A Fine-Grained Outcome-Based Learning Path Model

Fan Yang, Frederick W. B. Li, and Rynson W. H. Lau, *Senior Member, IEEE*

***Abstract*—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. SCORM and IMS-LD have been established to define data structures for supporting systematic learning path construction. Although IMS-LD includes the concept of learning activity, no facilities are offered to help define its semantics, and pedagogy cannot be properly formulated. In addition, most existing work for learning path generation is content-based. They only focus on what learning content is delivered at each learning path step, and pedagogy is not incorporated. Such modeling limits the assessment of student learning outcome only by the mastery level of learning content. Other forms of assessments, such as generic skills, cannot be supported. In this paper, we propose a fine-grained outcome-based learning path model allowing learning activities and their assessment criteria to be formulated by 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.**

***Index Terms*—Learning activity, learning path, outcome-based teaching and learning.**

I. Introduction

LEARNING PATH defines how a course of study proceeds. It comprises steps for a student to go through in order to learning the course content. 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 approach). Assessments should also be included for evaluating student learning progress. In practice, a student is expected to achieve some abilities, 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 skills refer to the ability to formulate, evaluate, and synthesize matters within a subject. Such skills may be shared among subjects of similar nature. Generic skills refer to the ability that can be applied to various subject domains and student future development.

Pedagogy formulation and student assessment are the 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) to help 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 listening to oral presentation" and "learn by experimentation," respectively. Although lecturers can implement more fine-grained pedagogies, these pedagogies are hard to be 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 a teaching subject. However, subject-specific and generic skills are usually left as written documentation rather than being used for assessing student achievement, since they may require evaluating the student learning outcomes achieved from a set of relevant subjects, which is not trivial to implement.

Existing work on learning path generation for e-learning [5], [10], and [14] are generally content-based without modeling pedagogy or learning activity. Students are usually assessed only by the mastery level of the learning content in each learning path step. As subject-specific and generic skills are learning activities dependent, they cannot be properly assessed.

SCORM [17] and IMS-LD [21] are popular standards defining data structures for learning paths. SCORM follows the content-based approach without supporting the assessment of generic skills. Although IMS-LD includes learning activities in its data structure, it only provides a container to hold learning activities without offering any facilities to help define the semantics. As a result, teachers need to manually specify such definitions, which may be hard to reuse.

In this paper, 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 model to facilitate the assessment of different forms of student learning outcomes, including subject-specific knowledge and skills, and generic skills. Our work does not deal with adaptive learning. The details of our contributions are

1) *Pedagogical support*: We model a learning activity as a composition of learning tasks, enabling teachers to construct learning and teaching approaches in explicit forms. We also model learning tasks to tie in with the learning outcomes based upon Bloom's Taxonomy [2], [13], and [18], such that teachers may formulate comprehensive assessment criteria, as they are doing in conventional classroom teaching environments.
2) *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.
3) *Reusability*: Our model allows teachers to reuse teaching and assessment approaches. It is done by applying a designed learning activity structured 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 a new learning activity.

The rest of this paper is organized as follows. Section II summarizes existing works. Section III presents our new learning path model. Section IV discusses the implementation of the prototype system. Section V presents and discusses some experimental results. Finally, Section VI concludes our work.

II. Related Work

A learning path is the implementation of a curriculum design. It comprises elements forming steps for students to go through the acquired 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.

Conventional classroom teaching: Under this setting, students usually share a common learning path due to the one-size-fit-all teaching approach. This learning path is typically predefined and mostly static, as teaching resources or constraints, such as teaching staff, classrooms, and period of study, are usually fixed. Although subject-specific knowledge/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.

Learning path generation: These systems construct adaptive learning paths by arranging selected learning contents in a proper sequence for study, aiming at improving student learning effectiveness. Karampiperis and Sampson [10] 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 backgrounds 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 estimated 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, [5] involves a pretest 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 [14] characterizes learning contents by learning styles [9] and [15] 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 approach). Learning outcome assessment is also confined to the mastery level of learning content.

For implementing pedagogy, LAMS [7] provides an interactive user interface allowing teachers to define a learning path based on a set of predefined learning activities, such as reading 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 [6]. It defines a learning activity as a composition of learning content, learning outcomes, teaching approaches, and tasks. However, the correspondences among the components are not modeled, i.e., it cannot formulate student learning outcome assessment if a learning activity involves several tasks.

Standards for defining learning paths: SCORM [17] defines an interface between learning contents and a learning management system (LMS) and supports exchanging learning contents among different LMS's. 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 and some are formed by a 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 [21] is a meta-language that is divided into three 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 to reuse. On the other hand, IMS-SS [22] offers a standard for controlling the flow of learning activities through predefined rules, branching definitions, and learning outcomes of student interactions with learning contents. This standard is also content-based without modeling pedagogy.

III. Learning Path Modeling

This paper proposes 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 paper extends [20] to define learning paths with two levels, namely learning activity (LA) and learning task (LT) levels (Section III-B), such that student achievement in both LA-specific and different types of abilities can be comprehensively revealed.

A. Overview

Existing learning path generation methods are usually content-based. As illustrated in Fig. 1(a) and (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 not generally 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. They rely on teachers to work out the solutions by themselves. This burden partly explains why learning path generation systems are not widely adopted for learning and teaching in practice.

To model the student learning process, we propose using LAs [6] instead of KEs as the building blocks of a learning path, as shown in Fig. 1(c), and model each KE as a set of LAs. As shown in Fig. 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 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.

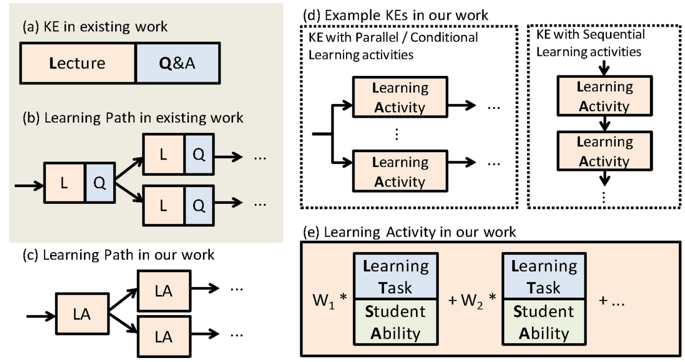


Fig. 1. Learning path formulation in existing work and in our work.

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

To model learning outcome (LO) requirement of an 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 SAs. The student-learning outcome from an 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 student ability/skill. The LA level learning path helps assess student learning progress made from a series of LAs, while an LT level learning path connects corresponding LTs from relevant LAs to help evaluate student ability or skill specific learning progress.

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

In contrast to [6], 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 ability specific assessment across a series of learning activities. Table I summarizes the major elements of our learning path model. We elaborate their details in the following subsections.

TABLE I
DEFINITION OF MAJOR ELEMENTS

Abbr.	Key Element	Definition
SA	Student Ability	Set of attributes indicate how students make progress in learning
LT	Learning Task	A fine-grained type of training helps students 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 students to go through and build up knowledge & skills
LS	Learning Stage	Finite period of time defined within time span of a learning path

TABLE II
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		

B. Formal Definitions

Student Ability: Student ability refers to a set of attributes describing if a student has acquired them after studying. These attributes may indicate whether the student can only recall subject content or may apply subject knowledge to solve problems in unseen situations, for instance. In practice, it is a popular approach to assess student-learning outcomes as a composition of student abilities. For example, a teacher may set various types of questions in an examination paper to assess different student abilities. Research on student abilities was first conducted systemically by a group of educators led by Benjamin Bloom [1]. They produced Bloom's Taxonomy to classify thinking behaviors into six cognitive levels of complexity. This taxonomy has been extended to cover three domains: cognitive (knowledge-based), affective (attitudinal-based) [13], and psychomotor (skills-based) [18]. It forms a comprehensive checklist guiding a teacher to ensure that a course design can help train up students with all necessary abilities. Table II summarizes Bloom's Taxonomy by listing the main characteristics of different student abilities according to the Bloom's domains (columns) and their corresponding levels of complexity (rows). To help formulate the assessment criteria of student learning outcomes, we propose using student abilities from Bloom's Taxonomy as the basis for assessment since they can comprehensively quantify the levels and the types of student's achievement. To define the criteria, a teacher needs to identify a set of student abilities used for assessment and put them into a student ability table (SAT), which is defined as follows:

$$SAT = \{A_1, \cdots, A_i, \cdots, A_{|SAT|}\} \quad \text{for} \quad 1 \le i \le |SAT| \quad (1)$$

where A_i refers to a specific kind of student ability and $|SAT|$ is the cardinality of SAT. To facilitate learning outcome assessment, for each student ability, 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 Bloom's Taxonomy domain, respectively. For example, the ability 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 student abilities can be defined in terms of $B_c(A_i)$ and $B_d(A_i)$, the reader may refer to Bloom's Taxonomy [1] or some quick references such as [3].

Although Bloom's Taxonomy covers a comprehensive list of student abilities, which can maximize the benefits of our model, we expect some teachers may prefer using a simpler student ability model or even define their own lists. Such a replacement will not affect any functionality of our model. In this sense, new versions of 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 a specific ability. By putting together a set of learning tasks, a learning activity is formed. Similar to the selection of student abilities, a teacher also sets up a learning task table (LTT), which comprises a list of learning tasks for constructing learning activities as follows:

$$LTT = \{T_1, \cdots T_i, \cdots, T_{|LTT|}\} \quad \text{for} \quad 1 \le i \le |LTT| \quad (2)$$

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 SAT is subjective, i.e., a teacher can design different types of learning tasks to train up students with the same type of student ability.

The design of learning tasks is typically course dependent. As we do not expect teachers having comprehensive knowledge of 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 task is set up for teaching declarative or functioning knowledge [2]. 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 student ability in memorization, while an in-class quiz can be set out to assess student understanding. Table III shows some sample learning tasks along with the corresponding types of knowledge, student abilities for assessment, and the Bloom's domains and levels of complexity.

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

$$\text{LA}=[w_1 \cdots w_i \cdots w_{|\text{LA}|}][T_1 \cdots T_i \cdots T_{|\text{LA}|}]^T \;\text{ for }\; 1 \le i \le |\text{LA}| \quad (3)$$

TABLE III

EXAMPLES OF LEARNING TASKS

Type of Knowledge	Learning Task	Student Ability 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

where $[.]^{\mathrm{T}}$ is a transpose function, w_i is a weight to indicate the importance of learning task T_i, $\sum w_i = 1$ and |LA| is the cardinality of LA. The weights associated with these learning tasks should add up to 1, meaning that if the weight of a student ability (which is associated with one of the learning tasks) is increased, the weights for the rest of the student abilities should be decreased, and vice versa. Specifically, if the weight of a student ability $\boldsymbol{w}$ is changed to $\boldsymbol{w'}$, the contribution of the other student abilities becomes $(1 - \boldsymbol{w'})/(1 - \boldsymbol{w})$. Therefore, the weight for each of the other student abilities $\boldsymbol{wr}$ should be changed to $\boldsymbol{wr} \cdot (1 - \boldsymbol{w}')/(1 - \boldsymbol{w})$. The LO of an LA can then be assessed by

$$LO = [w_1 \dots w_i \dots w_{|\mathrm{LA}|}][f_1(S_a(T_1)) \dots f_i(S_a(T_i)) \dots f_{|\mathrm{LA}|}(S_a(T_{|\mathrm{LA}|}))]^T \quad (4)$$

where $f_i()$ is a function to evaluate the student's level of achievement in a given student ability. The weights used in both (3) and (4) are the same ones, as the weight associated with a learning task also defines the importance of the associated student ability 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 the implementation, T_i may be a scalar for storing the ID of a learning task.

Instead of creating new evaluation functions themselves, teachers may reuse existing ones, such as simple marking (quantitative assessment), grading (qualitative assessment) or performing evaluation through the item response theory [4], if they are applicable to the types of student ability. 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 with a different type of student ability.

In fact, modeling an LA is not straightforward. Given that different teachers may adopt different teaching strategies, and different students may have different learning styles, the actual tasks used for setting up 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 an LA as a set of learning tasks. It offers course designers or teachers a way to properly define teaching strategies for delivering KEs. While an LT is an implementation of a low-level teaching technique that focuses on training and assessing students with certain ability, such as an informal in-class quiz and feedback, an LA is an implementation of a high-level teaching strategy that course designers or teachers use to approach a KE for training students with a composition of knowledge and skills.

Our model offers more accurate learning activity modeling 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 the 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 [15], 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: Collaborative learning activity (LA^{C}) is a specific LA designed for students to learn under a group setting. For a typical LA, the 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 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 $1 i \, |S|$, where $|S|$ is the number of students participating in the group. Mathematically, ψ_C and ψ_i are 1-D vectors of learning tasks 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 1-D vectors of weights 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

$$\mathrm{LA}_i^C = \begin{bmatrix} \Xi_C & \Psi_C^{\mathrm{T}} \\ \Xi_i & \Psi_i^{\mathrm{T}} \end{bmatrix} \quad (5)$$

where all elements in both Ξ_C and Ξ_i sum up to 1. Mathematically, the definitions of both $\Xi_C \Psi_C^T$ and $\Xi_i \Psi_i^T$ are equivalent to (3), and therefore the student-learning outcome can be evaluated by (4) when proper student ability evaluation functions are set in place. We refer collaborative learning tasks in (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

$$\mathrm{LA}^C = \begin{bmatrix} \Xi_C \Psi_C^T \\ \Xi_1 \Psi_1^T \\ \vdots \\ \Xi_{|S|} \Psi_{|S|}^T \end{bmatrix} \quad (6)$$

Note that the learning outcome of a student can be evaluated in the same way regardless whether a collaborative learning activity exists, since a collaborative learning activity only introduces learning tasks with assessment results shared by some students. These 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 an LA level and an LT level of learning paths. The LA level learning path is made 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 for student progress evaluation. Specifically, E is the set of edges while V is defined as:

$$V = \{\mathrm{LA}_1, \cdots, \mathrm{LA}_i, \cdots, \mathrm{LA}_{|v|}\} \text{ for } 1 \leq i \leq |V| \tag{7}$$

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. As illustrated in Fig. 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 systems [5], [10], and [14] 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 learning path generation results can be enhanced when student learning progress information is considered [4] and [14]. On the other hand, an LT level learning path is designed to link up certain learning tasks defined in relevant learning activities. Those learning tasks are designed to collectively teach and assess a specific type of learning outcome. In terms of the structure, similar to the LA level of learning path, an LT level learning path is also a directed graph, where its elements are LTs rather than LAs. As an illustration, an example of LA Computer Organization (LT) and its LTs are shown in Fig. 4(a) and (b), respectively. An example of an LA level learning path is shown in Fig. 2. Based on this learning path, two sample LT level learning paths, which assess communication and writing skills of a student are shown in Figs. 6 and 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 each time slot as a LS. A learning activity may take place in a designated learning stage or span over a number of learning stages. The definition of learning stage well matches the timetabling concept 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 an LA, we set up two functions, $LS_s()$ and $LS_e()$, respectively, as follows:

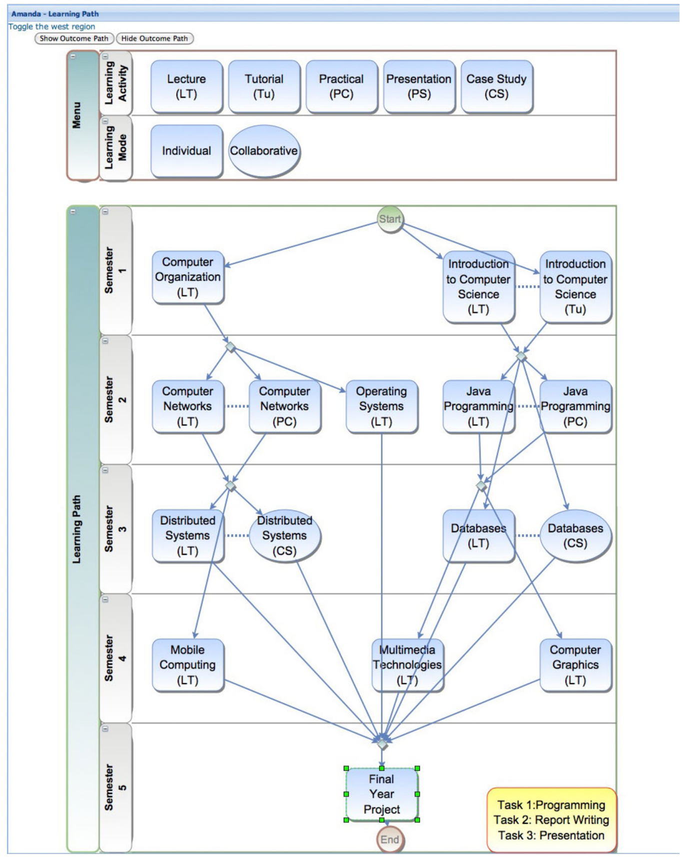


Fig. 2. Screen shot of our prototype.

$$sLS = LS_s(\mathrm{LA}) \tag{8}$$

$$eLS = LS_e(\mathrm{LA}). \tag{9}$$

To govern student-learning process, time constraints and dependencies are often set up among 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 satisfy the following constraint.

$$LS_s(\mathrm{LA}_j) = LS_s(\mathrm{LA}_k). \tag{10}$$

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

$$LS_e(\mathrm{LA}_j) < LS_s(\mathrm{LA}_k). \tag{11}$$

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 a student has acquired from a course over certain learning stages. With (4), learning outcome can be evaluated as a weighted composition of student abilities 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 an LT level learning path. This allows the assessment of generic outcomes or transferable skills [8], 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.

C. 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 paper. 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 student ability, 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, [16] proposes to allow both teachers and students to collaboratively set up assessment criteria for assessing student abilities across the domains of knowledge, attitude and skill, rather than simply using a standard Q&A assessment. On the other hand, [12] has found that student performance in a virtual laboratory (a practical learning activity) can be evaluated by assessing student abilities through different levels of cognition, particularly those higher ones, including analysis, synthesis and evaluation [1]. 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.

IV. Implementation and Case Study

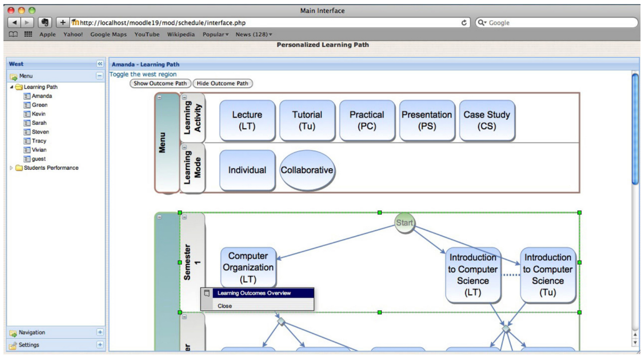
To evaluate our work, we have implemented a prototype system based on our fine-grained outcome-based learning path model. The prototype comes with a drag-and-drop graphical user interface to assist teachers in creating and manipulating learning path components graphically. The prototype is not currently a functioning learning management system; we have not yet implemented content management. Fig. 2 shows a screen shot of our prototype where a teacher is working on an LA level-learning path that comprises learning activities for all students in a computer science program. As shown at the upper part of Fig. 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. We invited each teacher to attend a one-hour personal session for conducting our case study. A briefing of our proposed model was given to a teacher before he/she used the prototype to construct learning paths and learning activities. Each teacher was required to answer a questionnaire.

Fig. 2 shows a sample-learning path constructed by a teacher. As an example, a "Lecture" type of learning activity – "Computer Networks (LT)" was constructed in Semester 2, which could be further customized by modifying its learning tasks and the associated weights. For instance, LA "Final Year Project" was selected to reveal its learning tasks, which are shown in the yellow box located at its right hand side. In addition to "Computer Networks (LT)," a "Practical" type of learning activity – "Computer Networks (PC)" was constructed. These two learning activities come together forming a KE, which is indicated by a dashed-line connection. Such a KE formulation allows students to follow multiple approaches when learning a subject and achieve more learning outcomes.

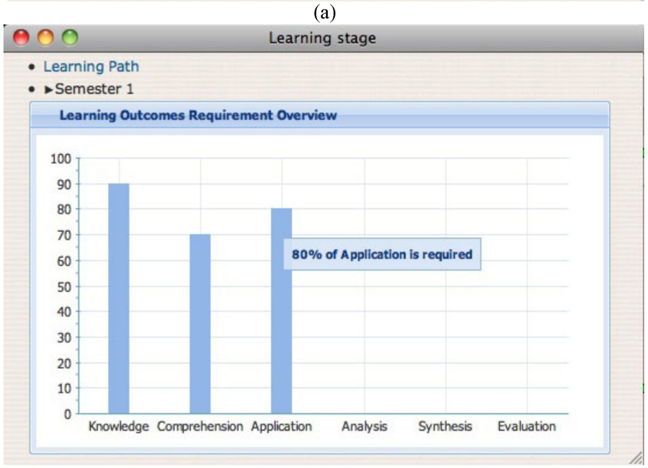
A student may conduct a learning activity if he/she has passed all pre-requisites. Note that arrows indicate pre-requisites, while rhombuses indicate multiple learning activities sharing the same pre-requisites or learning activities having multiple pre-requisites, e.g., "Distributed Systems" has both "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. This feature surpasses existing KE-based methods, which do not support the modeling of pedagogy and certain forms of learning outcomes. However, techniques should be developed to avoid teachers manually producing all settings.

Teachers then proceeded 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. 3(a) shows a learning stage – "Semester 1" was selected. Its learning outcome settings are shown in Fig. 3(b), indicating that in Semester 1, student learning outcomes are assessed based on knowledge, comprehension and application abilities under the cognitive domain of Bloom's Taxonomy. The chart also shows the total percentage of each ability collected from all learning activities within the learning stage, indicating its importance. Such weights cannot be adjusted.

We also asked teachers to work on individual learning activity. Fig. 4(a) shows that learning activity "Computer Organization (LT)" in Semester 1 was selected for editing. The lower part of Fig. 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 "Learning Activity" subsection under Section III-B. 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

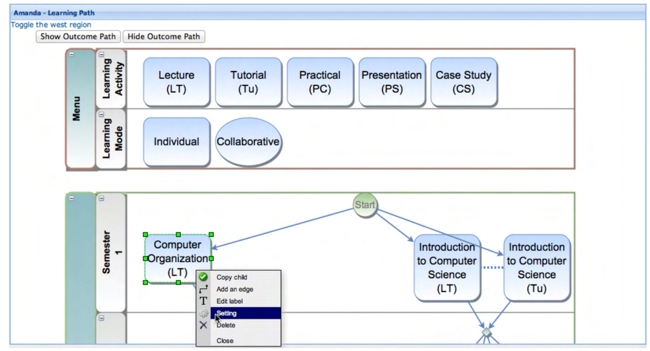


(a)

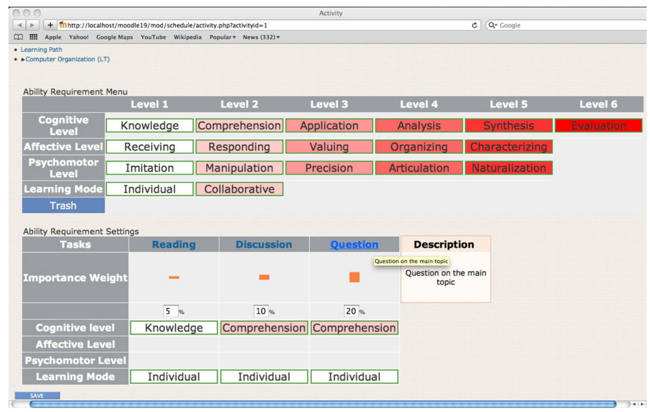


(b)

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



(a)



(b)

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

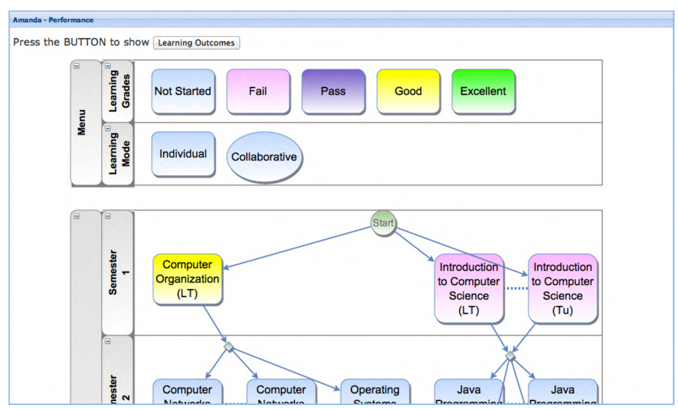


Fig. 5. Screen shot showing the progress of a student.

outcome setting of a learning task by dragging-and-dropping student abilities from the ability requirement menu, as shown in the upper part of Fig. 4(b).

For demonstration purpose, our prototype also supports basic learning progress evaluation. We classify a student-learning outcome of a learning activity with a few learning grade levels, ranging from "Fail" to "Excellent." As shown at the top of Fig. 5, they are represented by different colors. Fig. 5 shows that a student has just completed Semester 1 and received a "Good" learning grade (in yellow color) in "Computer Organization (LT)." But the student has failed both the "LT" and "Tu" learning activities in "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.

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 ability. This function can be activated by pressing the "Show Outcome Path" button at the top-left side of the user interface shown in Fig. 4(a). Fig. 6 shows the LT level-learning path for communication skill while Fig. 7 shows the path for writing skill. To illustrate the assessment of student abilities, we use a percentage value to show the difficulty level of certain student ability required at an 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 student ability. Using Fig. 6 as an example, at the beginning, two LAs are involved in Semester 1 to train 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, he is expected to have gained very mature communication skill with a 100% of difficulty level, if he can pass the assessment of the corresponding LT set in the "Final Year Project" learning activity in 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 student ability. In case if a student fails in certain student ability, he can be supported

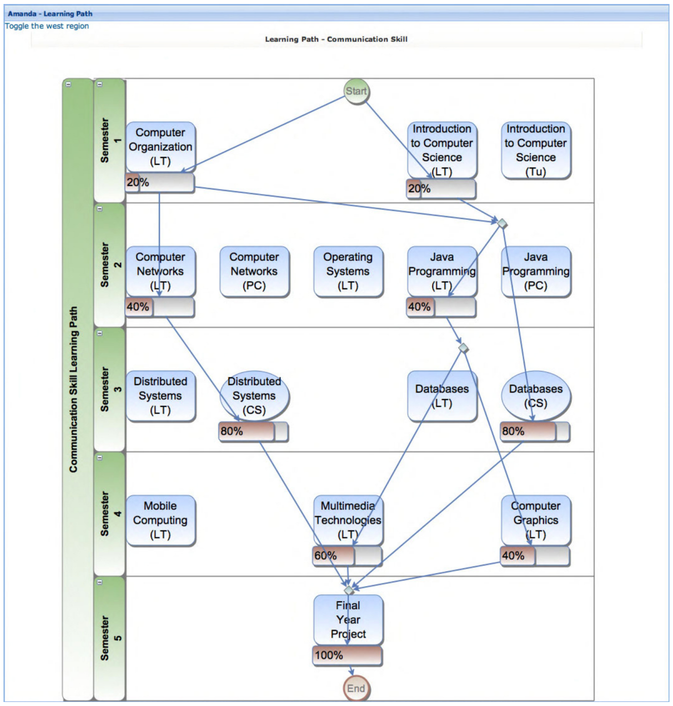


Fig. 6. *LT* level learning path for communication skill.

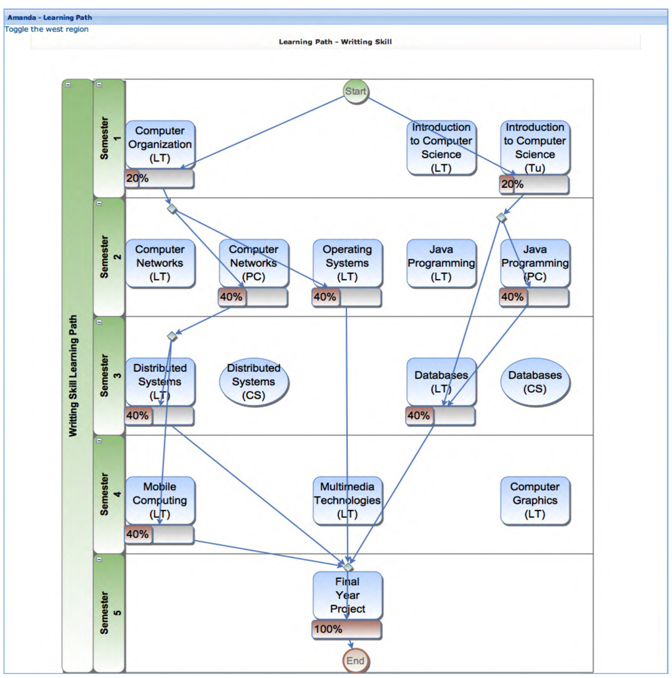


Fig. 7. *LT* level learning path for writing skill.

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.

V. Experimental Results and Discussions

Following the case study as depicted in Section IV, we have collected teachers' feedback on the proposed learning path model. The evaluation model and the results are shown as follows.

Research questions: 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 paper. 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. We use 13 questions to access the following research questions.

1) *RQ1:* Can the new model provide a more systematic and intuitive way for teachers to construct learning paths?
2) *RQ2:* Does it produce learning paths that address the diverse needs of different courses?
3) *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 answer the questions based on a five-point likert scale (Totally Agree = 5, Agree = 4, Neutral = 3, Not Quite Agree = 2, and Disagree = 1). We use ANOVA [11] to analyze our results. We also have another five questions to collect teacher's personal information, including teaching experience, teaching discipline, e-learning tools experience, and teaching methods/styles.

Sample building: Fifteen 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.

1) *Groups under KB:* Science (seven teachers), engineering (six teachers), and arts (seven teachers).
2) *Groups under TE:* 0–1 year (six teachers), 1–4 years (four teachers), 5–9 years (five teachers), and 10 years or above (five 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 been involved in designing or modifying teaching activities. This indicates that most of our test users have a good understanding of the 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 and the scores were normally distributed as assessed by a Shapiro–Wilk test. Methods that can analyze only two groups, e.g., Wilcoxon test, are not applicable.

Statistical results and conclusions: As shown in Fig. 8, the teachers have rated an overall average score of 3.95 out of 5, meaning that they have a good satisfaction of using our model

TABLE IV

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 LObjs	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 LObjs	Determined by number of *LAs* or by number of *LTs*	Determined by number of KEs	Determined by number of *LAs*
Sequence of LObjs	Ordered by *LAs* or by *LTs*	Ordered by KEs	Ordered by *LAs*

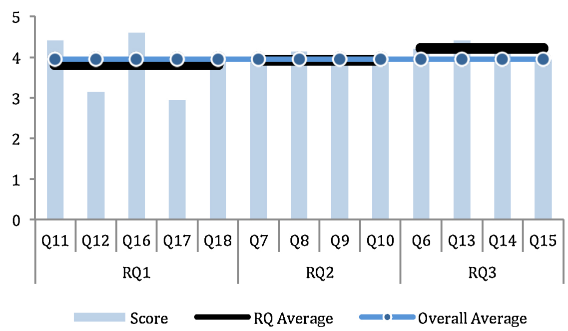


Fig. 8. Summary of scores from the questionnaire.

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 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 for Q12 and Q17 are rated lower than the other questions. These questions asked whether the prototype could 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 paper, we believe that this is an important issue to work on for our future work. Particularly, it is related 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 student abilities from 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 students with a specific ability. 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.

Analytical comparison: To depict the differences between our model and existing methods [5]–[7], [10], and [14], we examine the nature of the constructed LP and the nature, the number and the sequence of the learning objects (LObjs) used to build a learning path from different methods. Table IV summarizes the comparison. The most significant difference of our model is that it offers multiple learning 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 an LA to form a LObj, and that they determine the number and the sequence of LObjs. In contrast, we model a LObj with two levels: LA or LT based, which leads to two different types of LObj sequences.

VI. CONCLUSION

In this paper, we 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 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 approach. We 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 was 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 strategies 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 suggested two possible directions of future work: user interface design and setting up templates for learning paths and their components. 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 [15] and [19] to work with the template-based idea to produce adaptive fine-grained learning paths.

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F. Yang received the B.Eng. degree from Northwestern Polytechnical University, Xi'an, China, and the M.Sc. degree from the National University of Defense Technology, Changsha, China. She is currently pursuing the Ph.D. degree from the School of Engineering and Computing Sciences, Durham University, Durham, U.K.

Her current research interests include adaptive e-Learning technologies and multimedia systems.

Frederick W.B. Li received the B.A. degree in computing studies and the M.Phil. degree from Hong Kong Polytechnic University, Hong Kong, in 1994 and 1998, respectively, and the Ph.D. degree in computer science from the City University of Hong Kong, Hong Kong, in 2001.

He is currently a Lecturer (Assistant Professor) at Durham University, Durham, U.K. from 2003 to 2006, he was an Assistant Professor at Hong Kong Polytechnic University. From 2001 to 2003, he was the project manager of a Hong Kong Government Innovation and Technology Fund (ITF) funded project. His current research interests include distributed virtual environments, computer graphics and e-Learning systems.

Dr. Li serves as an Associate Editor of the *International Journal of Distance Education Technologies* on communications technologies. He has served as a Guest Editor of three special issues of the *International Journal of Distance Education Technologies* and two special issues of the *Journal of Multimedia*. He has served on the conference committee of a number of conferences, including the Program Co-Chair of ICWL 2007, ICWL 2008, IDET 2008 and IDET 2009, and Workshop Co-Chair of ICWL 2009 and U-Media 2009.

Rynson W.H. Lau (M'93–SM'06) received the Ph.D. degree from the University of Cambridge, Cambridge, U.K.

He has been a Faculty Member at Durham University, City University of Hong Kong, and Hong Kong Polytechnic University. His current research interests include distributed virtual environments, computer graphics, and multimedia systems.

Dr. Lau also serves on the Editorial Board of *Computer Animation and Virtual Worlds*, *International Journal of Virtual Reality*, and the IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES. He has served as a Guest Editor of a number of journal special issues, including IEEE Internet Computing, the IEEE TRANSACTIONS ON LEARNING TECHNOLOGIES, *ACM Transactions on Internet Technology*, the IEEE TRANSACTIONS ON MULTIMEDIA, the IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS, and IEEE Computer Graphics and Applications. In addition, he has also served on the core committees of a number of conferences, including Program Co-Chair of ACM VRST 2004, ICWL 2005, ICEC 2007, ACM MTDL 2009, the IEEE U-Media 2010, and Conference Co-Chair of CASA 2005, ACM VRST 2005, ICWL 2007, IDET 2008, ACM MDI 2009, and ACM VRST 2010.