affective domain and the first 4 levels of psychomotor domain of Bloom's Taxonomy. Results show that S2 performed much better than the teacher's expectation in both stages. This suggests that S2 had developed the required set of learning skills very well.

Fig.6. 3 depicts the balance degree of NPAs of all students, where *s_1=all students*, *s_2=All subjects*, *LS=early stage, a=balance degree of NPAs*. The left half of the figure shows the balance degree for Science students, while the right half is for Arts students. We sorted the results based on the balance degree within each subject major for sake of readability. S2 has a more balanced development in NPAs comparing to other students. Such a balance degree is significantly above the teacher's expectation. In addition, S2 has developed a higher balance degree in Science subjects than Arts subjects. Overall, the teacher expects that S2 would not have any major problem when moving forward to later stages, and encouraged S2 to keep on studying in this way.

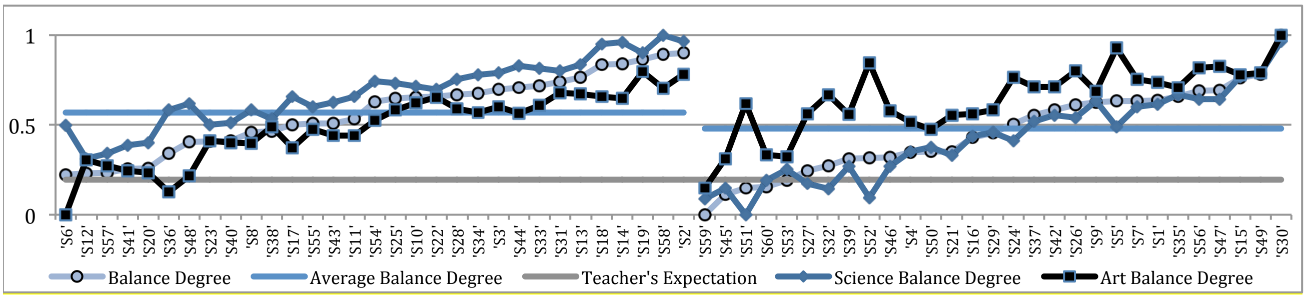


Fig.6. 3 Students' development in NPAs during the interim stage

During the *mature stage*, the students were mainly assessed by the high levels of attributes to examine whether they had properly developed more advanced skills to handle more complicated parts of the study. Fig.6. 4 shows S2 had continuously performed better than the teacher's expectation, where *s_1=all students, s_2=All subjects, LS=mature stage, a=performance on PAs*. Part of the reason was S2 had built up a solid foundation during earlier stages. Fig.6. 5 shows S2 had scored very high from PPF, i.e. S2 had both a high progress potentiality in PAs and high degree of balance in NPAs. Hence, the student had developed advanced skills very well. Although scores from PPF of

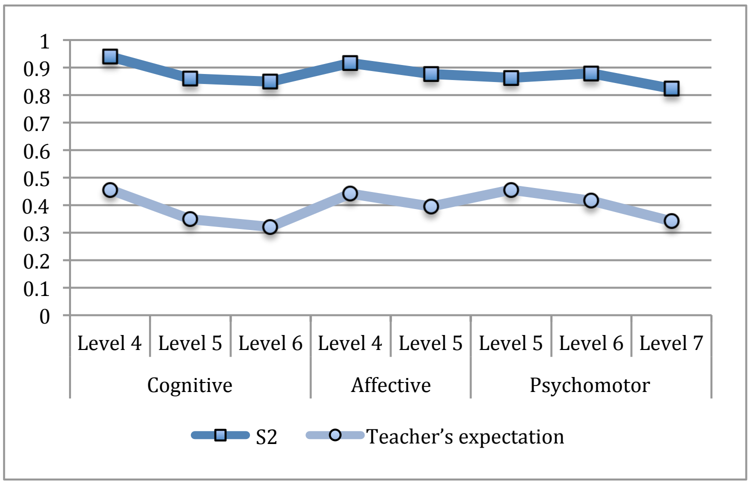


Fig.6. 4 Mature stage performance of S2.

S2 was lower in Arts subjects than Science subjects, the scores were above average, which means S2 would likely to perform better than average students.

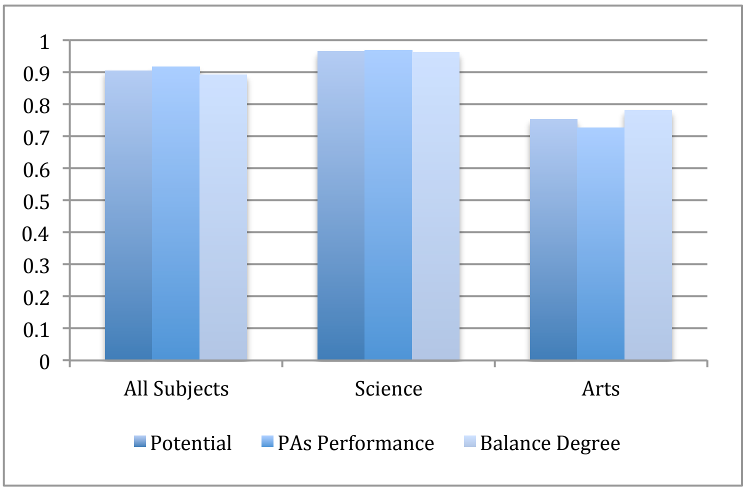


Fig.6. 5 PPF scores of S2

We also construct FCM for the students to examine the causal relationships among attributes to suggest students the ways for improvement. Fig.6. 6 (a) and Fig.6. 6 (b) shows the FCM for all students and S2, respectively. The FCM was constructed using the high-level Bloom's attributes (i.e. domains) and the attributes from learning styles and learning modes. As shown in Fig.6. 6 (a) if a student could make more balance development on each learning styles and learning modes, the psychomotor domain skills of the student could get improved, due to the positive causal relationships (all weights = 0.59). Once the psychomotor domain skills were improved, the student would significantly improve the cognitive domain performance (weight = 0.92) and slightly improve the affective domain skills (weight = 0.39). If the student improved the affective domain skills, the psychomotor domain skills would be significantly improved (weight = 0.96). As shown in Fig.6. 6 (b), the FCM of S2 also had similar causal relationships among attributes, except the weights were much stronger. This means that S2 could make all-round improvement more easily than the other students in average.

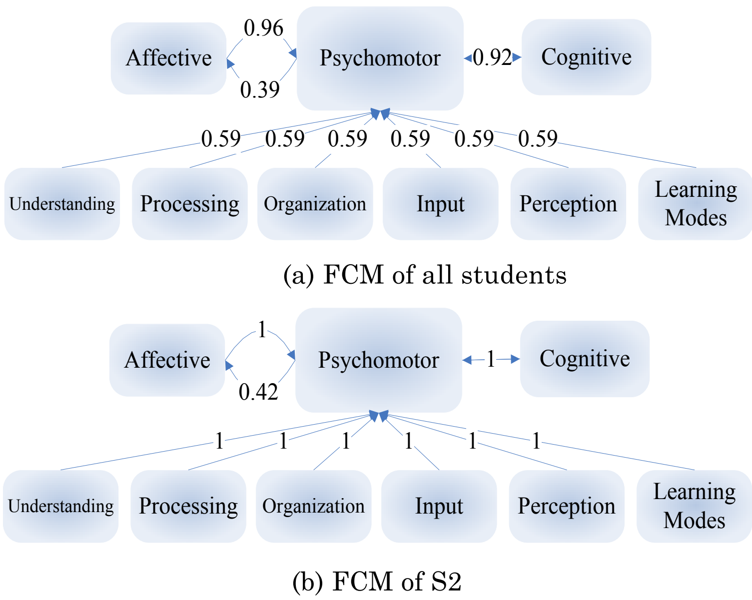


Fig.6. 6 Attributes causal relationships

Finally, we examine the continual progress and development made by S2. Four tests were conducted on S2 during the year of study. As shown in Fig.6. 7, S2 made similar learning performance and development on PAs and NPAs, respectively. Until taking test 2, S2 had been improving and had a very high level of achievement in progress. However, the progress of S2 started to deteriorate after test 2. It might be due to the fact that the subject materials were getting more complicated during the later stages. Fortunately, S2 were still performing by making an above-average progress.

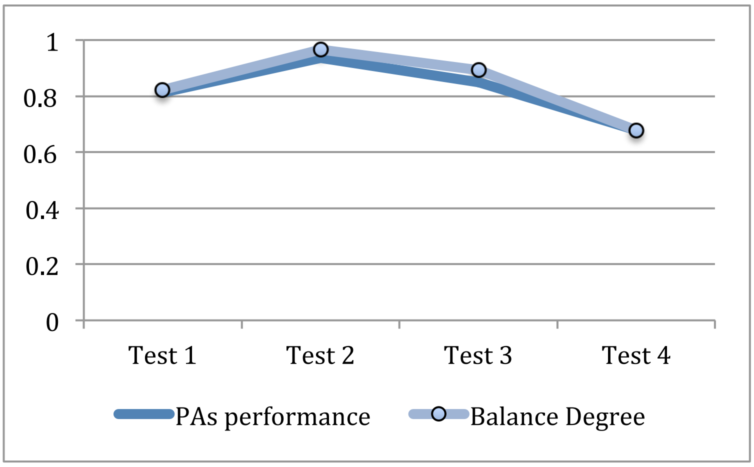
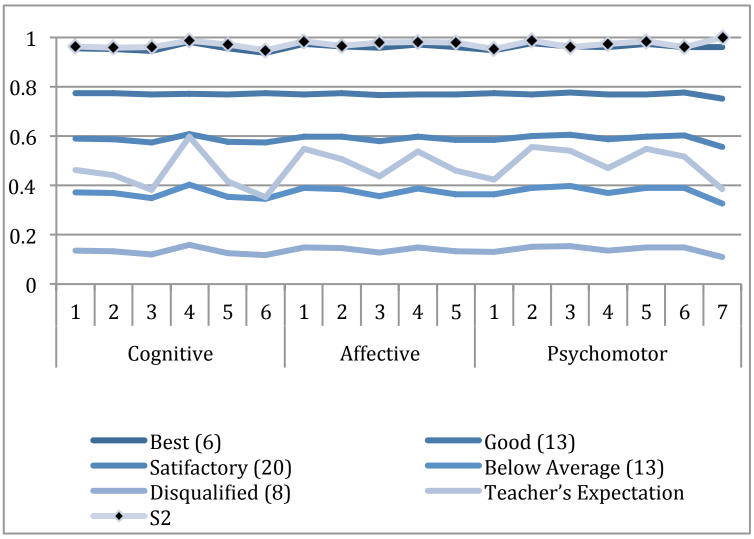


Fig.6. 7 Continual progress made by S2.

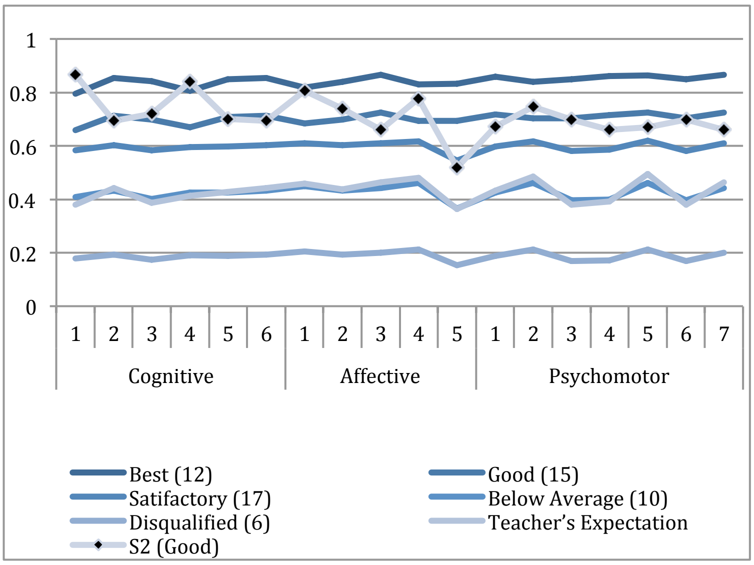
6.4.3. Progress and Development of Student Groups in Different Subjects

We examine the progress and development of all students by all Bloom's attributes (Fig.6. 8). We classify students into different learning performance groups by running Fuzzy C-mean on the student attributes against teacher's performance metrics.

Each student group is depicted with a different color. We also show the number of students in each group in the legends of the figures. Fig.6. 8(a) and Fig.6. 8(b) present the results from Science, and Arts students, respectively. We mainly discuss Fig.6. 8(b), while Fig.6. 8(a) can be interpreted in a similar way. As shown in Fig.6. 8(b), students of the "best" and "good" types performed evenly across all attributes, while other types of students performed not well in some attributes, e.g. they generally performed poorly with the level 5 attribute of the affective domain. However, an individual student, such as S2, might perform differently from the group that the student belonged. Although S2 was classified as a student with good learning performance, the student also had weakness in the level 5 of the affective domain attribute. On the other hand, teacher's expectation fell into the range of the below average students. This indicates that most of the Art students performed much better than the teacher's expectation. Hence, the teacher's expectation was too low and would be recommended to adjust higher.



(a) Science Subjects

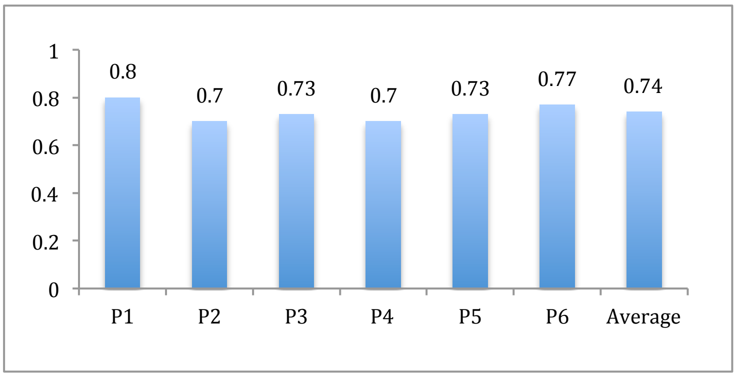


(b) Arts Subjects

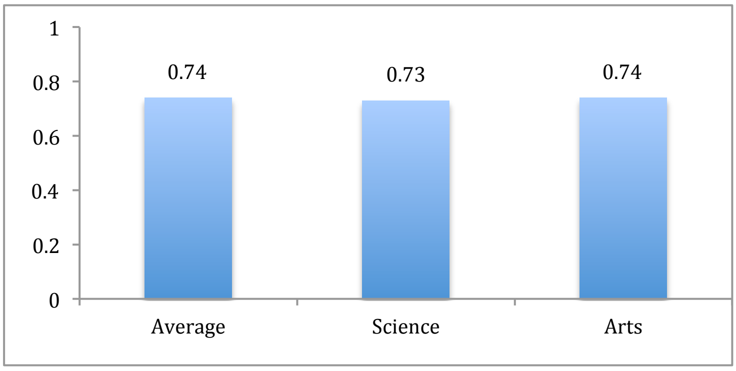
Fig.6. 8 Student grouping results

6.5. Evaluation

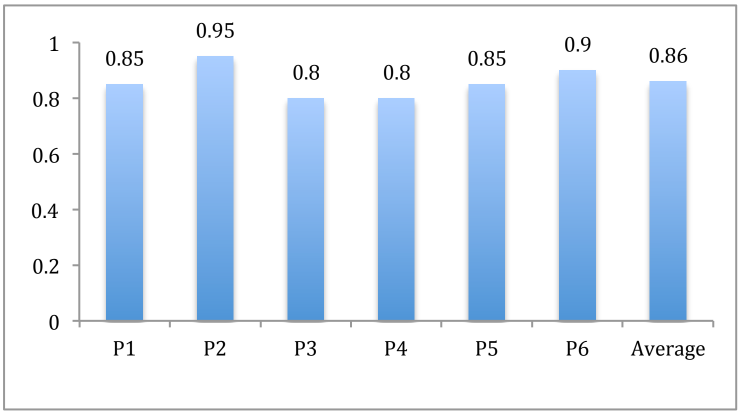
Besides involved in our experiments, the teachers and students also helped evaluate our method by answering questionnaires. These questionnaires show the results of student learning progress generated from our method. Teacher's questionnaire shows the overall learning progress and the progress of different groups of students. And students' questionnaire shows individual student's learning progress and the group progress of the student belongs to. Because these students and teachers are Chinese, so the questionnaires are conducted in Chinese as shown in Appendix B (Analysis results for teachers) and Appendix C (Analysis results for teachers). Both teachers and students evaluate our results mainly from the aspects of if the results coincide with their cognition and can help them better understand the learning progress. We have asked them opinions on our 6 parts of experiments (P1 – P6). P1, P2 and P3 concerns results describing the early, interim and mature stages of study. P4 concerns student progress over time. P5 concerns student grouping. Finally, P6 concerns the strength of impact of each attribute for different groups of students. We respectively asked opinions from teachers and students about how accurate our experiment results explain student learning performance and how good our results in helping students understand their learning performance and make improvement. We used a Likert-type scale with scores from 1 to 5 in each of the questions P1 – P6. Scores 1 – 5 means totally disagree, agree with a small part, agree with half of the experiment results, mostly agree, and totally agree, respectively. Based on the scores obtained, we normalized them within the range of [0, 1] as shown in Fig.6. 9 to intuitively illustrate the level of agreement by teachers and students. As shown in Fig.6. 9, the average score 0.74 shows teachers mostly agree our results explain student learning performance accurately. Specifically, as shown in Fig.6. 9(b), such level of agreement applied to both teachers of the Science and Arts subjects as they got almost the same scores. Fig.6. 9(c) shows opinion from students. Results show that students had a very high level of agreement (scored 0.86 in average and scores of P2 and P6 >= 0.9) that our results well depicted their learning performance and could help them to make improvement.



(a) Teachers' opinion



(b) Subject teachers' opinion



(c) Students' opinion

Fig.6. 9 Evaluation results

6.6. Summary

We have developed student descriptors, which are formed by SAM, PPF and FCM to mathematically model both students' PAs and NPAs, the changes of these attributes over time and their causal relationship. This supports comprehensive student progress analysis. We have also developed student progress indicators to pedagogically depict student progress and development in both individual and group of students setting, and also show such information against the teacher's expectation. We have conducted experiments with 60 students and have disseminated information on student progress and development based on our method. Our evaluations show that both the teachers and the students mostly agree that our method can well explain student progress and development, and the information that we depicted can clearly illustrate how a student can make improvement. As a future work, we are now working on visualization methods to help disseminate student progress and development in a more intuitive way.

Chapter 7

7. Conclusion and Future Work

7.1. Introduction

This thesis focuses on developing methods for constructing learning paths in terms of "learning resources", "learning approaches", and "learning quality" to support student learning. To find out a model that helps teachers design teaching approaches, we define different teaching approaches for learning activities and organize them into a learning path which indicates the learning sequence of different learning activities. And to find out the appropriate learning resources, we automatically generate well-structured learning resources from loosely connected Web resources. These learning resources are delivered to students, who have different knowledge backgrounds, learning interests, and knowledge levels, to study knowledge. In the end, to provide methods to help teachers and students determine student learning quality in a more intuitive way, we evaluate student learning performance to analyze their learning progress using the proposed student attribute descriptors and student progress indicators.

7.2. Research Contribution

7.2.1. A Fine-grained Outcome-based learning path model

Existing methods generate learning paths based on attributes that describe learning contents and student learning performance. However, these content-based works do not properly incorporate the teaching and learning approaches. As a result, the learning outcomes are assessed by the mastery levels of learning contents. However, it is hard to assess other forms of learning outcomes, such as generic skills. In addition, the learning activities only provide simple forms of teaching methods that make them hard to be defined and reused for another courses.

We have proposed a fined-grained outcomes based learning path model which provides a learning path construction method to design the components of the learning path and to change the setting of these components based on learning outcomes. The proposed model allows the assessment methods open to different types of learning outcomes, supports different teaching approaches to different types of courses, and also students can obtain more comprehensive guidance.

Our outcome-based learning path model incorporates the Bloom's Taxonomy [Bloo56] for learning path construction to support more precise learning outcome assessment. In fact, the proposed model is also open to different types of learning outcome assessment methods and inference algorithms [Cona02, Chen06]. This feature allows an ITS that is built on top of our learning path model to easily incorporate specific subjects and even a combination of methods for evaluating student learning performance more accurately and comprehensively.

The proposed model offers an adjustable fine-grained learning activity formulation to support the implementation of different teaching approaches in a learning path. This also enhances the modeling of KEs to allow a KE to be delivered and assessed in different ways.

In the proposed model, the components of a learning path have relationships and constraints among each other. This simplifies the implementations of learning path construction systems. We also implement a prototype to display our system, and ask experienced teachers to use it and evaluate our model. In the user study, our model displays excellent functionalities that teachers with different knowledge backgrounds and different teaching experiences have shown their great interests, saying our model is useful and helpful to design learning path and to guide student learning.

According to the discussion above, the fine-grained outcome based learning path model fulfills the research objective of finding out the teaching approaches and answers the question of how to learn, so that teachers can provide different teaching approaches for different courses, which can evaluate different types of learning outcomes including both subject-specific knowledge and skills as well as generic skills.

7.2.2. Learning Path Construction based on Association Link Network

The learning resources are not easy to manually create, especially when designing for different students. Reusing Web resources to form learning resources offers a way for rapid course construction. However, the challenges are how to identity the properties of the Web resources, including the relevance, importance and complexity, etc., and how to find out the relationships among them, especially, how to find out tailored learning resources for different students with different learning abilities and knowledge backgrounds, etc.

To address these problems, we proposed an Association Link Network based learning path construction method to automatically find out the personalized learning resources according to students' knowledge backgrounds, learning preferences, learning abilities, etc. This method can automatically construct well-structured learning resources from loosely connected Web resources as teacher knowledge model. The learning path is extracted from teacher knowledge model, which contains three-abstraction levels, i.e. keyword, topic, and learning resources ALNs. The learning path with three-abstraction levels provides more information about the relationships among knowledge, which can help students better understand the knowledge. Also, the method comes with a test generation scheme which can automatically generate tests and assess student understanding against learning resources.

In the ALN-based learning path construction method, we apply Association Links Network to form teacher knowledge model which identifies the associations among unorganized Web resources. Given the mass Web resources, even if we have no idea about their knowledge domains, concept structures, or learning outcomes, we still can structure the knowledge via the model. It can provide a very efficient way to organize Web resources rather than ask teachers to manually create learning resources.

Our system incrementally extracts adaptive learning path from the teacher knowledge model, which automatically converts the LRs into associated UOLs as the learning path with a set of three different ALNs. The learning path also has three abstraction levels. Any node in an ALN also can be respectively mapped to some other nodes in the other two ALNs, so that students can have more information to understand knowledge concepts with the help of the associated nodes of knowledge concepts.

We construct a test generation scheme to automatically assess student understanding against a LR within a UOL. We use the associations between topics or keywords as the rules to test if students can build up the correct association between major concepts. This automatic scheme saves a lot of efforts than manually designed tests. In the end, two comparison studies are designed to demonstrate that students using a system-recommended learning path can have better and more stable learning performance than using manually-selected learning path by a teacher.

As the discussion above, the proposed ALN based learning path construction method fulfills the research objective of automatically finding out the appropriate learning resources to construct personalized learning path which helps students better understand the knowledge and achieves their learning outcomes.

7.2.3. Fuzzy Cognitive Map based Student Learning Progress Indicators

Existing works on student learning progress mainly identify student learning progress as a set of state changes made by a student regarding certain learning attributes and whether the student meets with the teachers' expectations. However, such progress information is quite primitive. It is not sufficient to form indicators to help students and teachers make improvements on learning and teaching, unless they pay extra cognitive efforts to manually extract more comprehensive learning progress information from the feedbacks. It is because learning attributes are not independent but may have certain causal relationships among each other, which can also be dynamically changing over time. In addition, at different learning stages, student learning progress may be governed by a different set of learning attributes. For example, a student may be expected to mainly train up with concept memorization at an initial stage rather than focusing on the ability of applying knowledge. However the situation becomes in the opposite when a student is going through a mature learning stage. On the other hand, a teacher may need a higher level of student learning progress information, such as the performance distribution within a cohort, the portion of students meeting the teachers' expectations, or whether a student or a group of students is/are developing certain learning skills, to support teaching approaches adjustment.

Our work is developed to provide a comprehensive solutions to address such complicated needs. We proposed Fuzzy Cognitive Map based student learning progress indicators which collect student performance on student performance related attributes and non-performance related attributes, analyze how their performance is changing and what factor can cause the changes of performance on certain attribute, categorize students into different types according to their different learning progress, and also propose a progress potential function to predict student learning performance in the future.

We propose a student attribute matrix to formulate all levels of both performance related attributes and all aspects of non-performance related attributes. In the student attribute matrix, the row vector represents one kind of student attribute and the components in the vector represent quantified values of attribute levels, It is easy to measure student progress from different perspectives of student attributes. On the other hand, it supports the fuzzy property that a student may stay in two or more levels according to different cases. It is better to formulate a non-linear function to calculate the effect of one attribute on one another. With the student attribute matrix, we also can group students together by one of these attributes or by a selection of attributes.

Fuzzy Cognitive Map (FCM) is used to infer the causal relationships among student attributes which behave as the concept nodes in the map. With the FCM, we can analyze the learning behaviors of a single student, or a group of students with similar attributes. More importantly, it can analyze the factors that affect student learning progress, and describe the causal relationships among these factors, i.e. how a factor affects each other in terms of student learning progress.

According to the discussion above, the proposed student learning progress indicators fulfill the research objective of guarantee the learning quality and answer the question of how well students have learned. Teachers can adjust teaching approaches and try to help students have a balanced development to handle different learning environments.

7.3. Limitations and Future work

The outcome-based learning path model currently formulates a representation of a learning path. Basically, we can prepare learning path templates to best fit with each type of students, so teachers do not need to manually create the learning path. However, it still cannot automatically construct a learning path. Because it has to depend on teachers to manually adjust the requirements and learning outcomes of each learning activity as well as the sequences among them. These adjustments will cause a lot of extra work for teachers. And on the other hand, teachers cannot clearly know every student’s learning status, so the adjustment may contain some errors. As a future work, we will work on some automatic algorithms for managing and adjusting the learning outcomes and the delivery of learning activities, based on which we plan to develop an adaptive e-Learning system.

In order to find out appropriate learning resources, we construct learning resources directly from the Web resources and identify the attributes of these learning resources to suit different types of students, and also we can make sure there is no similar learning resource exists in the teacher knowledge model. However, the selected learning resources in a learning path are obtained from different websites and created by different authors, their formats/styles of describing knowledge and skills are not consistent enough for students to smoothly obtain knowledge. Students may get confused if the contexts between learning resources are not well connected, or if the learning resources use different symbols to express the same terminology, etc. All of these deficiencies will affect students' understanding. It is necessary to find out a way to improve the consistency of the learning resources. As a future work, we will investigate methods to address such presentation and consistency problems, in order to allow students to learn more smoothly with the Web resources constructed learning materials.

Student learning progress can provide dynamic information about how students' performance on some attributes is changing, such as how student learning performance is changing over a particular attribute, predicting a student's learning performance according to the student's previous performance as well as peers learning performance, etc. However, our work only shows limited perspectives of student learning progress. On the other hand, teachers from different knowledge disciplines may be interested in different perspectives of student learning progress. They may feel some of the progress we have provided is not very useful for their teaching. If we can provide them a progress customization tool where they can customize their interested learning progress, then it will improve their teaching quality a lot. Also, if the dynamical learning process and various perspectives of student learning progress could be visual to teachers and students, they would better understand student learning progress, so that students can enhance their learning, and teachers can adjust their teaching approaches accordingly. As a reference, we could use the visualization tool [Gource] not only to present the progress across different stages, to show student learning performance in multi-resolution, but also to present the relationship among different types of attributes.

7.4. Conclusion

This chapter summarizes our works presented in the thesis, highlights the contributions including the proposed methods, the advantages, and how they achieve the research objectives, discusses the limitations of the works and the future works to overcome the limitations. This research has proposed a fine-grained outcome-based learning path model, which teachers can use to design learning tasks, learning activities, and learning path for different types of students. This research study also proposed a learning path construction method which can automatically generate learning resources from loosely connected Web resources. This research proposed a Fuzzy Cognitive Map based student progress indicator to analyse and present student progress and to find out the factors that may affect student learning performance. The future work depicts possible directions of this research study. The future improvements of the work include automatically adjusting the components and their settings of the outcome-based learning path, presenting the learning resources in a consistent format, and designing a more effective way to visually present student learning progress. If such research work can be successfully done, more contributions on constructing learning path will be achieved.

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Appendix A

Questionnaire on Learning Progress Scheme

Covering Letter

This study is organized by Miss Fan Yang, a PhD student in the School of Engineering and Computing Sciences, Durham University, who is working on a research project in e-learning.

Project introduction

Learning path construction is a complicated task, which involves formulating and organizing activities, defining ways to evaluate student learning progress and to match such progress with designated learning outcome requirements. Our project proposes a mathematical model to formulate learning paths and learning activities. This model can lead to the implementation of a generic system to support learning path design for teachers from any subject disciplines. We have developed a simple prototype based on this model and are now conducting this user study to evaluate our work.

Abstract of the questionnaire

The results of this study will determine if our system can provide a convenient environment for you to design a course in terms of its learning path, track student learning progress and evaluate their performance, and provide feedback to help students enhance their learning quality.

Note that at this stage, the design of our prototype e-learning tool focuses only on its functionalities, i.e. generating learning paths, evaluating student progress and learning outcomes, rather than focusing on the user interface design.

Other Information

If there are questions about particular items, simply respond: ‘Just answer the question as you interpret it’.

You will not be identified by name. All information provided by you will be treated as strictly confidential.

Your participation would help us confirm the importance and usefulness of our research on designing personalized learning path for different students.

If you have any problem, please feel free to contact me.

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Your participation is very much appreciated and will allow us to focus on critical issues related to control student learning progress and evaluate learning outcomes.

The questionnaire should only take less than 10 minutes to complete. Could you please return it by 10 June 2010?

Questions: (19 questions)

It is recognized that teachers are likely to respond quite differently to the enclosed questions. Please answer all questions in such a way as to reflect most clearly your viewpoints.

There is no right or wrong answer. Answer the questions in the order in which they appear on the paper. Most questions will require you to circle your selected response. Others will require you to write down a few words. Do not leave blanks.

We thank you for your contribution to this important research.

1. What's your subject?

    □Science

    □Art

    □Engineering

    □Other, please specify:

2. Do you have any experience of using e-learning tools?

    □Yes.

    □No, but I know what it is.

    □No, I have no idea about it.

3. How many years of teaching experience do you have?

    □ 0-1 year

    □ 1-3 years

    □ 3-5 years

    □ More than 5 years

4. Do you have any experience of designing/modifying teaching materials?

    If yes, how do you design/modify teaching materials?

    □ No.

□Yes, I design/modify my teaching materials by hand.

□Yes, I design/modify my teaching materials with professional software. Please specify what kind of software are you using: ______________________________.

□ Yes, I use others. Please specify: ______________________________.

5. When you design your teaching materials, you need to define student learning outcomes. How do you find the criteria to define student learning outcomes?

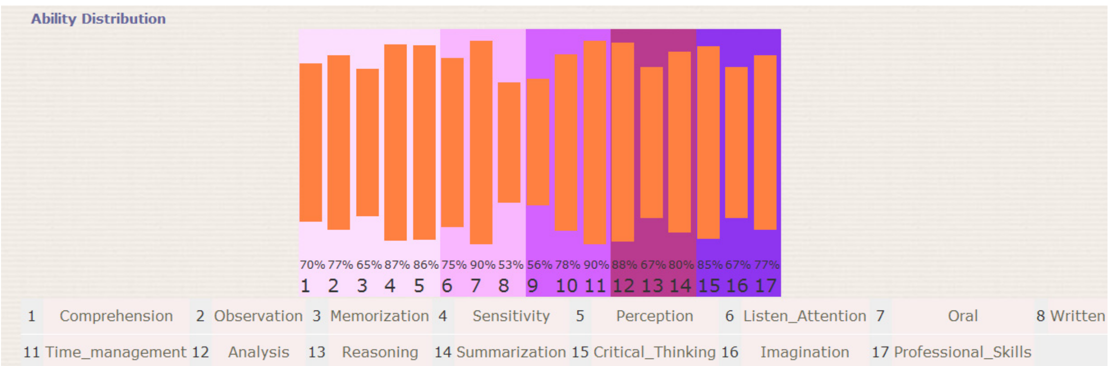
□Subject area

□Difficulty level

□Skill set

□Others:______________________________.

6. Student ability refers to a set of attributes describing how a student has been trained up while studying a subject area. These attributes may indicate whether a student can only recall the subject content or can apply subject knowledge to solve problems in unseen situations, for instance.



An example of a student ability table

Teacher can use these abilities for assessment and put them to a student ability table. How will you rank the usefulness of the student ability table?

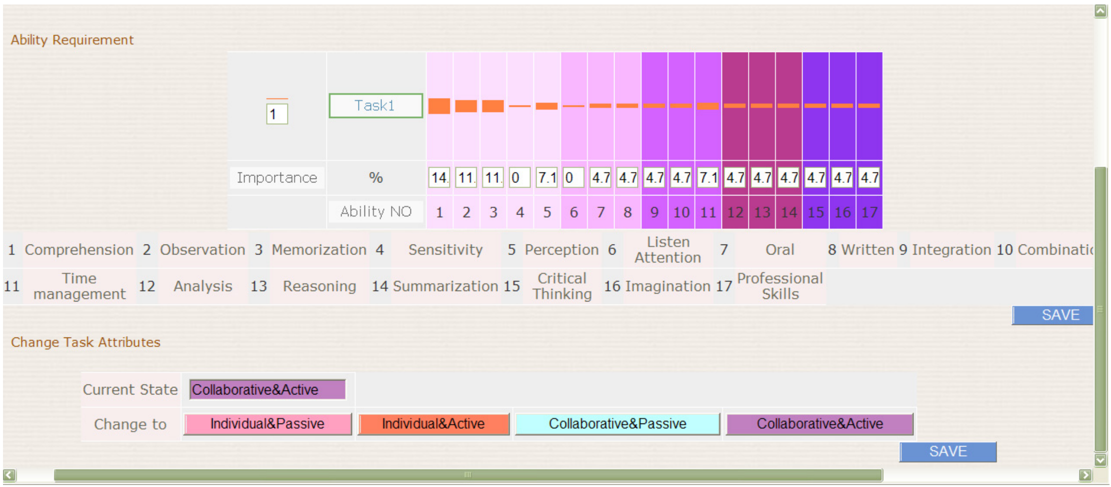
□Very useful

□Useful

□Not so useful

□Not useful at all

7. To support a more fine-grained formulation for describing the learning processes of knowledge elements, we propose the idea of learning task, which is simple in nature and is designed for training up a student with a certain abilities in the way they prefer, including individual or collaborative and active or passive.



An example of a single learning task

How do you find this idea will help you design what a student needs to learn?

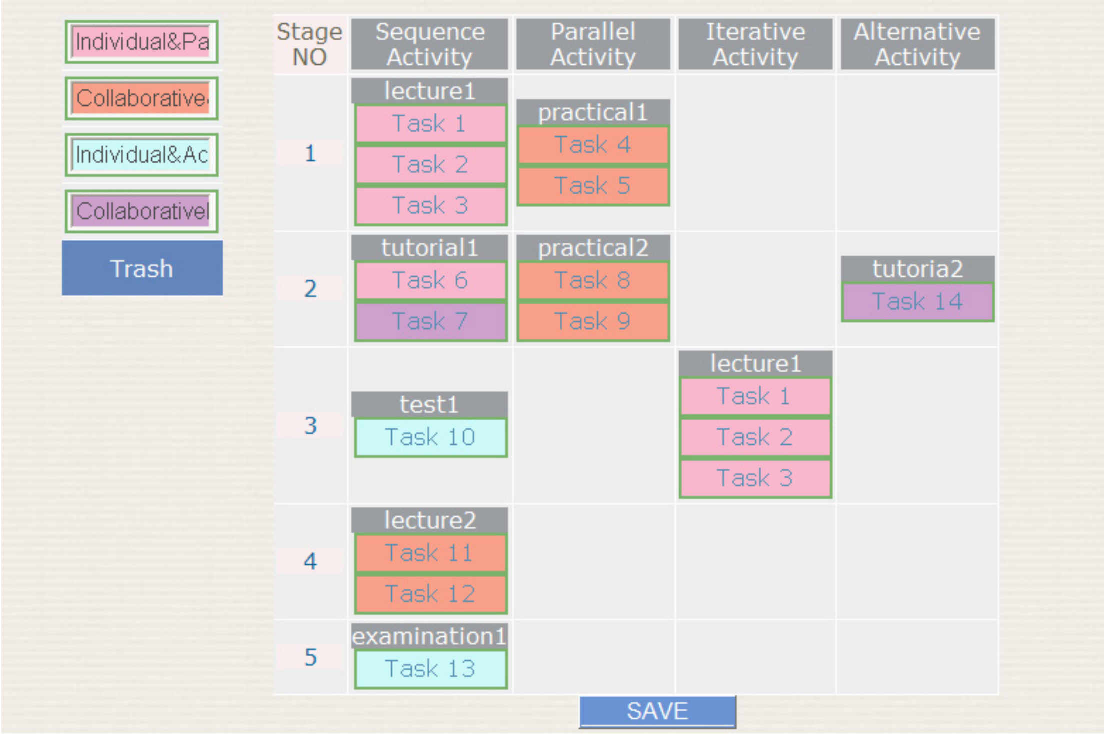
□Very useful

□Useful

□Not so useful

□Not useful at all

8. We divide an activity into tasks help a teacher have a better understanding on how to create/organize the activity. As somehow, a task is more closely related to abilities, so it is a bridge between an activity and a set of abilities. For example, a 'lecture' activity may include 'delivering bookwork type of materials' task for training up the student comprehension skill, 'question-answering' task for testing out the student understandings.



Divide an activity into several tasks

Do you think this will help you have a better picture on why the student needs to create an activity, and how this activity can help a student to make progress/to improve the student's abilities?

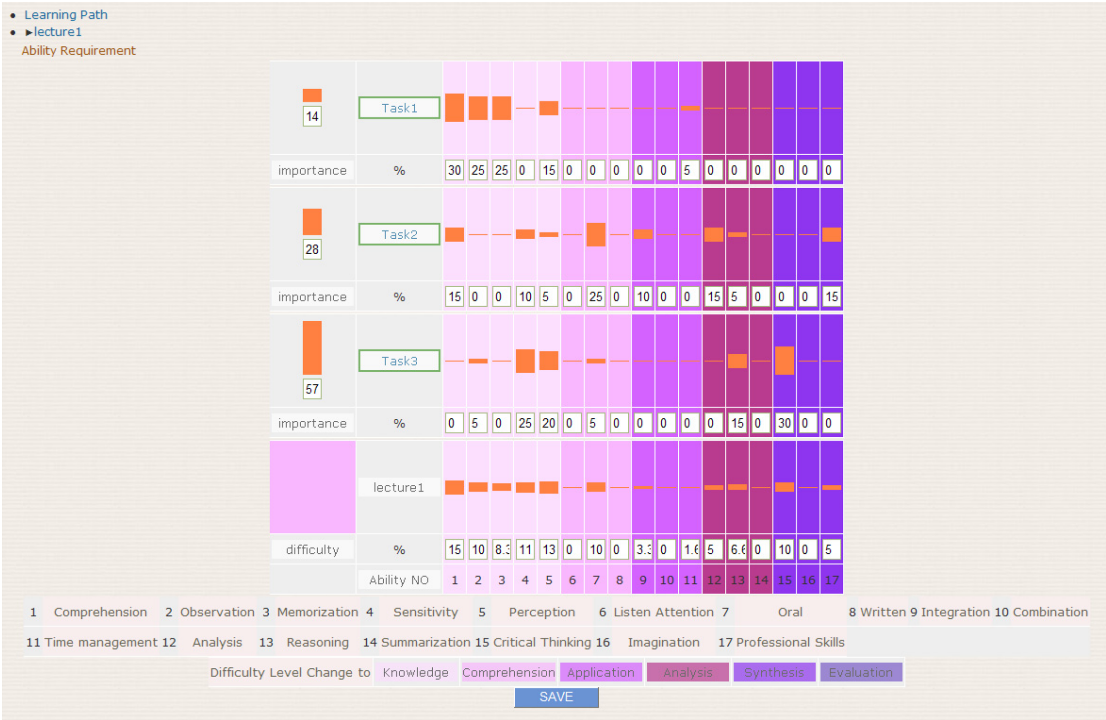
□Very useful

□Useful

□Not so useful

□Not useful at all

9. When designing a course, it is typical for a teacher to establish a set of learning activities, such as lecture, tutorial or practical, to support students learning different knowledge elements. Teacher is expected to put together a list of learning tasks to form the basis for constructing learning activities. By changing the abilities requirements and tasks importance weights, the difficulty level of a learning activity would be changed as well.



An example of a learning activity

How do you find this idea will help you decide the learning process and learning outcome of a learning activity?

□Very useful

□Useful

□Not so useful

□Not useful at all

10. Especially, collaborative learning activity refers to the learning activity that students are learning collaboratively in a group setting. This type of learning activity is modeled to comprise two types of learning tasks: collaborative and individual, where they are designed to be performed by a group of students collaboratively and by each individual student within a group respectively. For example, a ‘Sell your Product’ collaborative learning activity assigns student A an individual task ‘design advertisement’ and assigns student B an individual task ‘design PPT’ and each student has been assigned different individual task, but all of them should do the collaborative task together: Presentation.

From the student's perspective, each student typically requires to perform only collaborative learning task and the student's own individual learning task.

How do you find this idea will help you decide the idea on the group setting of a collaborative learning activity and also assess the learning outcome of a group students?

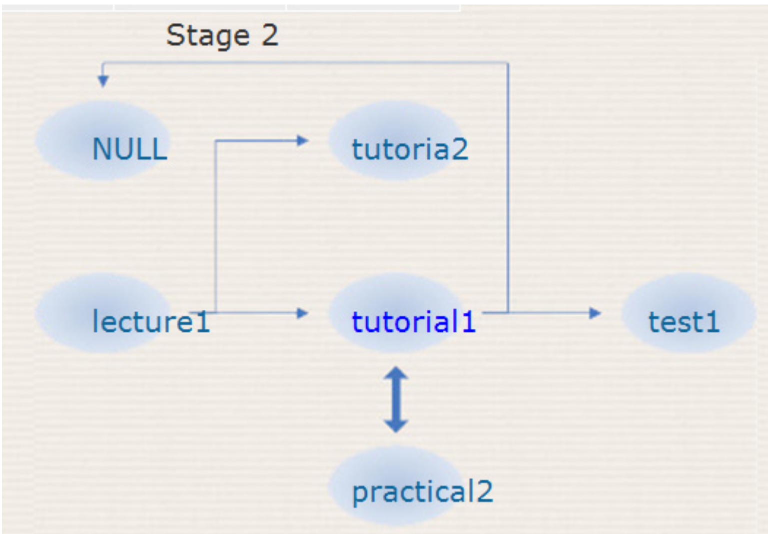
□Very useful

□Useful

□Not so useful

□Not useful at all

11. To allow a student to build up the student's knowledge progressively, it is a common practice for a teacher to divide the entire learning process of a course into a finite sequence of time slots, namely learning stages. During each learning stage, a student only needs to focus on studying a subset of knowledge elements through designated learning activities. For example, if the starting learning stage that 'tutorial1' is taken place, then the student should start to learn it. And if the ending learning stage that 'tutorial1' is taken place, then the student should finish learning.



An example of a single learning stage

How do you find this idea will help you better manage the learning process?

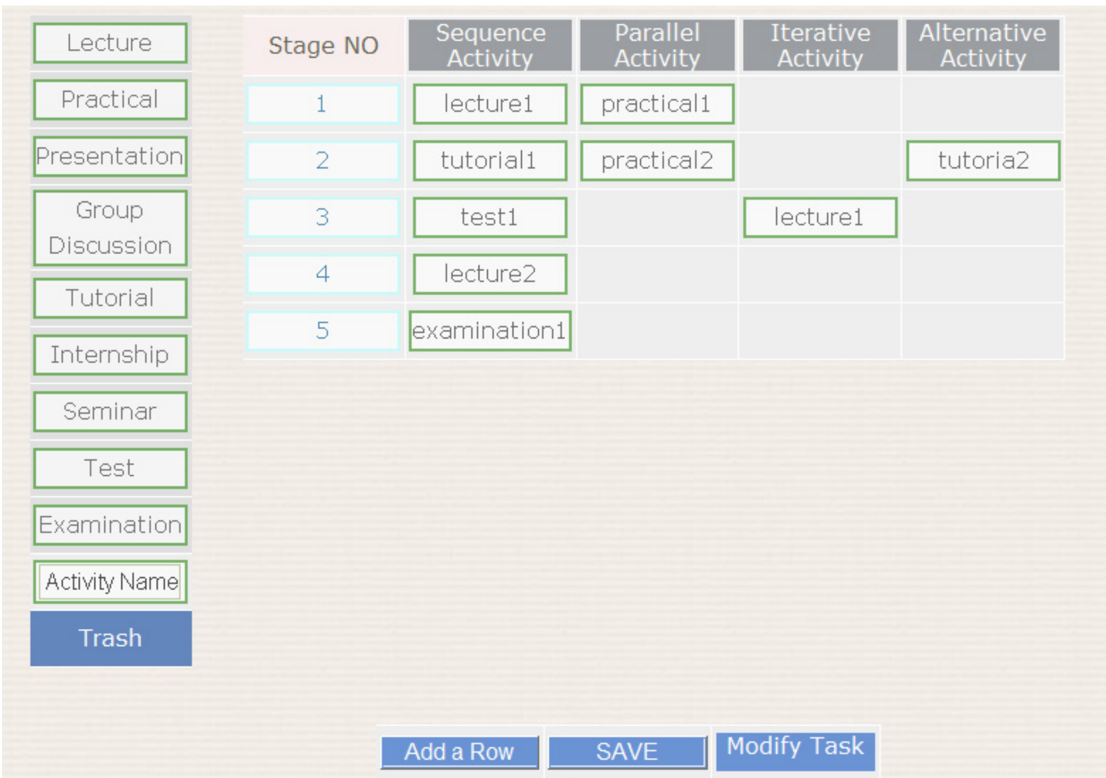
□Very useful

□Useful

□Not so useful

□Not useful at all

12. A learning path comprises a set of learning activities. There exist time constraints and dependencies among the learning activities. The starting learning stage decides when to learn a learning activity and the ending learning stage decides when to finish a learning activity. And the time constrains also useful for verifying the coexistence dependency between two learning activities. They are useful especially when two or more learning activities are running together. For example, the ending stage of 'lecture1' is the starting stage of 'tutorial1', which decide 'lecture1' is the prerequisite of 'tutorial1'. Also, 'lecture1' and 'practical1' share the same starting stage and ending stage, then both of them should be taken as the same time.



An example of a learning path

How do you find this idea will help you better design the learning path?

□Very useful

□Useful

□Not so useful

□Not useful at all

13. Learning process describes the current state of a student regarding how much knowledge that the student has been built up in a subject area. In our project, learning process can be obtained by evaluating the accumulated learning outcomes of the student across a relevant number of learning stages.

Would you find this idea helpful when you apply the results to set up rules for defining the prerequisite of a learning activity or to adjust the learning path for enhancing student learning?

□Very helpful

□ Helpful

□Not so helpful

□Not helpful at all

14. We also allow different assessment methods to be incorporated for better capturing student performance or learning outcomes. Based on a well developed theory Bloom's taxonomy, we can assess a student in three domains: cognitive (knowledge based), affective (attitudinal based) and psychomotor (skill based). For example, Bloom's Taxonomy classify the cognitive domain into six levels from easy to difficult: knowledge, comprehension, application, analysis, synthesis and evaluation.

How do you find this idea will help you better assess a student performance?

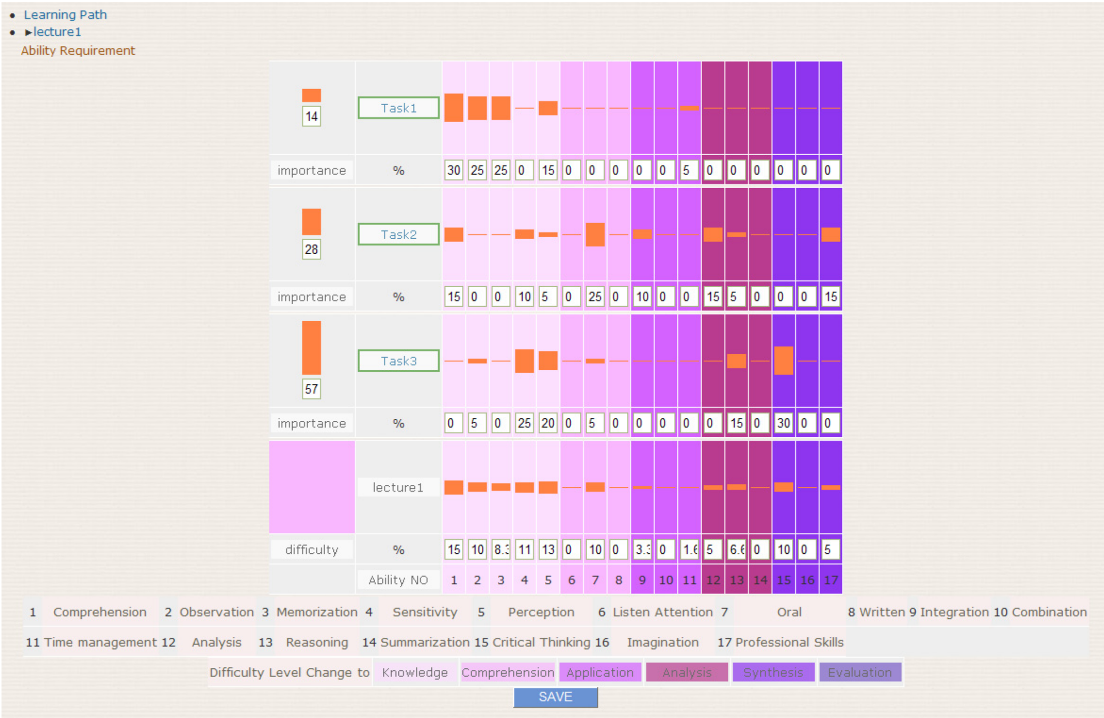
□Very useful

□Useful

□Not so useful

□Not useful at all

15. To assess student learning outcome, we propose to use student abilities as the basis due to its practicality and the availability of the Bloom's Taxonomy. A student ability specific evaluation function can generate a score to describe the level of achievement of a student in a particular student ability. The evaluation function could be simple marking, grading or item response theory.



How do you find this idea will be easier to assess a student performance?

□Very easy

□ Easy

□Not so easy

□Not easy at all

16. Is that possible to apply our e-learning tool to in your teaching subject?

□All of them could be applied to my teaching subject.

□Most of them could be applied to my teaching subject.

□Part of them could be applied to my teaching subject.

□None of them could be applied to my teaching subject.

17. What's the biggest difference from the e-learning tools you had experienced before?

    From the aspect of functionality____ _____ _____ _____ _____ _____

    From the aspect of convenience_____ _____ _____ _____ _____ _____

    From the aspect of flexibility _____ _____ _____ _____ _____ _____ _____

    From the aspect of accuracy_____ _____ _____ _____ _____ _____ _____

    From the aspect of understandability_____ _____ _____ _____ _____ _____

    Others__ _____ _____ _____ _____ _____ _____ _____ _____ _____ _____ _____

18. When you design your teaching materials, which aspect do you focus most? Could you provide some details how you design your teaching materials?

    __ _____ __

19. Please make any further comments on the design / usage / clarity / or suggestions for improvement of this system below.

    __ _____

Appendix B

Questionnaire: Analysis results for teachers

提供给老师的分析结果

本次实验分析的课程包括：数学，物理，化学，政治，历史，和英语。其中视前 3 门为理科科目，后 3 门为文科科目。基于上次从各位老师那里收集来得数据，各位老师分别根据衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）给出了自己的教学要求，我们基于这些方面，对学生进行评估，并将其表现在刻度 0 到 1 范围内划分为 5 个等级：极差，较差，中等，良好，以及优秀。

1. 学习的初级阶段

该阶段包括了衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）里的几个较低级别，为一般情况下老师用到的衡量级别。

知识认知：认识并记忆，理解，应用；

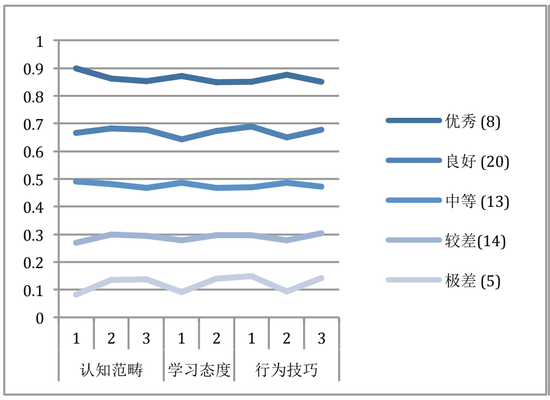
学习态度：接受知识，做出响应；

行为技巧：使用感官线索指导活动的能力，学习前的准备工作，根据指导进行练习。

1.1 分类结果

则这 60 名同学的整体分布结果如下图所示：（图 1－1）全部课程；（图 1－2）理科；（图 1－3）文科。其中，每一类的学生人数都表示在类别后的括号内。可以看出，对于这 5 类学生，综合所有科目， 每一类学生在各个范畴的各个方面都有稳定的表现。一个基本规律是：在一个范畴表现较好的学生，在其他范畴也会有较好的表现。同样的结论适用于理科科目（图 1－2）和文科科目（图 1－3）。但是在这 3 个范畴上，这 60 名同学（1）在理科上的整体表

现要普遍好过在文科上的表现；（2）在理科上的差异（两级分化）明显大于在文科上的差异。



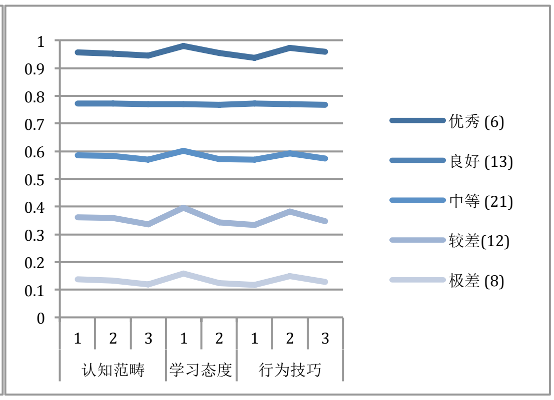


图 1—1. 所有课程　　　　　　　　图 1—2. 理科科目

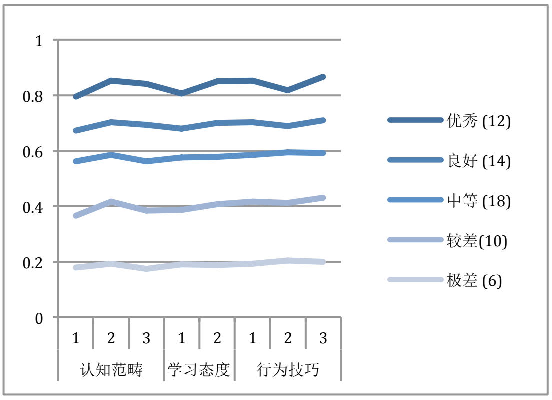


图 1—3. 文科科目

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1—5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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1.2 各个属性间的关系

根据上次的问卷调查，我们不仅仅收集了各位老师在知识，学习态度，行为技巧 3 个范畴的教学要求，以及学生的参与模式（同学合作或单人作业）同时也收集了各位老师在学习内容（具体或抽象），表达方式（视觉表达或口头表

达），知识组织方式（归纳 / 收敛知识，或演绎 / 发散知识），学生参与态度（主动或被动），教学顺序（从前到后一步一步教授知识，或从整体到细节教授知识）5 个方面所形成的教学风格。我们相信，一个属性的变化（进步或退步）会影响到其他属性的变化（进步或退步），所以我们根据学生的表现，分析了这 9 个属性的相互关系。

综合各门课程，60 名学生在初级阶段所呈现出来的 9 个属性的相互关系如图 2－1 所示，每一个节点表示一个属性，箭头表示出发节点对终止节点有影响，箭头上的权重表示一个属性对其他属性影响的相对大小（权值 0 为无影响，权值 1 为影响最大）。可以发现学生的认知范畴，学习态度，和行为技巧 3 者之间是相互影响的，任何一个的进步都会引起另外 2 个属性的进步。而学生的学习风格的平衡发展又会直接影响到学生认知范畴和行为技巧的表现。其中学习风格的平衡度对认知范畴的影响作用要大于对行为技巧的影响作用。

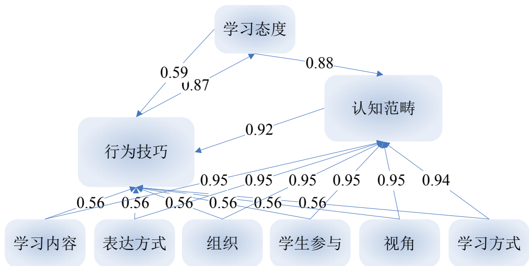

图 2－1. 60 名学生在初级阶段所呈现出来的 9 个属性的相互关系

综合所有课程，根据所有学生在初级阶段的表现，学生各个属性对其他属性的总影响力分布如图 2－2 所示。因为初级阶段只衡量了学生的初级能力，所以衡量这 3 个范畴对较优和较差学生的区分力度也相应较小。所以在该阶段，学生各种学习风格的平衡发展主要影响了学生在其他方面的表现。另外，无论是对每一类学生，还是分别对文科理科科目进行分析，各个属性所呈现出来的相互关系都基本相似，只有影响力大小有略微差别。

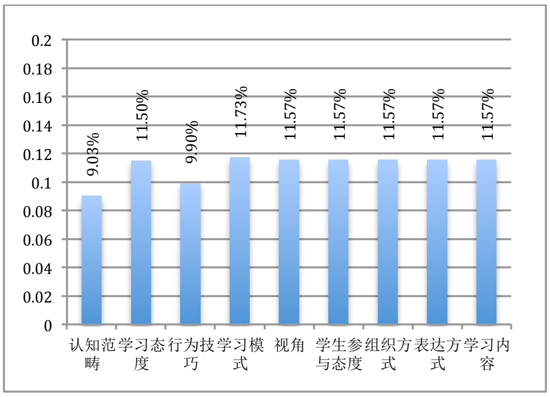

图 2—2. 根据所有学生在所有课程上初级阶段的表现，各个属性对其他属性的总影响力分布

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1—5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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2. 中期阶段—进步潜力

该部分分析了学生取得更大进步的可能潜力。如果学生不仅仅在这 3 个范畴上的表现良好，并且可以根据老师不同的教学模式，平衡地发展自己的学习风格，以此来适应各种各样的学习要求和学习环境，那么该学生就具备了较大的潜力做出更大的进步，并且具备更强的自学能力。对于该类学生，无论老师设置何种难度的学习活动，或使用何种方式的教学手段，他们都可以取得良好的表现。相反，对于‘进步潜力’较低的学生，老师应当有针对性的按照其擅长的学习风格对其进行指导。中期阶段的评估同时也指示了是否该学生是否按正确的方向发展自己做出进步。

以下 3 图分别是根据学生们的 9 个属性在所有课程，理科，和文科的表现进行的分析结果。对于每一附图，横坐标表示了学生 ID，左边的纵坐标表示了他们的相对表现（0：最差；1：最好），右边的纵坐标表示了他们的类别等级（1：极差；5：优秀）。图中的 3 条曲线分别是学生的潜力在 3 个范畴的总体表现，

以及学习风格的平衡发展程度。总的来说，对于这 60 名学生，不论对于何种课程组合， 在 3 个范畴的总体表现越好的学生，他们学习风格的平衡发展程度也就越高，相应的他们的进步潜力也就越大。当然也有例外：学生 S15 属于优秀，S2 仅仅是良好，但 S15 却比 S2 学习风格的平衡发展程度低（图 3－3）。但是对于同一个学生的不同课程组合，他在 3 个范畴的总体表现并不一致，他学习风格的平衡发展程度也不相同，相应的他的潜力也有差异。例如，在所有课程以及理科上，学生 S2（黑色着重表示在各个图中）在 3 个范畴中各方面的表现，他属于优秀，但是在文科上却属于良好。

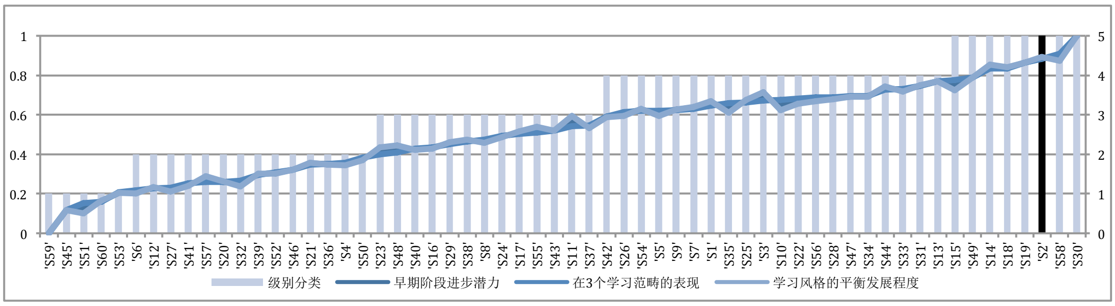

图 3－1. 所有课程

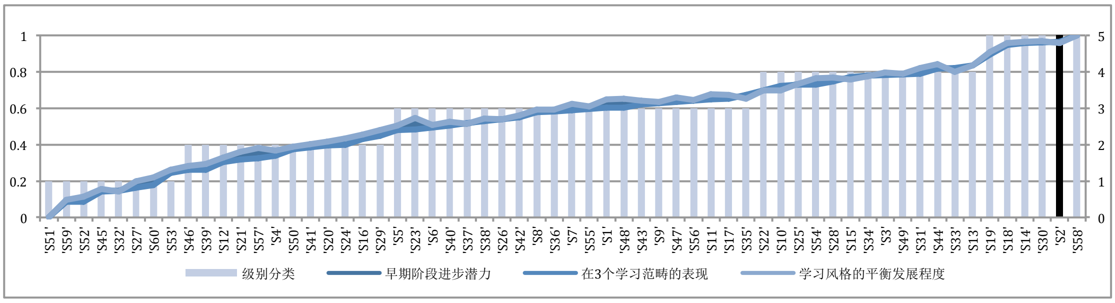

图 3－2. 理科

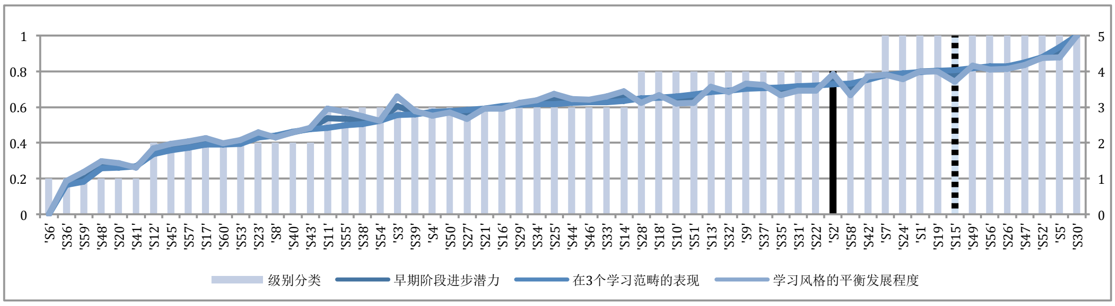

图 3－3. 文科

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1－5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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3. 成熟阶段 Mature stage

该阶段包括了衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）里的低级别和高级别。特别用于区分优秀学生和一般学生。

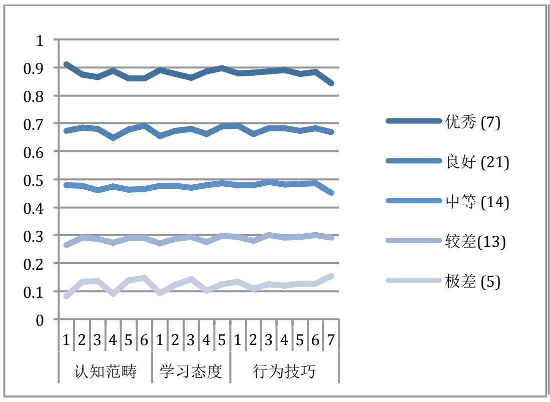
知识认知：认识并记忆，理解，应用，分析，综合，创造能力；

学习态度：接受知识，做出响应，评价，组织，形成价值观影响自己的行为；

行为技巧：使用感官线索指导活动的能力，学习前的准备工作，根据指导进行练习，对所学知识可以灵活运用，所学技能已经熟能生巧，随机应变能力，基于高度发达技巧创造新的行为模式来解决具体问题。

3.1 分类结果

则这 60 名同学的整体分布结果如下图所示：（图 4－1）全部课程；（图 4－2）理科；（图 4－3）文科。其中，每一类的学生人数都表示在类别后的括号内。我们可以得出和‘初级阶段’完全相同的结论。可以看出，综合所有科目， 每一类学生在各个范畴的各个方面都有稳定的表现。同样的规律是：在一个范畴表现较好的学生，在其他范畴也会有较好的表现。同样的结论适用于理科科目（图 4－2）和文科科目（图 4－3）。但是在这 3 个范畴上，这 60 名同学（1）在理科上的整体表现要普遍好过在文科上的表现；（2）在理科上的差异（两级分化）明显大于在文科上的差异。不同的是，学生在各个类别上的分布和初级阶段相比有小小不同。



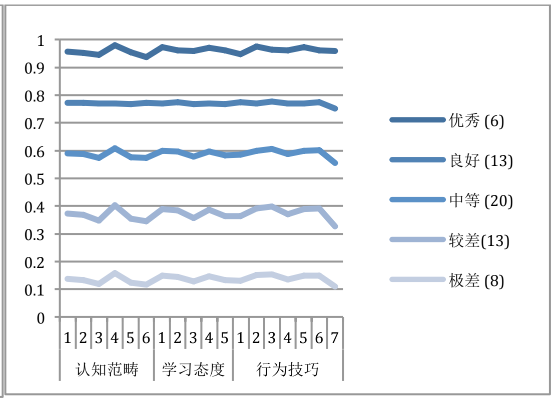


图 4－1. 所有课程　图 4－2. 理科

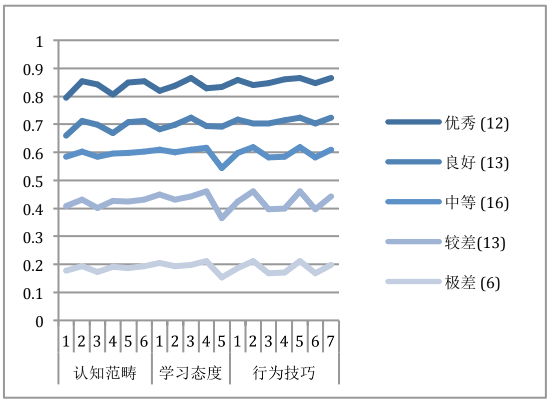


图 4－3. 文科

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1－5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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3.2 成熟阶段－进步潜力

类似于第 2 节中中级阶段的分析，以下 3 图分别是根据学生们的 9 个属性在所有课程，理科，和文科的表现进行的分析结果。对于每一幅图，横坐标表示了学生 ID，左边的纵坐标表示了他们的相对表现（0：最差；1：最好），右边的纵坐标表示了他们的类别等级（1：极差；5：优秀）。图中的 3 条曲线分别是学生的潜力在 3 个范畴的总体表现，以及学习风格的平衡发展程度。同初级阶

段的分析结果基本相似，不同之处在于对学生的分类结果有略微差异，其中有 9 名学生的潜略有提高，另外 8 名学生的潜能略有下降。总的来说，对于这 60 名学生，不论对于何种课程组合， 在 3 个范畴的总体表现越好的学生，他们学习风格的平衡发展程度也就越高，相应的他们的进步潜力也就越大。当然也有例外：学生 S15 比学生 S2 在 3 个范畴的总体表现更好，但 S15 却比 S2 学习风格的平衡发展程度更低（图 3—3）。但是对于同一个学生的不同课程组合，他们在 3 个范畴的总体表现并不一致，他们学习风格的平衡发展程度也不相同，相应的他们的潜力也有差异。例如，根据学生 S2（黑色着重表示在各个图中）3 个范畴中各方面在所有课程以及理科上的表现，他属于优秀，但是在文科上却属于良好。

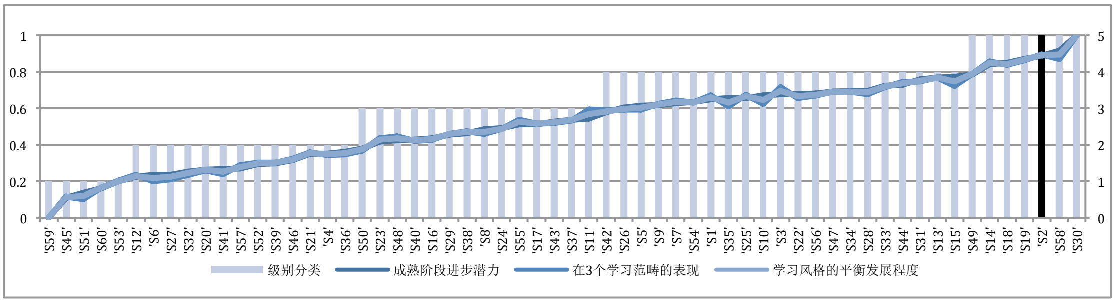

图 5—1. 所有课程

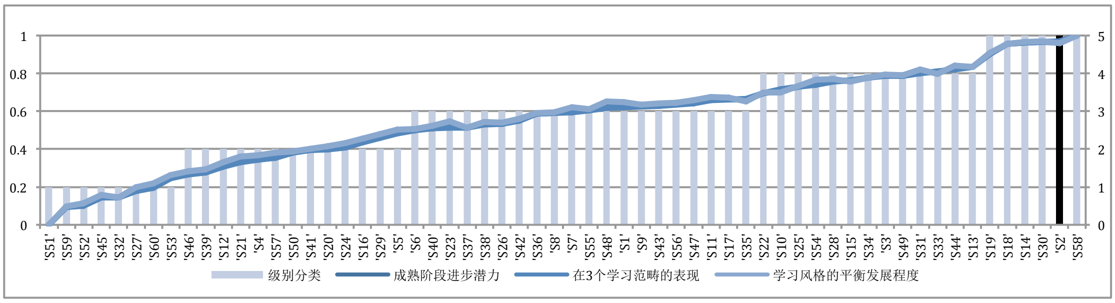

图 5-2. 理科

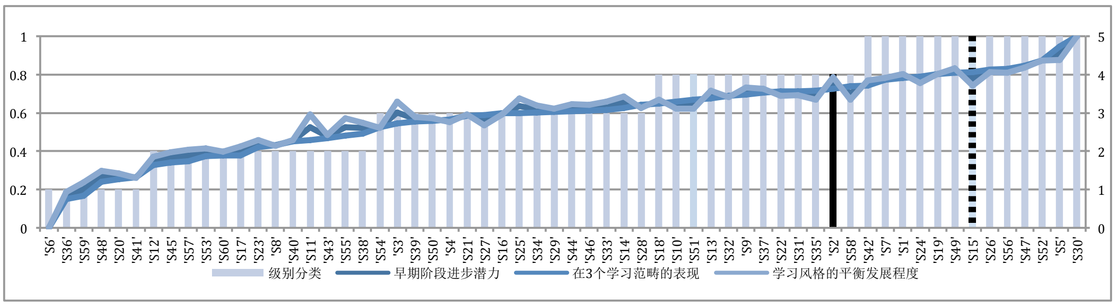

图 5—3. 文科

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1—5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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3.3 各个属性间的关系

同 1.2 中所描述的实验相似，一个属性的变化（进步或退步）会影响到其他属性的变化（进步或退步），所以我们根据学生在‘成熟阶段’的表现，同样分析了这 9 个属性的相互关系。综合各门课程，60 名学生在初级阶段所呈现出来的 9 个属性的相互关系如图 6 所示。行为技巧成为了核心属性，它分别和学习态度，认知范畴相互影响。而同时，由于学生的学习风格反应了学生学习行为的各方面特点，所以学习风格中任何一个属性的变化都可以影响到学生在行为技巧方面的表现。

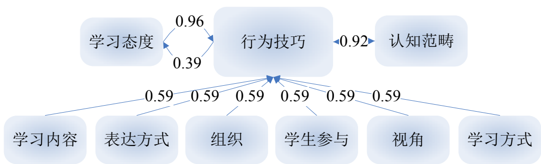

图 6. 根据所有学生在所有课程上成熟阶段的表现，各个属性之间的相互影响

而根据所有学生在所有课程上成熟阶段的表现，图 7 给出了各个属性对其他属性的总影响力的分布情况。明显在成熟阶段，学生的行为技巧成为了对其他属性影响力最大的属性。而其他属性都基本上有着相等的影响力。另外，无论是对每一类学生，还是分别对文科理科科目进行分析，各个属性所呈现出来的相互关系都基本相似，只有影响力大小有略微差别。

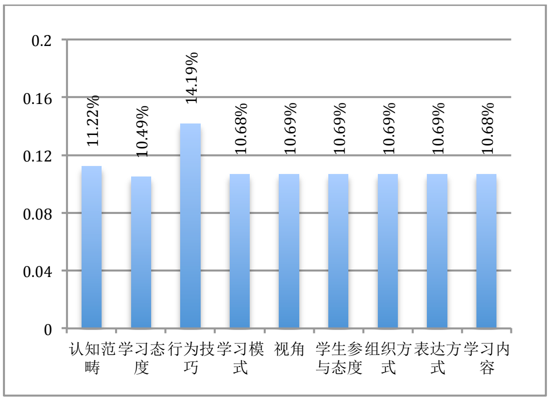

图 7. 根据所有学生在所有课程上成熟阶段的表现，各个属性对其他属性的总影响力分布

请问各位老师，根据您在教学实践中对这 60 名学生的学习情况的了解，该分析结果是否和您的理解一致？（请从 1－5 打分，1：完全不一致；2：小部分一致 3：半数一致；4：大部分一致；5：基本一致；）

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Appendix C

Questionnaire: Analysis results for student S2

提供给学生的分析结果

本次实验分析的课程包括：数学，物理，化学，政治，历史，和英语。其中视前 3 门为理科科目，后 3 门为文科科目。基于上次从各位老师那里收集来得数据，各位老师分别根据衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）给出了自己的教学要求，我们基于这些方面，对学生进行评估，并将其表现在刻度 0 到 1 范围内划分为 5 个等级：极差，较差，中等，良好，以及优秀。

1. 学习的初级阶段

该阶段包括了衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）里的几个较低级别，为一般情况下老师用到的衡量级别。

知识认知：认识并记忆，理解，应用；

学习态度：接受知识，做出响应；

行为技巧：使用感官线索指导活动的能力，学习前的准备工作，根据指导进行练习。

1.1 分类结果

综合所有课程（图 1－1），学生 S2 在 3 个范畴的各个方面的表现被归为‘优秀’，并且他的各个方面还略高于优秀生的平均水平，远高于老师对学生的最低要求。

综合理科课程（图 1－2），学生 S2 在 3 个范畴的各个方面的表现被归为‘优秀’，并且他的各个方面几乎和优秀生的平均水平保持一致，远高于老师对学生的最低要求。

综合文科课程（图 1—3），学生 S2 在 3 个范畴的各个方面的表现被归为‘良好’，并且他的各个方面还略高于良好生的平均水平，甚至某些方面还可以达到‘优秀生’的水平，同时也高于老师对学生的最低要求。

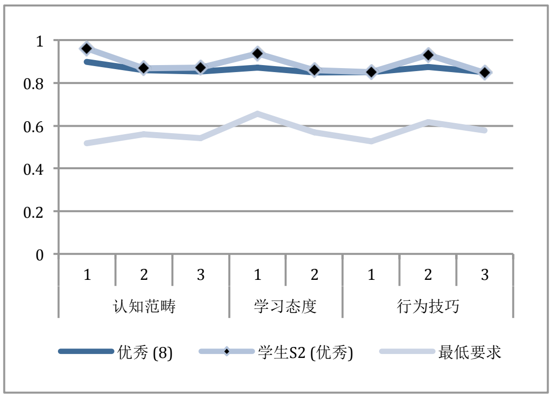

图 1—1. 所有课程

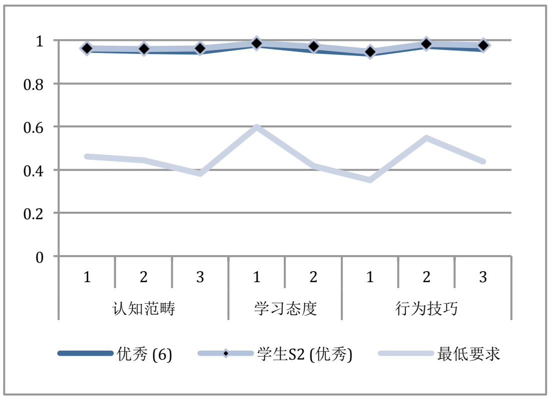

图 1—2. 理科

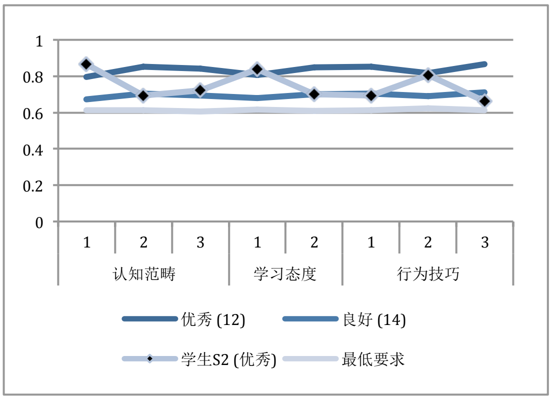

图 1—3. 文科

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1—5 打分，1：完全不清楚自己的学习情况；2：不太清楚自己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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1.2 各个属性间的关系

根据上次的问卷调查，我们不仅仅收集了各位老师在知识，学习态度，行为技巧 3 个范畴的教学要求，以及学生的参与模式（同学合作或单人作业）同时也收集了各位老师在学习内容（具体或抽象），表达方式（视觉表达或口头表达），知识组织方式（归纳 / 收敛知识，或演绎 / 发散知识），学生参与态度（主动或被动），教学顺序（从前到后一步一步教授知识，或从整体到细节教授知识）5 个方面所形成的教学风格。我们相信，一个属性的变化（进步或退步）会影响到其他属性的变化（进步或退步），所以我们根据学生的表现，分析了这 9 个属性的相互关系。

综合各门课程，学生 S2 在初级阶段所呈现出来的 9 个属性的相互关系如图 2－1 所示，每一个节点表示一个熟悉，箭头表示出发节点对终止节点有影响，箭头上的权重表示一个属性对其他属性影响的相对大小（权值 0 为无影响，权值 1 为影响最大）。可以发现学生的认知范畴，学习态度，和行为技巧 3 者之间是相互影响的，任何一个的进步都会引起另外 2 个属性的进步。而学生的学习风格的平衡发展又会直接影响到学生认知范畴和行为技巧的表现。其中学习风格的平衡度对认知范畴的影响作用要大于对行为技巧的影响作用。

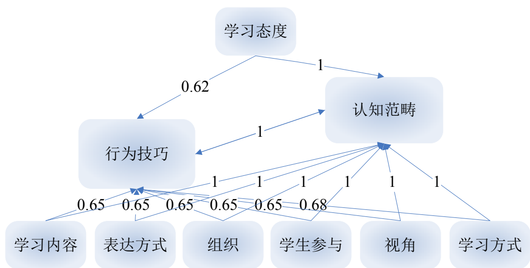

图 2－1. 学生 S2 在初级阶段所呈现出来的 9 个属性的相互关系

初级阶段综合所有课程，学生 S2 各个属性的总影响力分布如图 2－2 所示。另外给出了优秀生和所有学生的情况作为参考。因为初级阶段只衡量了学生的初级能力，所以衡量这 3 个范畴对较优和较差学生的区分力度也相对较小。所以在该阶段，学生各种学习风格的平衡发展主要影响了学生在其他方面的表现。另外，无论是对每一类学生，还是分别对文科理科科目进行分析，各个属性所呈现出来的相互关系都基本相似，只有影响力大小有略微差别。

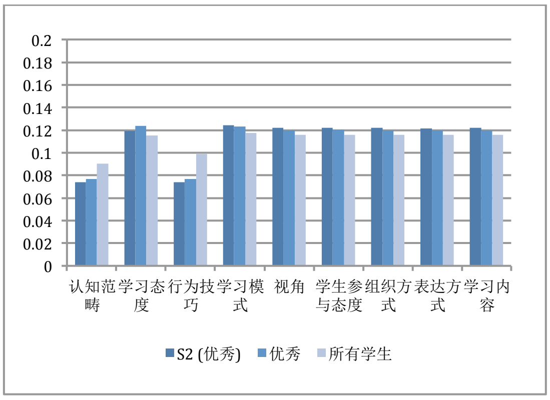

图 2－2. 初级阶段综合所有课程，学生 S2 各个属性的总影响力分布

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1－5 打分，1：完全不清楚自己的学习情况；2：不太清楚自己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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2. 中期阶段－‘进步潜力’

该部分分析了学生取得更大进步的可能潜力。如果学生不仅仅在这 3 个范畴上的表现良好，并且可以根据老师不同的教学模式，平衡地发展自己的学习风格，以此来适应各种各样的学习要求和学习环境，那么该学生就具备了较大的潜力做出更大的进步，并且具备更强的自学能力。对于该类学生，无论老师设置何种难度的学习活动，或使用何种方式的教学手段，他们都可以取得良好的表现。相反，对于‘进步潜力’较低的学生，老师应当有针对性的按照其擅长的学习风格对其进行指导。中期阶段的评估同时也指示了是否该学生是否按正确的方向发展自己做出进步。

以下 3 图是根据学生 S2 的 9 个属性分别在所有课程，理科，和文科的表现进行的分析结果。对于每一附图，横坐标表示了各类学生以及学生 S2，纵坐标表示了他们的相对表现（0：最差；1：最好）。图中的第一组柱状图表示学生的潜力，第二组柱状图表示其学习风格的平衡发展程度。总的来说，不论对于何种

课程组合， 在 3 个范畴的总体表现越好的学生，他们学习风格的平衡发展程度也就越高，相应的他们的进步潜力也就越大。但是对于同一个学生的不同课程组合，他在 3 个范畴的总体表现并不一致，他学习风格的平衡发展程度也不相同，相应的他们的潜力也有差异。在所有课程以及理科上，学生 S2 在 3 个范畴中各方面的表现属于优秀，但是在文科上却属于良好。

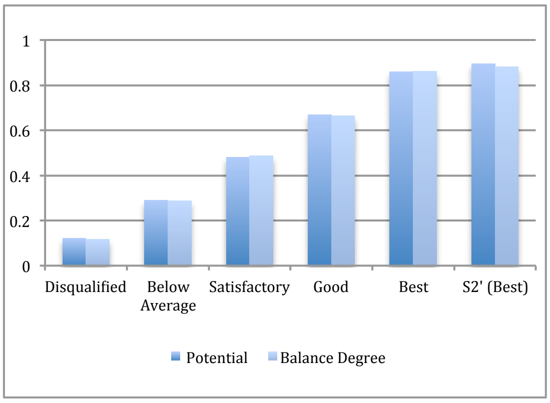

图 3—1. 所有课程

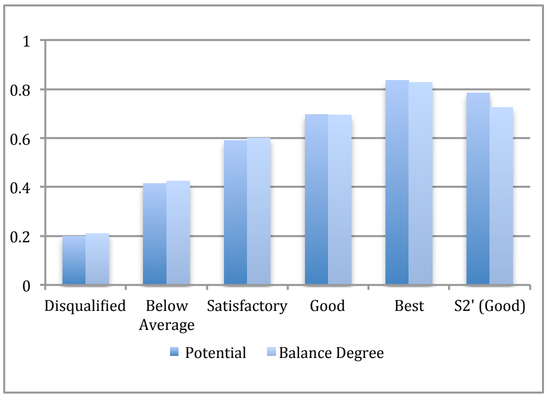

图 3—2. 理科

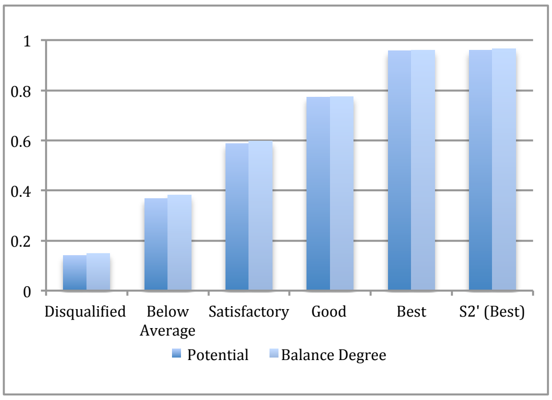

图 3—3. 文科

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1—5 打分，1：完全不清楚自己的学习情况；2：不太清楚自己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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3. 成熟阶段 Mature stage

该阶段包括了衡量学生表现的三个范畴（知识认知，学习态度，和行为技巧）里的低级别和高级别。特别用于区分优秀学生和一般学生。

知识认知：认识并记忆，理解，应用，分析，综合，创造能力；

学习态度：接受知识，做出响应，评价，组织，形成价值观影响自己的行为；

行为技巧：使用感官线索指导活动的能力，学习前的准备工作，根据指导进行练习，对所学知识可以灵活运用，所学技能已经熟能生巧，随机应变能力，基于高度发达技巧创造新的行为模式来解决具体问题。

3.1 分类结果

学生 S2 成熟阶段的整体分布结果如下图所示：（图 4－1）全部课程；（图 4－2）理科；（图 4－3）文科。其中，一类的学生人数都表示在类别后的括号内。我们可以得出和‘初级阶段’完全相同的结论。可以看出，综合所有科目， 每一类学生在各个范畴的各个方面都有稳定的表现。在一个范畴表现较好的学生，在其他范畴也会有较好的表现。同样的结论适用于理科科目（图 4－2）和文科科目（图 4－3）。但是在这 3 个范畴上，学生 S2 在理科上的整体表现要普遍好过在文科上的表现。根据所有课程以及理科课程，S2 都是优秀生，但是根据文科课程，虽然这 3 个范畴的部分方面他还是可以达到优秀生的水平，却也在学习态度范畴的最高等级这一方面被划分为中等，所以总的来说他在这 3 个范畴上的表现只能算是良好。

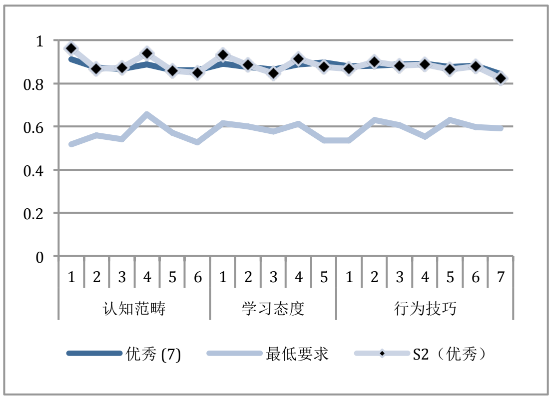

图 4－1. 所有课程

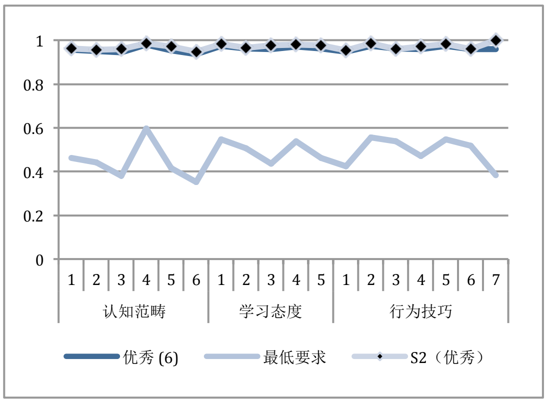

图 4－2. 理科

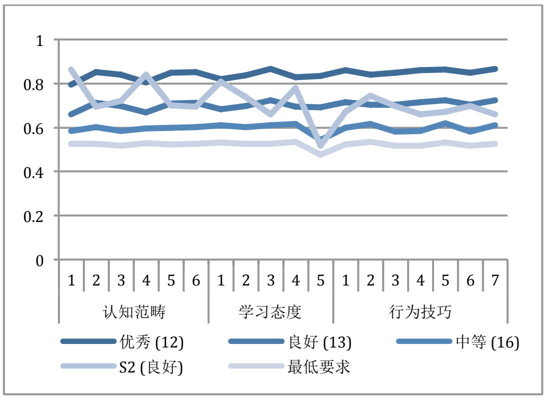

图 4－3. 文科

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1－5 打分，1：完全不清楚自己的学习情况；2：不太清楚自己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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3.2 成熟阶段－进步潜力

类似于第 2 节中中级阶段的分析，成熟阶段同初级阶段的分析结果相似，在此不再赘述。总的来说，S2 仍属于优秀生。学生 S2 在 3 个范畴中各方面在所有课程以及理科上的表现属于优秀，但是在文科上却属于良好。

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1－5 打分，1：完全不清楚自己的学习情况；2：不太清楚自己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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3.3 各个属性间的关系

同 1.2 中所描述的实验相似，一个属性的变化（进步或退步）会影响到其他属性的变化（进步或退步），所以我们根据学生 S2 在‘成熟阶段’的表现，同样分析了这 9 个属性的相互关系。综合各门课程，学生 S2 在初级阶段所呈现出来的 9 个属性的相互关系如图 5 所示。行为技巧成为了核心属性，它分别和学习态度，认知范畴相互影响。而同时，由于学生的学习风格反应了学生学习行为的各方面特点，所以学习风格中任何一个属性的变化都可以影响到学生在行为技巧方面的表现。

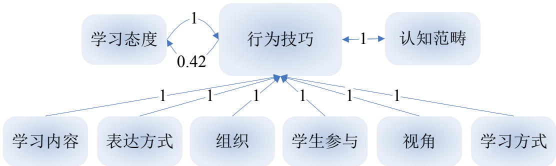

图 5. 根据学生 S2 在所有课程上成熟阶段的表现，各个属性之间的相互影响

而根据学生 S2 在所有课程上成熟阶段的表现，图 6 比较了 S2，优秀生，以及所有学生的各个属性对其他属性的总影响力的分布情况。明显在成熟阶段，S2 的行为技巧成为了对其他属性影响力最大的属性。而其他属性都基本上有着相等的影响力。另外，无论是对每一类学生，还是分别对文科理科科目进行分析，各个属性所呈现出来的相互关系都基本相似，只有影响力大小有略微差别。

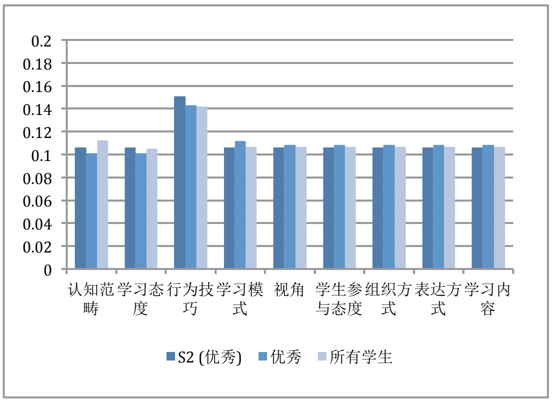

图 6. 成熟阶段，根据学生 S2 在所有课程上的表现，其各个属性对其他属性的总影响力分布

请问如果您是学生 S2，该分析结果能否帮助您更好的理解自己的学习情况？（请从 1－5 打分，1：完全不清楚自己的学习情况；2：不太清楚自

己的学习情况 3：只了解到了一般情况；4：还比较清楚的了解了自己的学习情况；5：清楚的了解自己的学习情况；）

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Appendix D – Vitae

I received my Bachelor degree in Communication Engineering from Northwesten Polytechnical University in 2007, and then I spent my postgraduate study of MSc. in Information and Communication Engineering in National University of Defense Technology. I have been a PhD candidate in School of Engineering and Computing Sciences, Durham University since Nov. 2008.

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