# CONNECTING ELECTRONIC PORTFOLIOS AND LEARNER MODELS

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By

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# ABSTRACT

Using electronic portfolios (e-portfolios) to assist learning is an important component of future educational models. A portfolio is a purposeful collection of student work that exhibits the student's efforts, progress and achievements in one or more areas. An e-portfolio contains a variety of information about a person's learning outcomes, such as artifacts, assertions from others, self-reflective information and presentation for different purposes. E-portfolios become sources of evidence for claims about prior conceptual knowledge or skills. This thesis investigates using the information contained in e-portfolios to initialize the learner model for an intelligent tutoring system. We examine the information model from the e-portfolio standardized specification and present a method that may assist users in initializing learner models using e-portfolios as evidence for claims about prior conceptual knowledge or skills. We developed the EP-LM system for testing how accurately a learner model can be built and how beneficial this approach can be for reflective and personalized learning. Experimental results are presented aiming at testing whether accurate learner models can be created through this approach and whether learners can gain benefits in reflective and personalized learning. Monitoring this process can also help ITS developers and experts identify how an initial learner model can automatically arise from an e-portfolio. Additionally, a well-structured learner model, generated by an intelligent tutoring system also can be attached to an e-portfolio for further use by the owner and others.

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# GLOSSARY

*Intelligent Tutoring System (ITS)*: any computer system that provides direct - i.e. without the intervention of human beings - customized instruction or feedback to students

*Adaptive Learning Environment (ALE)*: a set of tools provided to fulfill the needs of a heterogeneous learning community

*Learning Management System (LMS)*: a software package that enables the management and delivery of online content to learners

*IMS Global Learning Consortium (IMS)*: a non-profit standards organization concerned with establishing interoperability for learning systems and learning content and the enterprise integration of these capabilities

*Electronic Portfolio (e-Portfolio)*: a collection of electronic evidence assembled and managed by a user, usually online

*Extensible Markup Language (XML)*: a W3C-recommended general-purpose markup language that supports a wide variety of applications

*Bayesian Belief Networks (BBN)*: a directed acyclic graph which represents independencies embodied in a given joint probability distribution over a set of variables

*Constraint Based Model (CBM)*: A natural way to express machine or human behavior is by explicitly writing down the *constraints* that have to be satisfied for that behavior.

*Bootstrapping*: starting a computer or building complex tools after building simple tools that allow for the creation of the more complex tools

# CHAPTER 1

# INTRODUCTION

Learning is a ubiquitous and lifelong activity. Learning activities are supported by multiple learning resource providers including institutions, enterprises, non-profit organizations and various individuals (friends, family etc.). Learners now have numerous methods and choices in acquiring and gaining knowledge throughout their learning activities, and many choices for keeping their learning experience and memories in many electronic formats on the Internet or digital archives. Electronic portfolios (e-portfolios) are being accepted and used widely in higher education as an important component of an e-learning environment. E-portfolios also show advantages and potential utility in personalized and life-long learning. E-portfolios emphasize the "learner's voice" as a personal account of learning and a coherent learning history. Benefits brought by e-portfolios include portable storage, link and search functions, convenient and up-to-date editing, and information sharing.

Computer assisted learning is becoming more and more widely applied, where adaptive and personalized tutoring that could never been achieved in traditional one-to-all lecturing can now be provided to individual learners. In e-learning, intelligent tutoring systems (ITS) can support adaptive and personalized learning. Personalization issues are also important in learning management systems (LMS) and other adaptive learning environments (ALE). Learners, as both consumers and potential learning resource providers in e-learning systems, play a more engaged role and tend to have much control over learning and personal information management. Learners expect their learning to be understood and supported continuously by instructors or computer tutors. In the context of lifelong learning, learners may experience many computer-assisted learning systems/environments that support introducing or updating learning records to learners' profiles (e.g. learner information, assessment information, etc.). The e-portfolio is a possible carrier for personal learning information. However, e-portfolio systems may have a wide range of specifications for information management. Integrating separate learning activities and building continuous and coherent records for learners requires efforts from learners, instructors, institutions and various e-learning applications that support standardized and specification-based information exchange. Two types of e-learning systems, e-portfolio and adaptive learning environments, are discussed in this research, as well as the interplay between them.

## 1.1 E-portfolios and E-portfolio Specifications

Electronic portfolios traditionally have been defined as an organized collection of digital and/or analog artifacts and reflective statements that demonstrate a learner's intellectual development over time [Barrett, 2001]. Tosh defined an e-portfolio as a web-based information management system that uses electronic media and services, where learners build and maintain a digital repository of artifacts, which they can use to demonstrate competence and reflect on their learning [Tosh, 2005]. The rapidly growing use of e-portfolios in higher education provides students a user-centered learning information management facility [Guo and Greer, 2005]. Many schools and universities have developed e-portfolio systems where students are encouraged to store and organize their learning materials during their formal schooling and to further carry on with augmenting that e-portfolio during lifelong learning. The main use of e-portfolios involves collection, reflection, evaluation and connection of knowledge artifacts. One defining feature of e-portfolios is that the learner is the owner, while others, including teachers, can contribute information to a learner's e-portfolio or review portions of the e-portfolio from time to time. The person ultimately responsible for the content in an e-portfolio is the learner. Another characteristic is that the content in an e-portfolio can be created across different platforms using different software frameworks, and should be distributable after being packaged and annotated. Interoperability and flexible dynamic content re-organization is another key feature.

To achieve interoperability for e-portfolios, specifications for standardization have been proposed, including IMS ePortfolio specifications and ePortfolio Interoperability XML Specification [IMS, 2005] [EPIX, 2005]. With these specifications, enhanced meta-data can be bound to e-portfolios making them easier to be interpreted and transferred across different systems. Although the format of content in an e-portfolio may be widely varied, the associated meta-data should conform to more standard and predictable structures. However, one difficulty of the unified data model approach is the lack of quick wins, as everything has to be standardized before anything can be achieved. Thus, seeking methods and mechanisms to managing the interactions between a variety of ontologies (introduction and discussion about ontology are presented in Chapter 2) and syntax with task applicability is one of the important highlights to be investigated in this work, which is also an approach becoming increasingly popular within what is broadly called "Web 2.0". Tim O'Reilly defines "Web 2.0" as follows [O'Reilly, 2005]:

*Web 2.0 is the network as platform, spanning all connected devices; Web 2.0 applications are those that make the most of the intrinsic advantages of that platform: delivering software as a continually-updated service that gets better the more people use it, consuming and remixing data from multiple sources, including individual users, while providing their own data and services in a form that allows remixing by others, creating network effects through an "architecture of participation," and going beyond the page metaphor of Web 1.0 to deliver rich user experiences.*

## 1.2 Learner Modelling in Adaptive Learning Environments and Intelligent Tutoring Systems

The goal of an intelligent tutoring system is to provide the benefits of adaptive and individualized instruction automatically and cost effectively [Ong & Ramachandran, 2000]. Learner models are specialized mechanisms for representing information and knowledge of learners inside intelligent tutoring systems (ITS) or personalized adaptive learning environments (ALE). In general, learner models are in the form of detailed cognitive (and sometimes affective) models of the learners, and are maintained along with learning interactions in order to recommend suitable learning resources or to provide individualized help during problem solving. Learner models frequently contain information about the knowledge levels of learners on various domain concepts of interest. When a learner begins to interact with an ITS, an initial learner model needs to be created/initialized. Most learner model initializations are done by using a detailed set of pre-tests or questionnaires and sometimes a set of typical default values are assumed for an initial learner model, and the accuracy of knowledge representation mainly relies on guesses or subjective assessments.

As most ITSs are built with the assumption that initial models are not very accurate learner models, most efforts have been put in research on how to justify learner models in a more effective and efficient way, while how to increase the accuracy of an initial learner model is deemed less important. E-portfolios contain a relative complete and detailed learning profile or history of one's learning activities. The use of e-portfolio systems/applications provides instructors and developers a chance to investigate and analyze these data sources. Can e-portfolios help create more accurate initial learner models? Development and design of an application/framework to initialize learner models with e-portfolio data could be challenging because (1) no literature about design and specifications of such systems can be found, (2) conflicts and compromise on specifications of learning information with annotation may be involved, (3) the process of defining a set of rules for mapping from e-portfolios to learner models need contributions from experts in certain areas, which has a high cost since it involves manual input, operation, analysis and evaluation.  However, it is worth investigating these matters because the learner model has been always a key component of adaptive learning environments, and it needs to be initialized whenever a new learner is enrolled. E-portfolios are likely the best and most reliable source of learner information.

## 1.3 Research Goals

The general goal of this work is to seek a better mechanism for achieving interoperability between e-portfolios and learner models in adaptive learning environments. It is possible in the not-too-distant future that teachers and students using ITSs will make use of their access to students' portfolios, where detailed learner information could be used for initializing learner models. Meanwhile, students may also wish to retain some of the assertions and reflective information captured in learner models through their learning activity and keep that information in their lifelong learning portfolios. This thesis addresses the interplay between e-portfolios and learner models through analysis of standardized information models of e-portfolios and by examining the process of student model initialization in a higher education context. A case study has been deployed in which we design and develop the EP-LM system that supports e-portfolio browsing, claiming skill levels on certain concepts as well as providing evidence for them using artifacts (assignment, exam, project, etc.) that are included in the e-portfolio. An experiment has been deployed aiming at testing whether accurate learner models can be created through this approach and if learners can gain benefit in reflective and personalized learning.

Two research questions will be investigated in this thesis:

Can we gain accurate initial values of a learner model by using e-portfolios as evidence in some kind of bootstrapping process?

To what extent can this approach to building and providing evidence for a learner model help students with their reflective learning?

## 1.4 Thesis Organization

This thesis is organized as follows: Chapter 2 provides a literature review on key issues of e-portfolios, user modelling, the statistical analysis method used, open student modelling and domain ontologies. Chapter 3 analyzes the process of learner model initialization and describes the EP-LM system design and implementation for bootstrapping learner models from e-portfolios. The main two components of EP-LM are an e-portfolio browser for displaying the artifacts included in an e-portfolio, and a learner model editor (evidencing page) where users can create and modify the values of a learner model. Chapter 4 presents the experiment aimed at testing how accurate a learner model can be when generated from e-portfolios. An accuracy model for evaluating the process of bootstrapping learner models is also proposed at the end of Chapter 4. Finally, the conclusion and future work are discussed in Chapter 5.

# CHAPTER 2

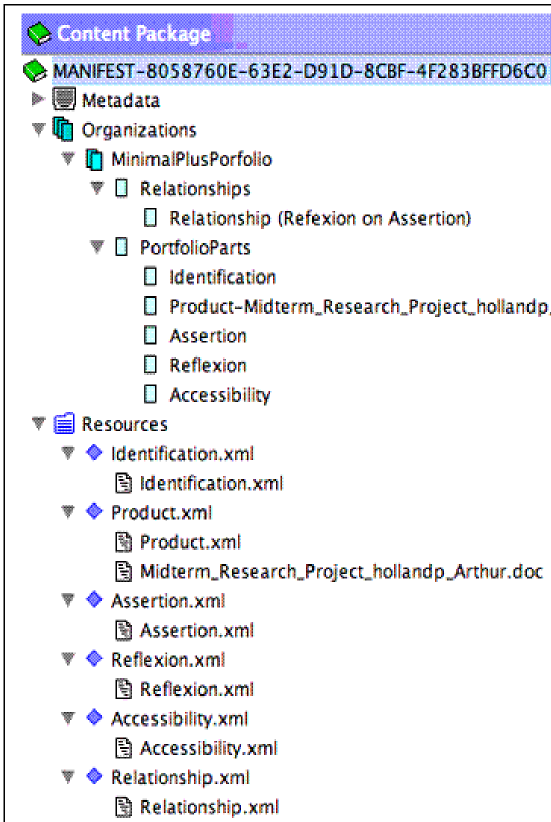
# LITERATURE REVIEW

## 2.1 E-portfolios

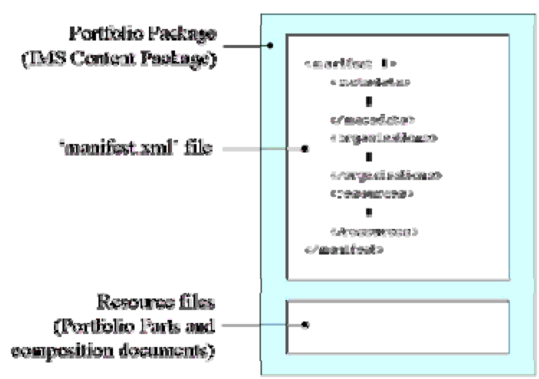
The phrase "e-portfolio" refers to three different themes: 1. the organized repository of all digital artifacts created by and maintained by the user, 2. user-created presentations in which a subset of artifacts are selected and organized as showcase for some purposes, 3. a set of tools that supports 1 and 2. Artifacts and presentations with annotations serve as the fundamental data source available for further reuse. E-portfolios need to be portable to ensure the educational continuity among programs within an educational institution that use e-portfolios, the integration of evidence about learning over time, and the smooth transfer of verifiable information about learning and evaluation between institutions, levels of education and employers [IMS ePortfolio Best Practice, 2005]. Research and practice towards a consensus on e-portfolio definitions and specifications have been carried out widely. A plausible set of specifications, the IMS E-Portfolio specifications built on the IMS Learner Information Package [IMS ePortfolio, 2005], will be discussed and chosen a reference for investigating a practical research problem. However, this paper will not focus on presenting and comparing all the current standards available for e-portfolios.

Table 1 shows a graphical representation of an e-portfolio example and a sample package structure. A *portfolio* is defined as a collection of portfolio parts that are collated in an IMS Content Package. All of the contextual information for a portfolio, e.g., presentation aids, relationships, etc., are also defined within the IMS Content Package. In essence the manifest file for the IMS Content Package is the XML representation of the Portfolio with each of the portfolio parts being supplied as resources in the content package. The set of resources contains any source materials that are described as part of the portfolio, e.g., examples of work, copies of certificates, etc. For the case of nested portfolios, each portfolio is defined in its own content package, i.e. with a single manifest file. Sets of portfolios are clustered by creating a top-level content package in which each portfolio package is a resource. This standard structure makes it easy for learners to query and track portfolio parts at different granularity levels and reference them in other applications by making reference simply to a universal resource identifier (URI).

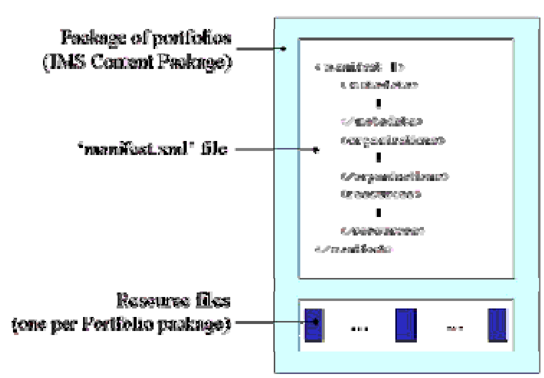
**Table 1: How an IMS e-portfolio is organized and packaged (IMS ePortfolio Specification, 2005)**




Graphical representation of reflection and assertion portfolio example.




A portfolio package.




Packaging more than one Portfolio.

Each *portfolioPart* consists of the following bulleted points quoted directly from the IMS specification:

- Identification: represents the identity of the Owner of the ePortfolio, and may include name, contact information, and demographics.
- Affiliation: store the description of an organization affiliation associated with the Owner of the ePortfolio, e.g., professional memberships.
- Product: contains materials produced by the Owner. These materials can consist of any material that can be stored or referenced electronically.
- Rubric: represent guidance as to how a portfolioPart has been, or is to be assessed.
- Relationship: represents the linking together of two <portfolioPart> elements.
- Competency: description of a skill the Owner of the ePortfolio has acquired.
- Goal: description of a personal objective or aspiration of the Owner.
- Interest: descriptions of a hobby or other recreational activity of the Owner of the ePortfolio.
- Qcl: is used to represent the qualifications, certifications, and licenses awarded to the Owner, that is, the formally recognized products of their learning and work history.
- Assertion: represent the <assertion> class in the information model that contains typename, comment, contentype, authorship, rationale, date, status, contactinfo, description, ext_assertion.

- Reflexion: represent reflections upon or about a part of the ePortfolio, such as providing a comment or explanation, identifying strengths and weaknesses, or highlighting particular aspects of the portfolio part.
- Transcript: store the summary records of the academic performance at an institution.
- Activity: education/training, work, and service (military, community, voluntary, etc.) record.
- Participation: represent a group of people, which may or may not include the Owner of the Portfolio.
- Securitykey: will be used to contain the passwords, security codes, etc. to be used when communicating with the learner.
- AccessForAll: technical preferences of the learner for interacting with systems and content.

These features of e-portfolios proposed by IMS were defined and extended from the IMS Learner Information Package specification [LIP, 01]. These catalogues can be used to describe not only essential learner and learning information, but also some contextual information for an e-portfolio, e.g. relationship, access and security control, etc. These standardized specifications need to be adapted and customized based on real problems. In e-portfolio systems that support the above specifications, learners should be provided options and guidance to input information in each category. However, the associated meta-data should be generated and packaged by an e-portfolio system according to the IMS e-Portfolio specification. Although contents in an e-portfolio are feasible to the learner, the student may not have full control over all the artifacts due to ownership issues.

### 2.1.1 Ownership and Privacy Issues

Ownership is a key issue that has been discussed since the concept of e-portfolio was first defined. Most research communities believe that *students* should be the owners of their e-portfolios because they are continuously responsible for collecting artifacts, editing information, organizing portfolios, and gaining benefit from reflective learning through a life-long learning activity. As long as ownership is granted and assured, students become more active involved learners[Graham, 2005]. However, although students are given control over content and viewing privileges of their portfolio information, there are still some certified artifacts that should be locked and not open for editing (e.g. transcripts and other third-party formal records). These qualification and certification documents that are put into (or linked from) students' e-portfolios by different institutions can become part of a portfolio presentation and will add confidence about the authenticity of the contents. There are also some copyright protected learning materials that are imported and stored in the student's e-portfolio. The owners of this kind of e-portfolio should be notified that it is not legal to distribute the copyrighted files without permission from the original writer.

Privacy issues are crucial technical problems that every online e-portfolio system/service needs to consider, such as access control, group view policy and permission to edit. E-portfolio systems should provide users some kind of interface to be able to manage privacy settings. Security encoding and digital signature techniques may be applied to provide a safer and more useful e-portfolio management service. E-portfolio policy makers and system developers should consider both ownership and privacy issues while designing and deploying such systems. However no further investigation of this issue will be included in this research.

### 2.1.2 Customized and Personalized Presentations

A portfolio presentation is defined as a particular composition of coherent portfolio items (artifacts), with a deliberately defined audience and rhetorical purpose [Grant, 2005]. E-portfolio presentations are sometimes referred to simply as a "portfolio" when presentations are prepared for reviewers to read based on some purposes. Sometimes one presentation needs to be created for multi-purpose review or assessment. The process of building a presentation is similar to initializing a prior learning outcome report, in which all kinds of electronic artifacts can be included as evidence to support the competency of the learner. To create a presentation, a target audience and a goal need to be addressed first. Based on the reviewer's request and thoughts of the owner of the e-portfolio, a basic presentation structure should be organized with a variety of e-portfolio artifacts selected from the repository and attached as evidence to enrich the presentation. For example, a presentation as part of a job application prepared for the identified employer could be expected to include any evidence that may strengthen one's chances to be hired for the particular position. However, some certain computer skills may be required to create e-portfolio presentations that contain hyperlinks, images and multi-media files. Integrating flexible functions to assist portfolio owners in building presentations can be helpful for every e-portfolio system.

### 2.1.3 E-portfolio Assessment and Prior Learning Assessment

The use of e-portfolios allows qualifications and learning assessment to focus more on the actual core of what needs to be assessed, rather than peripheral efforts to record and administer student work [Grant, 2005]. The trends in assessment seem to be moving from a numerical grading system to one of justification and reflection, with the use of documents that enrich the range of evidence presented. E-portfolios not only contain learning history in the form of e-documents, but can also serve as a carrier for both formal and informal learning assessment, e.g. assignment and quiz feedback, group member peer evaluation, etc.

Prior Learning Assessment (PLA) is defined as "the process of identifying, assessing and recognizing skills, knowledge, or competencies that have been acquired through work experience, unrecognized training, independent study, volunteer activities, and hobbies [HRDC, 1995]." PLA is normally performed by a third party who analyses a learner's e-portfolio or other assessment documents. Using information in e-portfolios for prior learning assessment is potentially the most accurate and effective method of evaluating students' prior learning activities.

One of the most important roles of an e-portfolios is to assist formal assessment. Some notable benefits brought by assessment e-portfolios include changing the assessments from paper to digital format, making the data more accessible, and supporting formative assessment for learning. However, there are also many concerns in the educational measurement literature about portfolio use, such as standardization of portfolio contents, level of agreement between evaluators, stability of estimations of student achievement, and rigour of standards used in evaluating the contents of portfolios [Anderson & Bachor, 1998]. Fournie and Van Niekerk at University of South Africa (Unisa) (Fourie & Niekerk, 1999) concluded in their research that the use of portfolio assessment was valuable, but several general problems were found:

- Some of the activities not clearly explained to student
- Students' need for a workshop organized at the front to support the completion of the portfolio
- Increased workload for lecturers if the study material and portfolio activities are not clearly written
- Not providing comments and/or continuous feedback on students' strengths and growth
- Not providing enough lecturer direction
- Possible controversies in grading
- Possible misunderstanding that a portfolio and portfolio assessment fits all purposes
- No absolute reliability of portfolio assessment

Some other constraints around computer skills, privacy, and intellectual property are also identified by DiBiase (2002) and Acker (2005). DiBiase describes problems such as it is time consuming to create maintain and evaluate e-portfolio, unequal access to technology and skills by students and teachers, cyber-plagiarism when students' work are shared online, and the risk of privacy information being revealed. Acker pointed out the problem of "the lack of easy ways to protect the intellectual property rights of students"; he said “maintaining ownership of the original work cannot be accomplished in a technical way, only through social norms and policy expectations” [DiBiase, 2002] [Acker, 2005].

We have identified several assessment benefits e-portfolios bring to an institution, and list them with the most significant problems or constraints on teaching (Table 2).

**Table 2: Pros and cons in the use of e-portfolio for assessment**

| Potential Benefit | Problems/Constraints |
|---|---|
| Support students’ development as a reflective practitioner | Instructors lack the time to work on this extra workload |
| Provide a mechanism for assessment in both formative and summative way | Adaptation to the current curriculum, insufficient pedagogical planning |
| Bridge personal learning space and institutional learning management system | Articulation of standards to apply, intellectual property and privacy issues |
| Provide coherent and richer content student learning records for university education | Effort in organizing, maintaining, and authorizing the content. Managing access for future academic and industry employers |
| Promote sharing and collaborative learning | Information exchange with departmental online course and discussion forum |

## 2.1.4 Intellectual Property Issues

Intellectual Property (IP) refers to personal creative thought and artifacts that a person creates. Copyright is legislation that protects the IP rights to creative thought and works. It is difficult to find literature that discusses how IP should be managed in the e-learning domain. It seems that future e-portfolio systems should provide copyright support functions or rules to both e-portfolio owners and consumers. An international organization, the ”Creative Commons”(CC), has proposed an alternative method to copyright, which introduces a way of “some right reserved” instead of “all right reserved” [Creative Commons, 2005]. The main purpose of CC is to encourage individuals and research groups to share creative activities and projects on the Internet.

### 2.1.5 Other Issues

Most of the current e-portfolio systems are concerned with individual users. However, there are situations where people work in groups to build e-portfolios. It seems to be helpful to provide sort of “group behaviour support” in e-portfolio systems. In Open Source Portfolio (OSP) 2.0 version, Common Interest Group (CIG) was introduced. The main purpose of CIG is to provide a chance for the members registered in the e-portfolio building community to meet the people who have the same interest and possibly share and help others.

Being aware of learning contexts is another important issue in the design of an e-portfolio system. It might be useful if an e-portfolio system was sensitive to the learning context. For instance, if the user speaks both English and French, the system should be able to provide multi-language support. However, since there is plenty of information stored in one’s e-portfolio, it could be fairly complex to actually implement all kinds of context aware functions.

E-portfolios contain valuable data that could be useful in User Modelling (UM). In general, an e-portfolio carries all the data about its owner, no matter how the data is organized. Regardless of whether there is any standard deployed, the wealth of information contained can provide a basis for building user models. It seems that using e-portfolios could become one of the ways to bootstrap any system. For example, when John goes shopping, the store could obtain some part of his e-portfolio by scanning his finger print, and know about the size of his clothes, the style he likes and so on. Moreover, some e-portfolios contain both the owner’s thoughts and comments from others, which could be used to build more complex user models.

It might be helpful if e-portfolio systems could provide tutorials to help students develop an understanding and essential skills to build an e-portfolio, such as "how to select appropriate evidence for your portfolio." After taking the tutorials, the users should be able to clarify which artifacts should be included into an e-portfolio and which are not. Since not all the information is suitable for a presentation, having the users realize and understand how to select appropriate material for their e-portfolios is an important issue in the design of the tutorials in an e-portfolio system.

## 2.2 Learner Modelling

A learner model is defined as an abstract representation of the learner, and a teacher's conceptualization of a learner, which is used in connection with applications of computer-based ITS [Holt, 1991]. Learner models frequently contain information about the knowledge levels of learners on various concepts of interest. Sometimes a comprehensive student model would include both a knowledge representation model and a cognitive model, including all the prior relevant learning, the learner's progress within the curriculum, and the learner's preferred learning style. When a learner begins to interact with a personalized adaptive learning environment or intelligent tutoring system, an initial learner model needs to be created/initialized. How to build a learner model involves a wide range of issues in both theory and practice. Traditionally, learner model initialization is done through a detailed set of pretests or stereotype questionnaire. The bootstrapping process collects information from the learner for both cognitive model and knowledge/skill level model.

Learner models may represent a student's learning goals, plans, skills, attitudes, emotions, beliefs and other facts about their existence. Learner models, as a specific kind of user model, are the medium by which computer programs explicitly "know" and "understand" their users, knowledge that is used for program adaptation, teaching, marketing or a multitude of other purposes [Winter, 2003]. User models generally have a template of categories regarding the information about the user that they wish to know, and a set of relationships that describe how the categories are related. These templates are then instantiated with values reflecting the facts about particular users and used for whatever purpose the program desires. Similarly, learner models can be created/initialized either explicitly by observing user behaviours using questionnaires and tests, or implicitly by using the model's structure and beliefs to infer information. A learner model can be constantly refined and updated as the individual changes, and as different inferences are propagated throughout the model.

## 2.3 Knowledge Representation in Learner Models

Cognitive learner models can be represented in a variety of formats in different contexts. This section discusses a variety of learner modelling techniques and their applicability to the modelling of learner and learning history from student e-portfolios.

### 2.3.1 Overlay, Perturbation and Buggy Models

Overlay models are one of the traditional ways to construct a user model. They are also suitable for the student model in an intelligent tutoring system. Most intelligent tutoring systems and adaptive learning environments deploy adaptive courses to students within a limited domain of knowledge. An expert model is built for the system that consists of the facts and procedures an expert would know in relation to that domain. Learner models can be created as overlays on the expert model, by observing the learning history and behaviours of the learners in some environment, and noting where their behaviours differ from the expert. This type of learner modelling is useful when simple inferences are needed about what skills and knowledge the user has obtained through their prior learning.

Perturbation models are a more sophisticated extension of overlay models, in that a user's knowledge is not assumed as only a subset of an expert's knowledge. Common domain errors and misconceptions not held by an expert can be included to augment a user's overlay model if the user's behaviours indicate that he holds those erroneous beliefs. By introducing e-portfolios when initializing a user's knowledge and skill model, we may be able to see evidence of these conflicts between the expert and student models.

As the number of misconceptions grows, it is difficult to fully capture them in an accurate model. This leads to discussion that the problem of student modelling is intractable in its general form. Currently, the most effective method is to use a "bug library" for each system to keep the errors that are often repeated over and over again by students. The process to create a bug library can be *enumerative* or *generative*. The enumerative process lists all possible bugs usually via an analysis of the problem domain and the errors that students make. The generative approach attempts to generate bugs from an underlying cognitive theory.

### 2.3.2 Constraint-Based Models

As one of the student modelling approaches, Constraint-Based Modelling (CBM) focuses on faulty knowledge, realizing that it is not sufficient to describe what the student knows correctly [Mitrovic, 1999]. Mitrovic's assumption in CBM is that diagnostic information can be tracked in the sequence of learning activities, and the student model does not represent the learner's action, but the effects of his or her actions instead. CBM was proposed based on Ohlsson's theory of learning from performance errors [Ohlsson, 1996].

Ohlsson suggested the use of an abstraction mechanism realized in the form of state constraints, where a state constraint is an ordered pair (Cr, Cs). Cr stands for the relevance condition and is used for identifying the equivalence class, or the class of problem states in which Cr is relevant. Cs stands for the satisfaction condition and is used to identify the class of relevant states in which Cs is satisfied. Each constraint specifies one characteristic of the domain that is shared by all correct paths. CBM represents domain knowledge as a set of state constraints, which define a set of equivalent problem states.

Advantages of CBM over other student modelling approaches are found including 1) CBM does not require an executable expert module as many other student modelling approaches do, 2) CBM reduces student modelling to pattern matching instead of using complex reasoning, 3) CBM does not require extensive studies of student bugs as in enumerative modeling [Mitrovic, 2001].

### 2.3.3 Bayesian Network Models

Bayesian belief networks (BBN's) are used to deal with situations that require reasoning with uncertain information [Jameson, 1995]. A BBN reflects the fact that our understanding of the world is often imperfect, whether through a lack of awareness of factors that affect a situation or an inability to gather information about those factors [Russell, 1995]. However, rational decisions and inferences must be made about situations, such as modelling a user's beliefs and knowledge, in which certainty is lacking, and these decisions must become statistical and probabilistic in nature. A BBN allows for reasoning about a situation by assigning probabilities of truth to beliefs and inferences regarding that situation.

BBN's were developed to deal with the complexity inherent in working with standard probabilistic reasoning methods. A domain is modeled with a collection of random variables representing entities in the problem domain that can take on a collection of values, with each value assignment having a certain probability of occurring. When each random variable is assigned a value, it is called an atomic event, which reflects a specification or instantiation of the domain, or an observation of the values of the variables in the real world. The probability of each atomic event occurring is specified by the joint probability distribution P(X0,...,Xn) where X0,...,Xn are the random variables in the domain. The joint probability distribution can be represented as an n-by-n-dimensional table with each entry in the table giving the probability of the conjunction of all of the variable values occurring in an atomic event. The joint probability distribution represents the sum of all possible states of affairs in the world regarding these two variables, so the addition of the probabilities of all the possible atomic events in this domain must be equal to one (i.e. one atomic event is true).

Reye proposed the “belief net backbone structure” that offers a practical means to represent and update Bayesian student models in both cognitive and social aspects of the learner in intelligent tutoring systems [Reye, 1998]. Bayesian Belief Networks provide a principled, mathematically sound, and logically rational mechanism to represent student models [Zapata, 2004]. Bayesian Belief Networks can also provide an inspectable cause and effect structure among their nodes and direct specification of probabilities in the model [Villano, 1992].

## 2.4 Mechanism and Specifications for Connecting Learner Models and E-Portfolios

Specifications for student model and e-portfolio have connections because both are designed based on learners and learning. Table 3 presents some possible relationships between learner models and e-portfolio components at an abstract class level. It shows how components of a standardized e-portfolio would relate to common requirements or processes in a learner model. The relationship has two directions, mapping evidence from e-portfolios to learner models and refining information about learning process in e-portfolios based on student models. Artifacts and their annotations in standardized e-portfolios may contribute to nearly all aspects of learner model information. For example, identification and participation can be mapped to general and personal learner information; activity, assertion and reflection can be used to evidence and support (meta) knowledge and skill level. Packaging and binding information can be used in supporting automated information extraction and cross-system transfer.

It is believed that attaching ITS-generated meta-data to a student's e-portfolio would be beneficial for further use by both human reviewers and other adaptive learning environments. Learner model information generated by an adaptive learning environment could itself be an important artifact in an e-portfolio and could potentially be transferable to other learning systems via the learner's e-portfolio. Once learner models are created and justified through an interactive learning process, both the learner model and the information about the process of creating these learner models are available for attaching back to e-portfolios. These models would be annotated using e-portfolio compatible specifications and categorized into a special kind of category that might be used by some other system in the future. The XML binding and packaging specifications for e-portfolios can also serve as a supplementary standard for learner model exchange.

**Table 3: Link a learner model to e-portfolio parts**

| Main category | Details and Comments | IMS ePortfolio Spec |
|---|---|---|
| Who is being modelled | degree of specialization<br>individuals or classes of learners | <identification><br><participation> |
| | temporal extent, learner history | <activity>, <affiliation>, <qcl>, <transcript> |
| What is being modelled | knowledge and meta knowledge | <activity>, <assertion>, <product>, <reflexion> |
| | learner goal/intentions | <goal> |
| | capabilities | <competency>, <qcl> |
| | preferences | <accessForAll>, <interest> |
| | motivations | <interest>, <goal>, <reflexion> |
| How is the model to be acquired | users outlining their own learning goals | *Packaging + Binding* |
| | users providing a self-description | *Packaging + Binding* |
| | users being given a pre-test on the subject area | <competency> |
| How is the model to be maintained | compare student activity and ITS planned solution | <activity>, <assertion> |
| Why is the model there | elicit info from learner | <assertion>, <competency> |
| | provide advice/help | <assertion> |
| | provide feedback | <assertion> |
| | interpret learner's activity | <assertion>, <activity> |

## 2.5 Domain Ontology

Domain ontology defines the terms used to explicitly and precisely describe and represent an area of knowledge [Heflin, 1998]. It is the description of concepts and relationships of a knowledge domain specified so precisely as to be understood and communicated by software agents. Ontologies form a vocabulary for representing knowledge. With this vocabulary, one can assert specific propositions about a domain or a situation in a domain.

For intelligent tutoring systems, previous research [Bourdeau & Mizoguchi, 2004] suggested that Ontological Engineering (OE) can be instrumental in representing the declarative knowledge needed, and it can add value in terms of intelligence for both authoring and learning environments. The knowledge representation in an ITS deals with domain expertise, pedagogy, interaction and tutoring strategy, which are usually implemented as a multi-agent system. ITS agents need to share common interpretations during their interactions, where OE can contribute because it supports common understanding of the structure of information among people or software agents, reuse of domain knowledge, and the making of explicit domain assumptions. Domain ontologies can be used in both interpreting portfolio information to learner models and designing learner model initialization processes in an ITS. Attaching domain ontologies to e-portfolios may also be beneficial.

## 2.6 Reflection and Open Learner Modeling

Research has suggested that by opening the learner model to both the learner and other peers within an e-learning system, the learner is able to reflect on the contents of the model [Hansen, 2003]. When the learner is provided with an interface to interact with the information of the model, he/she gains benefit in reflecting on the characteristics understood and described by the learning environment. This helps the learner gain a better understanding of domain knowledge, his or her current beliefs and the assessments made by the system.

Reflection not only consists of viewing the model, but may also involve interaction with the model. Research by Bull (1997) has shown that the student can not only view the information contained within the model, but can influence or change parts of the model or modelling process. This allows the student to determine what the system has discovered about him or her and challenge parts of the model if seen as inaccurate [Vassileva, 1999]. Furthermore, as the learner is able to view and manipulate the information stored within the student model, he/she can reflect on the learning process and is perhaps motivated towards the goals presented by the system.

Kay and Lum's (2005) research investigated how to build detailed scrutable student models to support learner reflection, by exploiting diverse sources of evidence from student use of web learning resources and providing teachers and learners with control over the management of the process. Questions addressed are how to interpret web log data for audio plus text learning materials as well as other sources, how to combine such evidence in ways that are controllable and understandable for teachers and learners, as required for scrutability, and finally, how to propagate across granularity levels, again within the philosophy of scrutability. The result shows that users demonstrated good, intuitive understanding of the student model visualization with system inferences.

## 2.7 Conclusion

In this chapter, we reviewed the literature about e-portfolio specifications and discussed how they can be connected with learner models. A variety of learner modelling techniques, ontology methods, and statistical analysis are also discussed. Finally, a review of open learner modelling research is presented. The concept and specification of e-portfolios serve as a form of evidence for certain cognitive skills or learning acquisition of learner models. To explore and test this research topic, a system has been designed and implemented (see Chapter 3) based on the learner modelling theories and techniques presented in this chapter.

# CHAPTER 3

# BOOTSTRAPPING LEARNER MODELS FROM E-PORTFOLIOS

Based on the analysis of e-portfolios in Chapter 1 and 2, it seems that e-portfolios become sources of evidence for claims about prior conceptual knowledge or skills. In this chapter, we discuss how to use the information contained in electronic portfolios (e-portfolios) to initialize learner models for adaptive learning environments. We first create sample course e-portfolios based on real-world data from an entry-level Java programming course and define a scenario for testing purposes in that we create/initialize learner models from the e-portfolios for a continuous advanced programming course. We developed the EP-LM system for testing how accurately a learner model can be built and how beneficial this approach can be for reflective and personalized learning. EP-LM supports e-portfolio browsing, claiming skill levels on certain concepts as well as evidencing the claims using artifacts (assignment, exam, project, etc.) that are included in the e-portfolio.

## 3.1 Mechanism and Specification

In adaptive learning environments, three main methods of bootstrapping a learner model are: 1. users outlining their own learning goals; 2. users providing a self-description (general personal information); 3. users being given a pre-test on the subject area. Both 1 and 2 are easy to adapt to e-portfolio information extraction with partial automation and assistance, but achieving 3 requires fairly detailed e-portfolio instances that need to be mapped and interpreted from a standardized information model. For this reason, we are focusing on an approach where a customized interface is provided for permitting students or teachers to link evidence from an e-portfolio with answers to questions about their knowledge-state. In this approach, students can make claims about their knowledge or skill levels and substantiate these claims with evidence from e-portfolio artifacts, annotations, or meta-data. The process of "evidencing" their claims is also an important reflection activity, which can be shown to support learning.

Figure 1 shows how a particular artifact that has been created by the learner can be linked to standard domain ontologies (terminology taxonomies) so that it becomes possible to discern what tasks or concepts the learner may have exercised in the construction of such artifacts. The knowledge contained in the e-portfolio meta-data can be translated into data in a learner model in several different ways according to the specific requirements of the ITS/ALE system. One can see that a set of rules needs to be defined before the translation can proceed. However, setting up these rules could be time-consuming and not reusable because every e-portfolio can be different and every learner model can have different information needs.

```xml
<?xml version = "1.0" encoding = "UTF-8"?>
<learnerinformation xmlns = "http://www.imsglobal.org/xsd/imslip_v1p0">
    <activity>
        <product>
            <typename>
                <tysource sourcetype = "proprietary">Program</tysource>
                <tyvalue xml:lang = "en">Java</tyvalue>
            </typename>
            <contentype>
                <referential>
                    <sourcedid>
                        <source>CMPT111 Assessment</source>
                        <id>Assignment 7: What would you like to draw?</id>
                    </sourcedid>
                    <indexid>Assgt7</indexid>
                </referential>
                <ext_contentype/>
            </contentype>
            <date> Friday, November 4, 2005 at 5pm  </date>
            <purpose>The purpose of this assignment is for you to become familiar with menus, loops, working with
            classes and creating graphics.</purpose>
            <description>
                <short xml:lang = "en">Using conditions and loops</short>
                <long >You are to create a program that asks the user what kind of graphics the user wants to
                display.You will need to create several classes. A driver class (Assignment7) and a class for each
                graphic you want to draw. Each graphics class should be designed to create a specific graphic.</long>
                <full>
                    <media mediamode = "JAVA" mimetype = "java" contentreftype = "uri">assi7_nsid.java</media>
                </full>
            </description>
        </product>
    </activity>
</learnerinformation>
```


**Figure 1: An example of annotation for “Product”**

As illustrated in Figure 2, assertions by a teaching assistant can provide useful clues about the student’s skill level after completing some project or assignment. It also contains other system information such as language used, time created, rationale, type and LIP-related information. These annotation files based on the standardized specifications make it possible to automatically extract some information annotated by defined XML tags. For example, information shown in Figure 2 can be retrieved automatically either by a query that returns the content which has the authorship “Chris Brooks”, or a query that returns all the files with the rationale type of “Marker’s comment”.

```xml
<?xml version = "1.0" encoding = "UTF-8"?>
<assertion xmlns = "http://www.imsglobal.org/services/testFinal/imsassert_v1p0"
    xmlns:lip = "http://www.imsglobal.org/xsd/imslip_v1p0">
    <lip:contentype>
        <lip:referential>
            <lip:indexid>assertion_01</lip:indexid>
        </lip:referential>
    </lip:contentype>
    <authorship>
        <language>en-GB</language>
        <text>Chris Brooks(TA)</text>
    </authorship>
    <rationale>
        <language>en-GB</language>
        <text>Marker's comment</text>
    </rationale>
    <lip:date>
        <lip:typename>
            <lip:tysource sourcetype = "standard">UKLeaP</lip:tysource>
            <lip:tyvalue>Create</lip:tyvalue>
        </lip:typename>
        <lip:datetime>2004-05-31T12:25:43</lip:datetime>
    </lip:date>
    <lip:description>
        <lip:short>User interface coule be imporved.</lip:short>
        <lip:long>After the user has entered the values, call the constructor of the appropriate class and then add
        the newly created object to the frame. Don't forget to set the visibility of the frame to true again after
        you have added the object.</lip:long>
    </lip:description>
</assertion>
```

**Figure 2: An example of annotation for “Assertion”**

## 3.2 Creating Real-World Sample E-Portfolios

In Chapter 2, we discussed standardized information models for both e-portfolios and learner models with the focus on the overlap of information models as well as mapping from one to the other. A standardized e-portfolio information model explains what information is generally contained in e-portfolios, while a set of specifications are defined to describe the organization of the e-portfolio. The IMS ePortfolio information model specifications have been chosen as reference for this research because it is deemed the most popular and plausible set. With these specifications, standardized meta-data can be bound to artifacts in an e-portfolio making them easier to interpret and maintain across different institutions and platforms/systems [Bourdeau, 2004]. The content in an e-portfolio may be widely varied, but the associated meta-data should conform to more standard and predictable formats. This standard structure makes it easy for developers and users to query and track portfolio parts at different granularity levels and reference them in other applications by making reference simply to a universal resource identifier.

The sample e-portfolios created for this research project are course e-portfolios that can be included as part of the learner's life-long learning portfolio. The sample e-portfolios contain all the teaching and learning materials shared by six student volunteers from an entry-level Java programming course taught over the summer of 2006. The course provides a broad introduction to fundamental concepts of computing, object oriented computer programming, and how to write programs in Java. We collected and organized the artifacts in the following categories:

- Lecture notes, tutorials and lab documents
- Assessment, which consists of 3 smaller and 3 larger assignments
- Five in-class quizzes, one midterm exam, one final lab exam and the final written exam
- Students' posts for Q&A and problem solving activities from the iHelp discussion forums

Some of the artifacts could be imported from existing learner support systems such as the electronic assignments submission system, but others are paper-based and need to be converted into electronic format. To keep it simple and easy to control, we chose to build the e-portfolios from scratch instead of using any off-the-shelf e-portfolio system. However, we used the IMS e-portfolio information model as reference when collecting, organizing and annotating artifacts. We also created and included meta-data describing some important ontological relationships among all the artifacts according to the course syllabus/concept map. The e-portfolios are presented in a webpage in html format that contains links to all the artifacts one click away. (Figure 3) At the end of the term, we interviewed the six student volunteers in order to let them evaluate the e-portfolios, to collect self-reflective comments on different artifacts, and to fill out a questionnaire claiming their knowledge levels on various concepts taught in the course. The interview results showed that all the six students believed that their e-portfolio covered/represented their knowledge and they were willing to share their e-portfolios with future instructors. However, one expressed some concern about privacy. We also found students with lower marks tended to have more self-reflective comments, some of which described or explained why and how they made mistakes, while some are comments about appropriateness of and performance on assignments and exams.

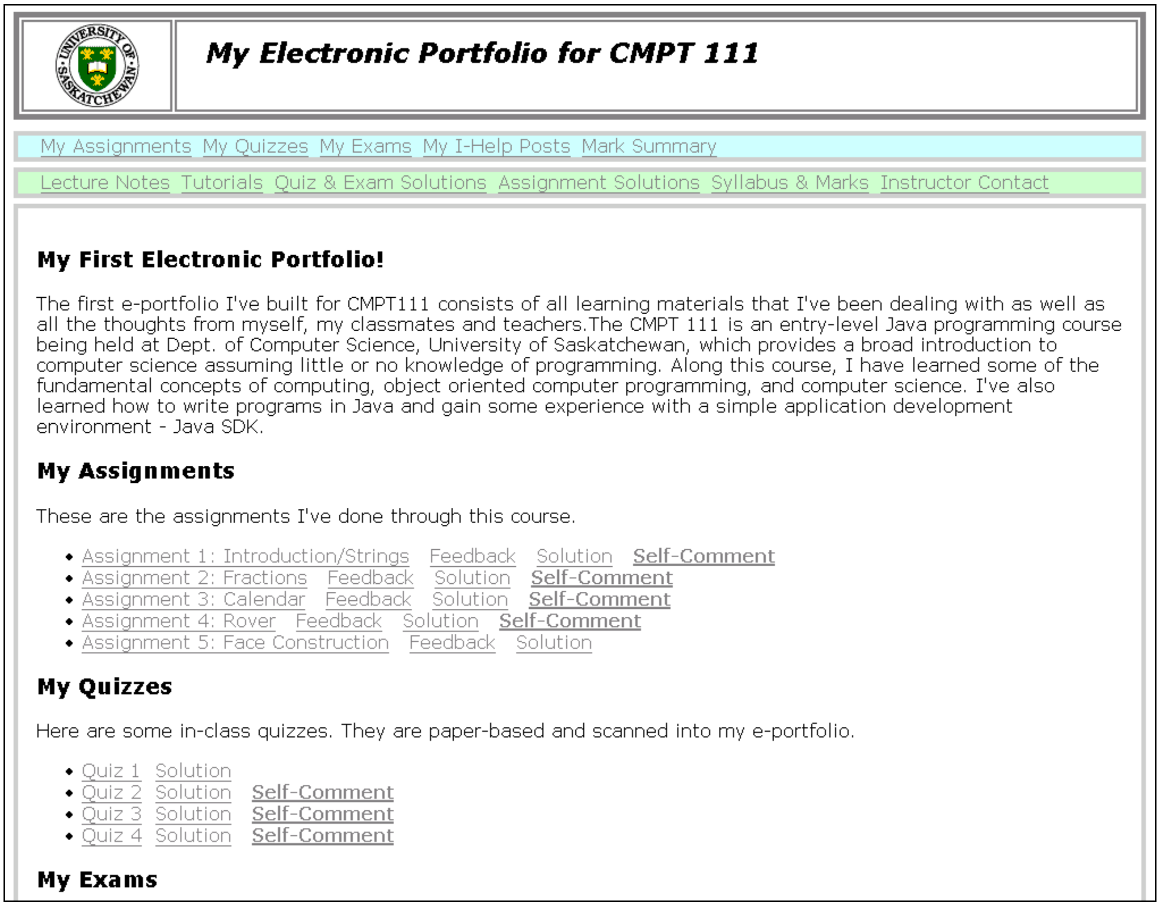



**Figure 3: Web interface of a sample course e-portfolio**

Figure 3 shows a typical e-portfolio that was created based on real in-class teaching and learning materials. The e-portfolio contains both the teaching and learning materials that are related to the course. We believe that such portfolios carry authentic evidence that can be used to support learner assessment and generate learner models.

In most educational settings, learners would be expected to generate their own e-portfolios, perhaps following some design template or evaluation rubric. Even when a template or rubric is provided, there will naturally be much variability in the portfolios. The variability could be found both at the presentation level and the file storage level. Assuming privacy and access control is not a problem (i.e. the students are willing to share the content in the e-portfolio, files can be uploaded and retrieved securely), mechanisms dealing with the variability in both levels need to be explored in order to achieve effective interpretation. If student-generated portfolios are to be used in this research, a couple of issues need to be addressed. First, we need to examine if all the e-portfolio artifacts are accessible (the URL is valid). Second, content text-matching at the presentation level should be conducted using the template delivered with the requirement/instruction of creating the e-portfolio. Finally, we need to notify the student about the result from the text matching about what needs to be added and which URL is inaccessible. Then this process can be iterated until a certain percentage of artifacts are successfully matched to the system template.

## 3.3 System Design

An analysis of learner model requirements for selected ITS/ALEs has led us to believe that an extension to a learner modelling component can be built to extract relevant information from a learner's e-portfolio. The extension to the learner model is essentially a set of rules and an interface to e-portfolios. The process for populating the learner model must fit with the specific requirements of the ITS/ALE, and hence needs to be engineered by the learning environment developer. Students should be involved in the process of initializing learner models by using dialogue and message confirmation in three steps: 1. establish a set of essential questions about cognitive state based on the requirements of the ITS/ALE; 2. present these questions to the student (or instructor) along with a suitable e-portfolio meta-data browsing tool; 3. ask the student (or instructor) to locate evidence in the portfolio to confirm claims made in answer to these questions.

Traditionally, learner models are created either by making default guesses about the learners or by having learners complete some diagnostic questionnaire through which they demonstrate their initial skill level. The accuracy is strongly affected by domain/subject matter, and tends to be hard to verify. Extracting information as learning evidence from e-portfolios to initialize student models will enrich the content of learner models and may potentially increase the accuracy. The learner models generated by our system (EP-LM) includes not only the student's knowledge level on each question/concept shown in Table 4 (e.g. How capable is the student with <concept i>?), but also lists of selected artifacts that may support the claims on each concept.

**Table 4: Main concepts that contribute to the learner model for an "Abstract Data Type" tutoring system**

| | |
|---|---|
| 1 | Define Variables/Methods/Classes |
| 2 | Method parameters/Return statement |
| 3 | Constructors |
| 4 | Control Structures |
| 5 | Object Concept |
| 6 | Nested Object |
| 7 | Complex object (or class with multiple data types) |
| 8 | Simple Arrays/Vectors |
| 9 | Search and sort array/vector |
| 10 | Concept of Abstract Data Type |

EP-LM is a system to initialize learner models from e-portfolios. This is accomplished by making claims about the skill level on various concepts and backing up the claim with evidence drawn from the e-portfolio. An overview of the EP-LM system with its high-level data flow is presented in Figure 4. The content and associated meta-data in an e-portfolio serve as the input. Although e-portfolios do not represent explicit models of cognitive capabilities, they contain evidence that may justify claims about the learner's knowledge or skills. The extension to the learner model is essentially a set of questions and an interface to e-portfolios. The questions for bootstrapping the learner model are defined based on the specific requirements of the adaptive learning environment (ALE) or intelligent tutoring system (ITS). Evidencing is the process of linking e-portfolio artifacts to claims about knowledge or skills. The evidencing process contributes to richer content because prior learning experience can be mapped to skill levels as supporting evidences in the learner models.

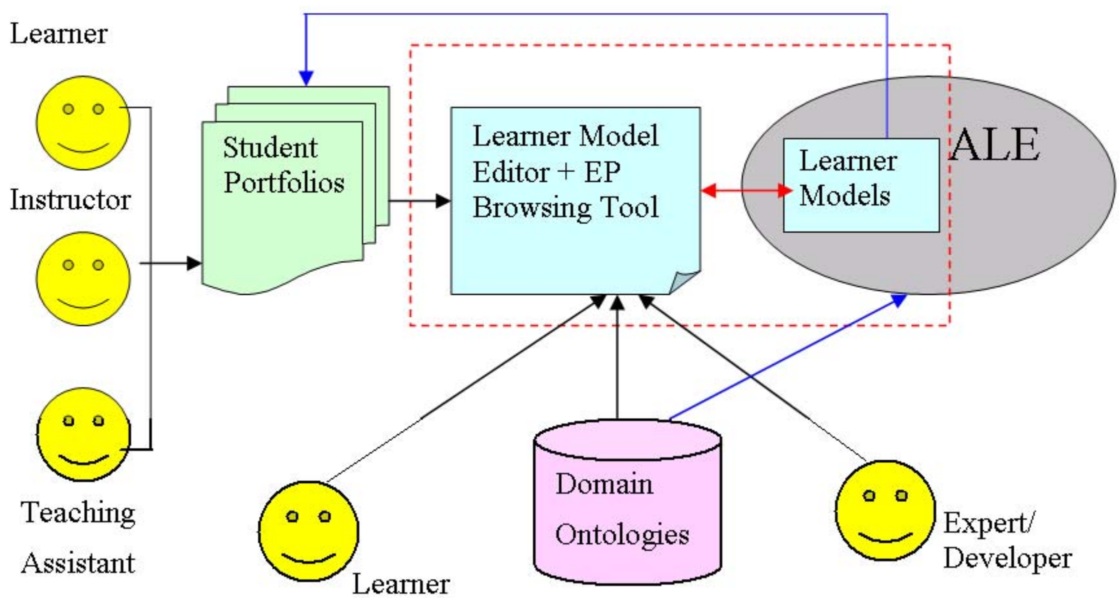



**Figure 4: An overview of the EP-LM system**

## 3.4 Implementation and Uses

The current version of our EP-LM system is implemented in JSP/Servlet and powered by the TOMCAT server. EP-LM supports e-portfolio browsing, claiming skill levels on certain concepts as well as evidencing the claims using artifacts (assignment, exam, project, etc.) that are included in the e-portfolio. To keep it simple and easy to test, the current version does not require sign-up and password. One only needs to input their name and select a student in the form below before starting. An overview of the ten questions/concepts (Table 4) will be shown first. The user will be led to the evidencing page (shown in Figure 5) when clicking the link "Start Here".

### 3.4.1 The Evidencing Page

For each concept, the user needs to specify a skill level or make a claim by clicking a radio button in the system interface. A view of the student's e-portfolio is shown at the bottom of the display (see Figure 5). Artifacts can be viewed either in a pop-up window and added (linked) to the claim as evidence, or by the “Add to Evidence” link right by the link of the artifact. The difference is that the user has the option to input comments and choose support type in the pop-up window, but no such information will be collected by using the “Add to Evidence” link. Each artifact can only be added once as support evidence to the current question/concept. Once the evidence is added, the user can modify or remove the added artifact from the “Selected Evidence” list. The user needs to make a claim before going to the next question, but he/she can come back to the previous questions and make changes anytime before the whole learner model is submitted.

The system provides an evidence-recommender feature for the user by highlighting some of the artifacts that are expected to be more relevant to the current question according to the course syllabus/ontology. For example, when the user is at the question “How capable is the student with the concept ‘simple array’?” the final exam and quiz 4 are highlighted because these two artifacts are recognized as related according to the ontology file. The relationships between the artifacts in the e-portfolio and all the ten questions are pre-defined and not changeable during the evidencing process. Instead of using individual student e-portfolios as reference, we analyzed the course syllabus and detailed descriptions/requirement for assignments, quizzes, lab exam and paper exams in order to define the possible link to the ten concepts/questions. The relationship is represented by a simple binary value without any consideration of weighing and aggregating. However, a possible refinement about the recommending feature will be discussed in analyzing the experiment results in Chapter 4.

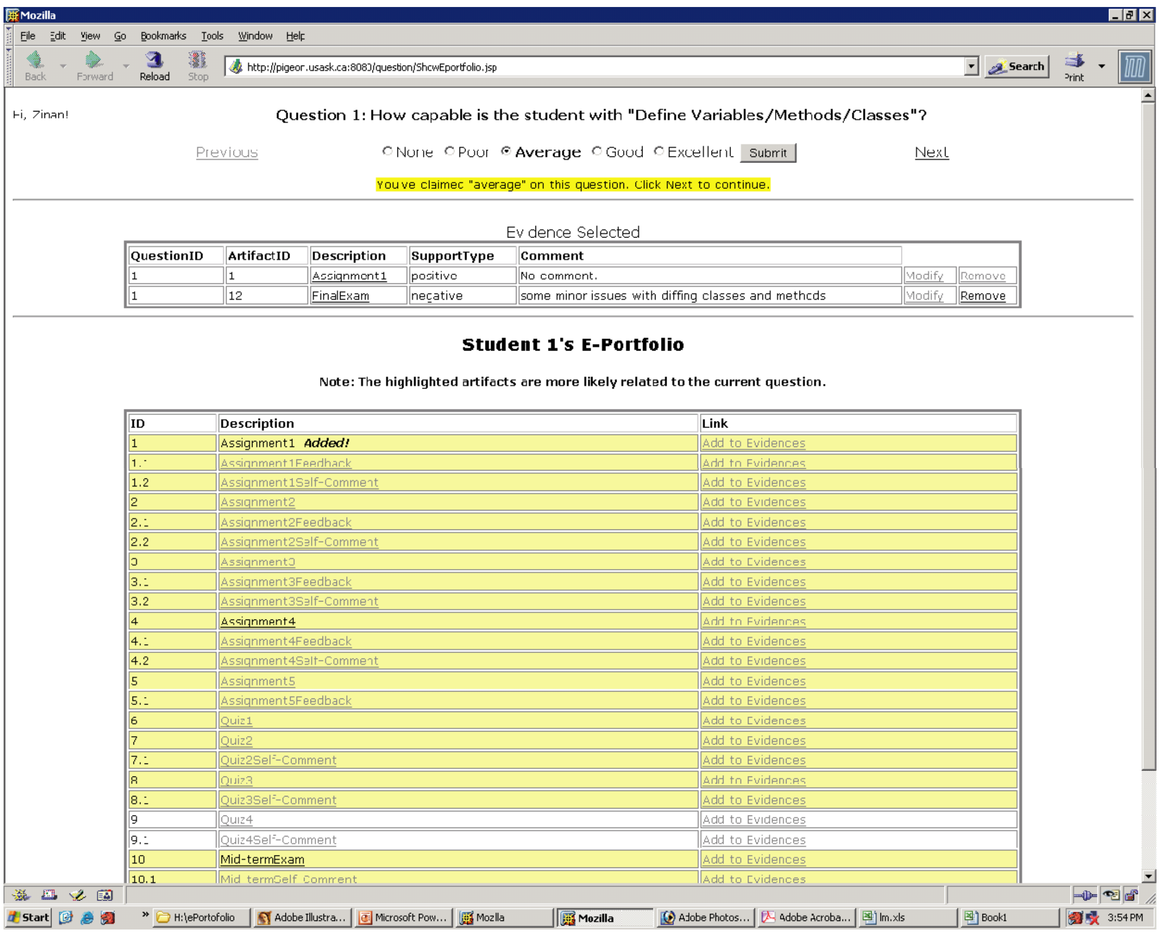



**Figure 5: An example of evidencing learner model with e-portfolio artifacts**

### 3.4.2 The E-portfolio Browser

Each time an artifact in the e-portfolio is clicked, the portfolio browser will be shown in a pop-up window (shown in Figure 6). The e-portfolio browser displays the artifact in an in-line frame located at the bottom. The current version of the portfolio browser has a limitation in supporting multi-media files. However, all the text-based files and image files can be displayed properly. The e-portfolio browser also has a built-in back button and a forward button at the top to control the document in the in-line frame in situations where there are hyper links or links to multiple sub-files in the artifact being viewed. The name of the artifact is displayed in a table at the top, where the user can also input supporting type (positive or negative) and provide comments. A drop-down list provides the user an option to attach the current artifact as evidence for other questions without having to browse the same artifact again. The evidence added to a different question will only be displayed in the "selected evidence" list on the page of that question.

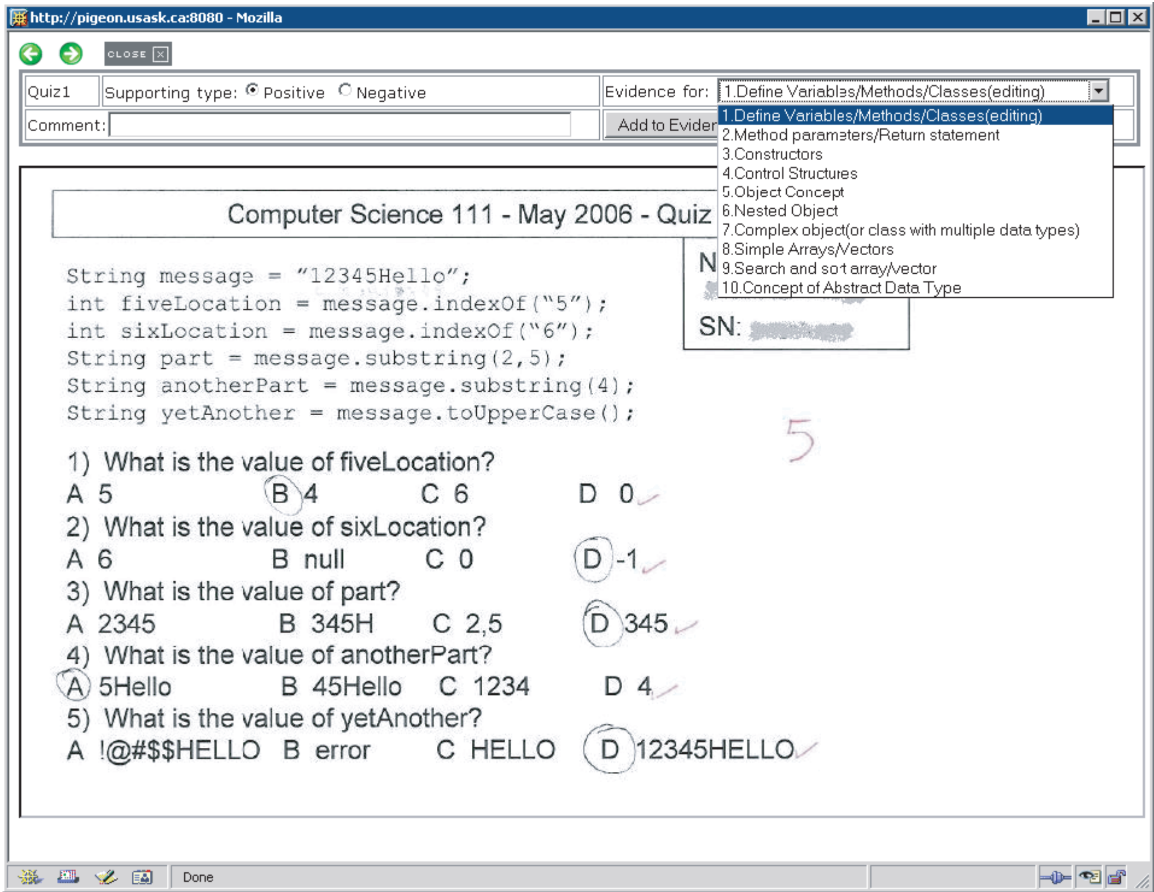



**Figure 6: Browsing an e-portfolio to select appropriate evidence.**

### 3.4.3 Generate the Learner Model

Figures 5 and 6 demonstrate an example of making a claim with evidence for a learner model initialization question via the student's e-portfolio with annotations. First a knowledge-level claim is made by the user by selecting a radio button in Figure 5. Then the "evidencing process" begins, i.e. the user reflects on the e-portfolio, locating evidence to support the claim, and linking that evidence to the claim. After selecting an item as a possible evidence source to view in the artifact list in Figure 5, a pop-up window appears (Figure 6) containing the detailed artifacts. The user can choose to fill some of the options for the evidence and click the "Add to Evidence" button to submit. When the pop-up window is closed, the focus will go back to the evidencing page and the "Evidence selected" list will be updated and shown in the refreshed page.

The learner models generated by our system (EP-LM) include not only the student's knowledge level on each question/concept, but also lists of selected artifacts that may support the claims on each concept. The learner models are saved in XHTML format with the possibility to convert to XML format or any other text format. The learner models are human-readable and can be retrieved and edited easily.

## 3.5 Activity Tracking

EP-LM is able to capture and record all the user's activities with time stamps for further analysis about evidencing activity, including viewing an artifact, attaching to a question/concept, remove from evidence, etc. The information contains the student name, evaluator name, question number, artifact information, action type and time in the database. The database has no problem with multiple users creating learner models simultaneously. The following types of activities will be tracked:

- Question loaded
- Artifact loaded
- Artifact attached to the current question from the quick link
- Artifact attached to the current question from the pop-up window
- Artifact attached to a different question from the pop-up window
- Artifact unloaded
- Claim made

## 3.6 Attaching Learner Models to E-portfolios

Since e-portfolios can serve as a data source to bootstrap learner models, it is conceivable that learning environments could also attach some information about the learner to his/her e-portfolio. Including a learner model from an ITS/ALE as an artifact in an e-portfolio is a simple idea. Normally the artifacts in an e-portfolio should be browseable in human-readable form and this leads to the requirement that learner models, in order to be useful e-portfolio artifacts, must also be inspectable by human users. Research in open learner modelling (e.g. Kay et al., 2005) has shown that inspectable and visualizable learner models can bring benefits to students and teachers. After completing a session with a learning environment, the open learner model could be transferred as a new artifact to the learner's e-portfolio. Attaching inspectable learner models to e-portfolios may provide another means for learner reflection. Meta-data associated with the learner model, such as system feedback and domain ontology could also be associated with the e-portfolio.

Learner models generated by learning environments are usually based on short- to medium-term observation over a narrow course of study, which should be stored as artifacts rather than just summary evidence (such as a single numeric grade) that directly causes changes to the learner's identification and characteristics. However, attached learner models are different from regular artifacts in e-portfolios because formal assessment could be contained that should not be changeable. Here again access control is crucial due to privacy and data integrity when content rich meta-data is generated by tutoring systems and attached to learner models for potential future information extraction. All kinds of tutoring systems should consider standardized specification compatibility when developing their learner model annotation modules. These special aspects of learner models are necessary for ensuring that future e-portfolios become true learning passports and a key part in lifelong learning.

## 3.7 Software Engineering Issues

The EP-LM system was designed and developed following the iterative, user centered methodologies. The current release was implemented using JSP, Servlet and JavaScript, powered by the TOMCAT server. The user interface was designed following HCI principles for use in a regular web browser that supports JavaScript. The system was developed in a two-tier architecture that uses no password-protected database. All the e-portfolio files are placed on the server side. The generated learner models are currently saved in a Microsoft Access database and displayed to the user in XHTML format. The system is also capable to output the learner models in the format of XML based on some specification.

The user interface of EP-LM was designed to keep it simple and easy to use. A brief introduction of the main functions is provided at the index page of the system. The login section is placed at the bottom of the introduction. The user needs to input his/her account name to login. The user can use the system to create learner models by making claims about the skill level on various concepts and backing up the claim with evidences drawn from the e-portfolio. The current release does not provide any help feature because the system was designed to use in a controlled experiment monitored by the developer/researcher. The system was implemented as a webpage with common forms and components (texts, tables, hyperlinks, buttons, and radio buttons) and thus is easy to use. The user is expected to spend two to three minutes to learn the main features by reading the introduction.

### 3.7.1 A Use Case

User Adam uses the system to initialize a learner model from the e-portfolio he built for his CMPT111 course.

- Login

Adam needs to type in his account name and select the e-portfolio that contains the evidence from the drop-down list at the login section on the index page.

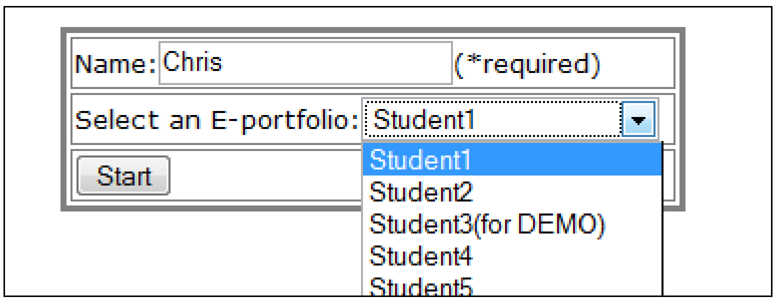



**Figure 7: Login form of EP-LM**

- Make a claim

Adam can choose a knowledge level (None, Poor, Average, Good and Excellent) for the concept by choosing an item in the group of radio button. He needs to click the submit button to submit his claim

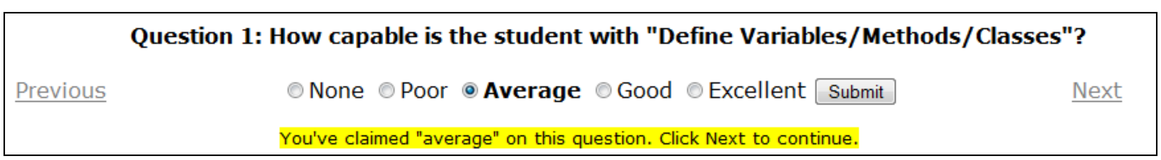



**Figure 8: User interface for claiming knowledge levels**

- Modify a claim

Adam can change the knowledge level by clicking a different button and click the submit button again.

- View an artifact

The e-portfolio artifacts are listed in a table at the bottom of the evidencing page. Adam can view an artifact that he thinks related by clicking on the name of that artifact. The artifact will be shown in a pop-up window.

| ID | Description | Link |
|---|---|---|
| 1 | Assignment1 | Add to Evidences |
| 1.1 | Assignment1Feedback | Add to Evidences |
| 1.2 | Assignment1Self-Comment | Add to Evidences |
| 2 | Assignment2 | Add to Evidences |

**Figure 9: The list of artifacts in the e-portfolio**

- Add an artifact as evidence

Adam can add an artifact as evidence in two ways: 1. Click the *Add to Evidence* button right beside the name of the artifact in the table, 2. Add it to the evidence list by clicking the *Add to Evidence* button in the pop-up window. An optional support type and comment can be input with the evidence.

- Remove an evidence from the selected evidence list

Once an artifact is chosen to be attached as evidence, it will be shown in the *Evidence Selected* list. Adam can remove any evidence from the list by clicking the *Remove* button right to the name of the attached evidence.

Evidence Selected

| QuestionID | ArtifactID | Description | SupportType | Comment | | |
|---|---|---|---|---|---|---|
| 1 | 1.2 | Assignment1Self-Comment | No type. | No comment. | Modify | Remove |
| 1 | 2.1 | Assignment2Feedback | No type. | No comment. | Modify | Remove |

**Figure 10: The list of selected evidence**

- Review the generated learner model

Adam needs to claim knowledge levels for all the required questions/concepts. The generated learner model will be shown in a table with the concept, claimed knowledge level and attached evidence. Adam is able to modify any claim by clicking the question/concept link to open the evidencing page.

## 3.8 Discussion

The EP-LM design and implementation are discussed in this chapter. An experiment aiming at testing how accurately a learner model can be generated through the system will be presented in Chapter 4. The demo system was developed mainly for testing purposes in a controlled environment. It has some limitations in automatic information extraction, ownership control and privacy protection.

### 3.8.1 Automatic Information Extraction from E-portfolios

For stimulating and practicing reflective learning, learners are encouraged to select evidence on their own. However, a mechanism for automatic attaching of evidence could be used to extract artifacts and/or annotations. The ultimate goal of this research is to maximize the automation of information extraction from the e-portfolio, as well as to provide students the opportunity of reflective learning.

General user data needed in an adaptive learning environment may be automatically imported from a learner's e-portfolio. The data that match the LIP specification (e.g. <name >) and e-portfolio specification (e.g. <identification>) of the e-portfolio can be automatically extracted or linked (mapped) to the required field in the learner models.

This can simplify and partially automate the first step of learner model initialization. The user can further fill in or modify slots if any do not satisfy the context.

More interesting is the initial knowledge about cognitive knowledge and skills about the content domain. While e-portfolios do not represent explicit models of cognitive capabilities, they will contain evidence that could justify claims made about knowledge or skills. For each domain-specific question developed by an ITS, related topics or keywords can be reached in some kind of domain concept maps. These keywords can be used to find the matching materials in an e-portfolio, as well as other files that have certain relationships with selected materials. Table 5 shows some major relationships between two kinds of elements in an e-portfolio. When a product is found matched with a certain topic, annotations such as assertion, goal and reflection would also be extracted and put into ITS extensions for learner model information management.

**Table 5: Some relationships between e-Portfolio elements**

| destination | Activity | Competency | Goal | Interest | Product | Qcl | Assertion, Reflexion |
|---|---|---|---|---|---|---|---|
| Activity | is part of, precedes | evidences, shows up, supports | supports | evidences | supports | supports, supple-ments | N/A |
| Affiliation | supports | supports | supports | N/A | supports | supports | N/A |
| Competency | evidences, supports, precedes | is part of, precedes | supports | evidences | supports | supports | N/A |
| Goal | N/A | aims at | supports, precedes | N/A | aims at | aims at | N/A |
| Interest | supports | supports | supports | is part of, precedes | supports | supports | supports |
| Product | evidences, supports | evidences, shows up | supports | evidences | supports, is part of, precedes | supports | N/A |
| Qcl | evidences, supports | evidences | supports | evidences | supports | supports | N/A |
| Assertion | attests, evaluates, presents | Attests, presents | attests, evaluates, presents | attests, evaluates, presents | attests, evaluates, presents | attests, evaluates, presents | attests, evaluates, presents |
| Reflexion | evaluates, reflects on | reflects on | evaluates, reflects on | evaluates, reflects on | evaluates, reflects on | evaluates, reflects on | evaluates, precedes, reflects on |

The relationships presented in Table 5 contain four main types: 1. support and evidence, 2. evaluate and attest, 3. reflect and 4. "is part of". These relationships help connect the artifacts in an e-portfolio in a more searchable way and make it easier to interpret the link from evidence to a student model. For instance, an automatic process might be developed to connect all the <Product> items that support a <Competency > item. This could be done if the standardized relationship XML files are accessible in the form shown in Table 5.

### 3.8.2 Potential Benefits from "Evidencing" Process

We claim that the evidencing process provides benefits in three aspects of learning:

- Richer content can be expressed: prior learning experiences can be mapped to skill levels as supporting evidences in the learner models.
- Reflective learning can occur as students get a chance to review their prior learning via assisted functions provided by the system.
- The approach promotes a portfolio-based assessment model.

These points were identified when we designed the system and further judged in the experiment in which five expert users were invited to test the system. This will be discussed in Chapter 4.

### 3.8.3 Privacy and Other Issues

Designers should expect that the learners will have some privacy control over their e-portfolios, which could cause some restrictions for the instructor or the system administrator who wishes to use the e-portfolio. The current demo system does not implement functions that control the ownership and generate different views for different types of users. However, it is important to include the publicity control functions when the e-portfolio system is integrated into other learning support environments.

Some e-portfolio artifacts contain not only self-reflective comments, but also feedback and comments from instructors and student peers. These comments could be positive or negative, or sometimes neutral. Since the owner of an e-portfolio is a learner (rather than a teacher), there is a concern that the learner might treat the negative comments in an incorrect way. Administrative and ITS developers should be careful with situations where some assessment results might contain biased and even completely wrong evaluations about a student, which could negatively affect the motivation for building and maintaining e-portfolios.

# CHAPTER 4

# EXPERIMENT AND EVALUATION

An experiment has been deployed to test the functionality of the EP-LM system, to evaluate the accuracy of the generated learner model, and to examine how beneficial this approach can be in terms of reflective learning. The experiment is designed to address two research questions:

1. Can we gain accurate initial values of a learner model by using e-portfolios as evidence in a learner model bootstrapping process?

To answer this question, we need to define a set of standard basis values for measuring the accuracy of the generated learner models. The median values of the expert evaluators' claims about the students' knowledge levels will be used as the basis value because they are the most accurate value statistically (neither the worst nor the best). Before computing the median values, we run the reliability test and significance test to ensure that the data collected are reliable and meaningful. Once the standard accurate values are selected, we are able to compare actual claims with the standard values and compute the accuracy. Through the analysis we can judge how accurate are the knowledge levels claimed by the evaluator (user who created the learner model). The results may show some common pattern across all the questions/concepts and students (evaluators agreed more on some questions for some students). This will lead us to explore the reason that may have caused this common pattern.

2. To what extent would this approach of building and evidencing learner models help students with their reflective learning?

Previous research has shown reflective comments from a human tutor and student peers about problem-solving activities to be effective in helping students reason about their own learning behaviours [Pon-Barry, 1997]. In the proposed system, users are provided opportunities to reflect on their prior learning activities (feedback, Q&A dialogue, etc.) when selecting evidence for questions that relate to certain domain knowledge. For some students who have a hard time remembering details about their prior learning activities, this evidencing process can be helpful as it "forces" them to browse the details of their own learning records in order to select the most related evidence. The EP-LM portfolio browser has two features that may further promote reflective thinking: 1. the user can select either a negative or a positive supporting type when attaching an artifact as evidence; 2. the user can input comments and further review them with the learner model.

## 4.1 The Pilot Experiment

Before the real experiment, a pilot study was conducted with two graduate students who work in the ARIES research lab to help test the functionality of the system and estimate the time required for the expected tasks. We did not invite real student subjects in order to avoid other human factors that may affect the result analysis. Only experts (teachers, researchers in computer science domain) were invited as users/evaluators to run though the experiment, and to provide insights about reflective learning benefits. Experts were called together for a meeting to help provide comments on the approach and related open issues, i.e. attached learner models in e-portfolios can be reviewed by the learner in the future.

## 4.2 Experiment Setup

The experiment was conducted on a controlled desktop computer in the ARIES lab through the EP-LM web interface and monitored by the researcher. The pilot experiments for evaluating the proposed system suggest that the average time for making each claim is about two and a half minutes. The process of creating a learner model from the e-portfolio by answering ten questions (and making claims) takes about half an hour for each student. Due to the time and cost issues, we decided to ask each expert evaluator to create learner models for four out of six students selected based on their overall rank in the class. (The four selected students had obtained marks for 65, 74, 87 and 93 out of 100) Before the experiment, an introduction section that describes the system functionality and planned experiment was provided to the expert participants.

### 4.2.1 The Testing Suite

The experiment test bed includes the following parts:

1. *Five sample student e-portfolios*. These were created based on real-class teaching and learning materials (one of them is a sample for the system introduction section and the other four are for the experiment). These sample e-portfolio artifacts were collected from paper-based documents (later scanned as e-documents) and electronic file submitting systems available in the Computer Science Department at the University of Saskatchewan, including the E-Handin and iHelp system. Self-reflective comments were collected through interviews with each student volunteer who shared the e-portfolio items. Adobe Acrobat version 7.0 was used for inputting the reflective comments. The annotations and concept map (ontology) of the course was written by the system

developer based on the curriculum of several Java programming classes according to the specification for standard e-portfolio information models. Each sample e-portfolio includes the following documents:

- Lecture notes, tutorials and lab documents
- Assessment, which consists of 3 smaller and 3 larger assignments
- Five in-class quizzes, one midterm exam, one final lab exam and the final written exam.
- Students' posts for Q&A and problem solving activities from the iHelp discussion forums.

2. *Pre-test questions for initializing learner models*. The questions used in this research project are shown in Table 4 in Chapter 3. We selected these concepts based on a scenario that the students have completed the Java programming course CMPT111 and will now continue to learn Abstract Data Types from an intelligent tutoring system. We selected the concepts that are related to the ITS and kept the format of the model close to the real learner models in some online tutoring system (e.g. a Java programming ITS that focuses on Java GUI programming). We designed the pretest questions based on the prerequisites of such programming tutoring systems. For example, a Java GUI tutor requires knowing the learner's previous study on some basic programming concept and knowledge of Java technology. Thus, the questions covered basic programming concepts, (e.g., OOP concept).

3. *The EP-LM implementation*. The system was developed using JSP+Servlet and JavaScript, powered by the TOMCAT server. The user interface is a regular web browser

that supports JavaScript. The system was developed in a two-tier architecture that uses no password-protected database. All the e-portfolio files are placed on the server side. The user is not able to upload from the client side in the current release.

4. *Experiment Participants*. Five experts were invited to participate in the experiment. Three of them had experience in teaching the same/similar course as CMPT111, from which the sample e-portfolios were developed. The other two were researchers and PhD candidates in the ARIES research lab. An overview introduction of the system and experiment was provided prior to the experiment. Each expert performed the process of initializing a learner model through the system interface for four students. The experts were also asked to review the results and fill out a survey to provide comments on both the system functionality and pedagogical issues after the experiment.

### 4.2.2 Experiment Tasks

Each of the five experts was asked to create four learner models using the four student e-portfolios. They need to made claims about knowledge levels on ten concepts related to the learner model that would be used for an "abstract data types" tutor. On each of the ten concepts (in Table 4, Chapter 3), each expert made an estimate of each student's current knowledge level on a 5-point scale where 5 indicates mastery and 1 indicates little knowledge.  The experts browsed the e-portfolios of the students and linked artifacts as evidence in supporting their estimates of knowledge levels. The experts spent roughly half an hour to evidence each student model using EP-SM.  In addition we had asked each of the students to make an estimate of their own skill level on the ten concepts without supplying evidence for their claims.

Once the learner models were created and the results were roughly analyzed, the experts were invited to a meeting where they discussed their agreement and disagreement on the claims made. Experts provided comments on the advantage of the approach and points that could be improved. The discussion helped us to draw conclusions about the study and to identify some interesting future work.

## 4.3 Analysis of the Experiment Data

The purpose of the experiment was to evaluate the accuracy of the learner models created through this approach and to discover how beneficial such an approach can be in terms of reflective and personalized learning. With six student volunteers we constructed authentic e-portfolios that documented their learning in an introductory Java programming course. We then selected four of the e-portfolios that covered the full range of student achievement levels in the course. We invited five domain experts to participate in the experiment, each of whom went through four student e-portfolios and proceeded through the "evidencing" process. The experts were also interviewed together where they had some discussions about their judgments and comments on the approach and results.

### 4.3.1 Data Collected

The data collected from the five expert participants for each of the four selected students include knowledge levels claimed for a specific concept, a list of evidence (with support type and comments) attached to the supported concept, time spent in viewing and attaching the artifact/evidence. One sample learner model created is shown in Table 6. We also had earlier asked the students who shared their learning documents for the e-portfolios to estimate the knowledge level for the same concepts as those in Table 4, Chapter 3.

**Table 6: A sample generated learner model**

| Q ID | Concept | Skill Level | Evidences | | | |
|---|---|---|---|---|---|---|
| 1 | Define Variables/Methods/Classes | excellent | 1 | Assignment1 | positive | No comment |
| | | | 2 | Assignment2 | positive | No comment |
| | | | 3 | Assignment3 | positive | No comment |
| 2 | Method parameters/Return statement | poor | 3 | Assignment3 | negative | returning the parameter shows some misunderstanding of returned values |
| | | | 3.1 | Assignment3Feedback | positive | No comment |
| | | | 3.2 | Assignment3Self-Comment | positive | No comment |
| | | | 4 | Assignment4 | negative | the getRechargeX method doesn't return the correct type or the correct value (reChargeX) |
| | | | 7 | Quiz2 | positive | No comment |
| | | | 8 | Quiz3 | positive | No comment |
| | | | 10 | Mid-termExam | negative | question # 8 shows some misconceptions with returned values, the wrtitten 1b and c shows a misconception about methods |
| | | | 12 | FinalExam | negative | part C, some increased knowledge from |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | before, but still problems |
| 3 | Constructors | average | 5 | Assignment5 | positive | No comment |
| | | | 10 | Mid-termExam | negative | question 4 a |
| | | | 12 | FinalExam | positive | page 10 |
| 4 | Control Structures | good | 2 | Assignment2 | positive | No comment |
| | | | 3 | Assignment3 | positive | No comment |
| | | | 4 | Assignment4 | positive | No comment |
| | | | 5 | Assignment5 | positive | No comment |
| 5 | Object Concept | average | 5 | Assignment5 | positive | No comment |
| | | | 10 | Mid-termExam | negative | No comment |
| | | | 12 | FinalExam | positive | No comment |
| 6 | Nested Object | none | | | | |
| 7 | Complex object(or class with multiple data types) | average | 12 | FinalExam | positive | No comment |
| 8 | Simple Arrays/Vectors | poor | 9 | Quiz4 | negative | No comment |
| | | | 12 | FinalExam | positive | Arrays question 3 |
| 9 | Search and sort array/vector | poor | 12 | FinalExam | negative | sorting section, searction section |
| 10 | Concept of Abstract Data Type | poor | | | | |

We used the collected data to analyze the accuracy of the process of generating the learner model, the evidencing activity, and the potential benefits in reflective learning. An example of the data collected as one expert browsed one student e-portfolio to construct estimates of student knowledge levels is presented in the following table. Table

7 also shows the computed mean value and standard deviation value among all the five experts, as well as the student's estimate on the same concept.

**Table 7: Sample experiment data for one student and one expert**

| Concept | Knowledge level Estimated by expert 1 | number of artifacts linked by expert 1 | Relevance | time (seconds) | Mean knowledge level estimate across experts | StDev knowledge level estimate across experts | Clarity (average of 1 to 5 scale) | Student's estimate of knowledge level |
|---|---|---|---|---|---|---|---|---|
| 1 | 3 | 3 | 0.59 | 384 | 3.6 | 0.89 | 4.5 | 3.5 |
| 2 | 4 | 2 | 0.66 | 573 | 3.2 | 0.84 | 4 | 2.3 |
| 3 | 3 | 2 | 0.42 | 56 | 3.4 | 0.55 | 3.75 | 3 |
| 4 | 5 | 3 | 0.57 | 411 | 3.4 | 1.34 | 3.5 | 4 |
| 5 | 5 | 1 | 0.18 | 140 | 4 | 1.00 | 4.25 | 3 |
| 6 | 5 | 1 | 0.07 | 120 | 2.2 | 1.79 | 2.5 | 3 |
| 7 | 5 | 1 | 0.13 | 78 | 4 | 1.00 | 4 | 3 |
| 8 | 2 | 2 | 0.56 | 199 | 2 | 0.00 | 4.5 | N/A |
| 9 | 2 | 1 | 0.56 | 116 | 2.2 | 0.45 | 3.75 | N/A |
| 10 | 3 | 0 | 0 | 64 | 2.4 | 0.89 | 2.5 | 1 |

## 4.3.2 Evaluate Data Consistency and Reliability

The accuracy of the generated learner model is probably the most important issue to be addressed. A first examination of accuracy was through comparing the inter-rater reliability among the experts' estimates of knowledge level of each learner on each concept. The Cronbach's alpha statistic was 0.809 with 95% confidence interval, which indicates a "good" level of agreement according to [Ebel, 1951] and [Fleiss & Cohen, 1973].

**Table 8: Cronbach's Alpha test result 1 – mean and std. deviation**

| | Mean | Std. Deviation | N |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Expert 1 | 4.02 | 1.19 | 40 |
| Expert 2 | 3.47 | 1.48 | 40 |
| Expert 3 | 3.52 | 1.50 | 40 |
| Expert 4 | 3.57 | 1.53 | 40 |
| Expert 5 | 3.75 | .92 | 40 |

**Table 9: Cronbach's Alpha test result 2 - coefficiency**

| | Intraclass Correlation(a) | 95% Confidence Interval | | F Test with True Value 0 | | | |
|---|---|---|---|---|---|---|---|
| | Lower Bound | Upper Bound | Value | df1 | df2 | Sig | Lower Bound |
| Single Measures | .458(b) | .314 | .614 | 5.22 | 39.0 | 156 | .000 |
| Average Measures | .809(c) | .696 | .888 | 5.22 | 39.0 | 156 | .000 |

Looking more closely at Table 7, there was a large standard deviation among experts on concept 6, the nested object concept. In debriefing interviews with the experts it was revealed that there was some variation in understanding of the intent behind this concept by the experts. The concept was not explicitly taught in the prior course, but some experts judged learners' readiness to easily learn the concept as the knowledge level they should specify. This leads us to conclude that there can be a notion of clarity (or vagueness) in specification of the concepts. The experts' estimates were averaged to obtain a composite estimate of knowledge by each learner on each concept. Learners' own estimates were compared against the experts' composite estimate using a paired t-test. Questions 8 and 9 were excluded because the students had not learned about the concepts by the time they were interviewed. The t-test results in Table 10, 11 and 12 show a positive correlation between students' estimates and experts' estimates (correlation=0.735), but the inequality of means shows no significant difference (with T=1.49 and significance=0.146). This indicates that the students' own estimates are not significantly different from the experts' opinions. Note again in Table 7 that this student did not agree at all with the experts on item 10. This has more to do with ontological as opposed to cognitive issues. The term ADT was unknown to the student, even though much of the foundational skill on this concept was gleaned by the experts in looking into the portfolio.

**Table 10: Paired samples statistics**

| | | Mean | N | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Pair 1 | Expert Ave | 3.71 | 32 | 1.03 | .182 |
| | Student | 3.48 | 32 | 1.27 | .224 |

**Table 11: Paired samples correlations**

| | | N | Correlation | Sig. |
|---|---|---|---|---|
| Pair 1 | Expert Ave & Student | 32 | .735 | .000 |

**Table 12: Paired samples test**

| | Paired Differences | | | | | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference | | Mean | Std. Deviation | Std. Error Mean |
| | Lower | Upper | Lower | Upper | Lower | Upper | Lower | Upper |
| Pair 1 Expert Ave - Student | .228 | .865 | .153 | -.083 | .54 | 1.49 | 31 | .146 |

## 4.3.3 Factors that Affect the Accuracy of Evaluation

We attempted to develop a model to characterize the accuracy of an evaluator (experts or possibly student) in judging the learner model after having been initialized from an e-portfolio using our system. It seems that the factors that can affect the accuracy include total time spent on making claims including time to review the potential evidence and attach the artifacts, the total number of attached pieces of evidence (attached artifacts), relevance of the evidence selected, and clarity vs. vagueness of the concept to be estimated and justified. After our analysis, the time factor was excluded in this evaluation because the time is considered as a threshold to measure if sufficient attention is spent on making the claims. All of our expert evaluators completed the tasks carefully and thoroughly spending what we considered to be an adequate amount of time. Further, data collected from web-based and other interactive learning systems, such as detailed logs of page visits, time spent on each page and links selected, give weak evidence that the user read the material or let alone learned it [Kay & Lum, 2005].

- Number of Evidence Claims

For each claim about one concept, the minimum number of evidence artifacts that the evaluators can choose to attach is zero, and the maximum is the number of artifacts in the entire course e-portfolio. Usually, only a subset of the e-portfolio artifacts is related to each concept/claim. It seems that the more the number of evidence artifacts attached, the more likely all items in this subset will be covered. However, too many evidence artifacts do not increase confidence in accuracy, and a threshold for the maximum value of the number should be used.

- Relevance of Evidence

Every time an artifact is selected and attached as evidence, the evaluator considers it related to the current concept (either positively or negatively). However, some evidence can be considered weak evidence because either the content of the artifact is of poor quality or the content is not relevant to the current concept. We tried to determine the relevance of each artifact in the evidence list by asking our expert evaluators to explain the sign of the support (whether it positively or negatively affected the claim) and to provide comments about the evidence attached. The quality of the artifact can be judged based on the frequency of that artifact being selected by any expert evaluator for evidence on any concept, and the relevance to a certain topic can be judged based on that artifact being selected by other/all evaluators for the current concept. We use the product of two normalized frequencies to represent the relevance value of every piece of selected evidence. For each concept, the relevance is the average value of the relevance values assigned to every attached artifact.

The EP-LM system provides an evidence-recommending feature when the evaluator selects some artifact as evidence in supporting the claim on a knowledge level. Some ontologically related artifacts are highlighted according to the analysis of the context. The experimental data can help refine the recommendation feature by suggesting a statistical rating on the level of relevance. However, the downside of this method is that some students may totally follow the highly recommended artifacts and dismiss some other important ones.

- Clarity vs. Vagueness Due to Uneven Interpretation of Concepts

A large standard deviation among expert evaluators on “the nested object concept” (concept 6) was found in the result, which reflects that there was some variation in understanding the intent behind the concept by the expert evaluators according to the interview. The clarity of a concept can be defined as the likelihood of a concept being interpreted and understood as the expected meaning. Generally the more knowledge about the concept is covered in the class and the less abstract the concept is, the more easily it is understood in the expected way. Clarity measures depend highly on the context and rely on the domain concept map and course ontology. The values of clarity of the ten concepts in our accuracy model are defined as the average clarity value (1 to 5 scale) from the five invited domain experts (shown in Table 7).

## 4.4 A Model for the Accuracy of Evaluation

Figure 11 shows the aggregation of all the factors contributing to the accuracy of the determination of the learner model created through our approach. The various factors affect the accuracy of this determination at different granularity levels. At the higher level, the accuracy of the judgment is determined by the number of attached pieces of evidence (Num_Evi), the relevance of all the evidence, the time spent and the clarity of the concepts affected by domain ontology and curriculum. At the second level, each evidence artifact  has four attributes that may contribute in an accumulative or selective way, including relevance of the artifact, time spent on viewing the artifact, support type (positive or negative), and comment.

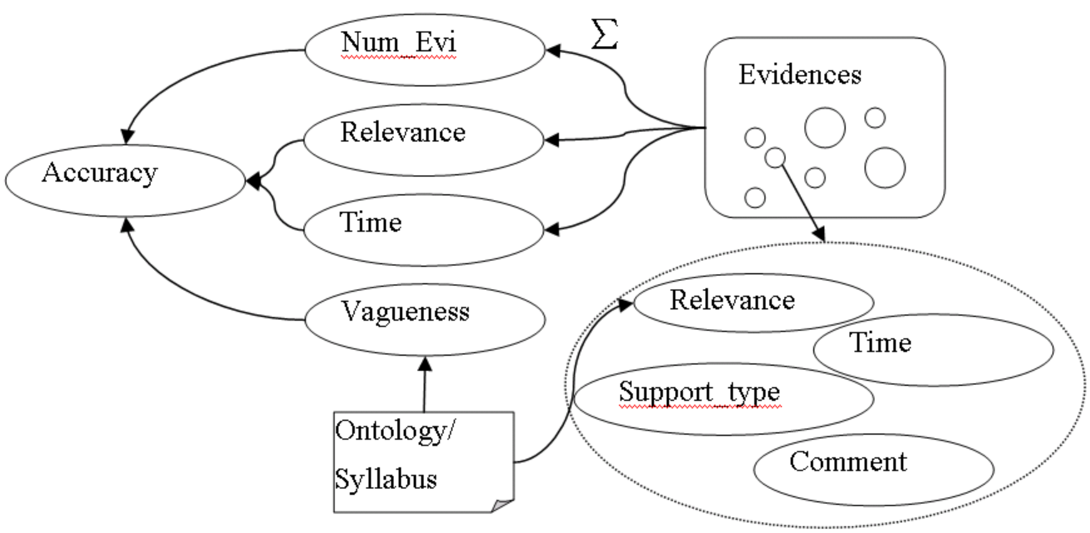



**Figure 11: The aggregation of factors that contribute to the accuracy**

We propose the following equations to help measure the accuracy of making each claim about knowledge levels. The average values of claims are chosen as the accurate basis value because the average results are selective and relatively accurate. (Claims are in the form of normal distribution according to the comparison of the average and median values) The accuracy of each claim (AOC) is defined by equation 1, where x is the current claim and μ is the average claim of the five experts. Equation 1 normalizes the value of AOC ranges from 0 to 1. $NOE_c$ is defined as the total number of all pieces of evidence attached with a concept. $R_c$ is the relevance of a claim. $C_c$ is the clarity of the concept. The result contains the weight of evidence number ($W_n$), relevance ($W_r$) and clarity ($W_c$) and can be used as standardized values for judging the accuracy of the process of creating learner models in the same/similar context.

$$\text{Equation 1: } AOC = 1-|x-\mu| / MAX(|\mu-min|,| \mu-max|)$$

$$\text{Equation 2: } AOC = NOEc*Wn + Rc* Wr + Cc*Wc +Constant$$

To validate this model, we use data for four of the five expert evaluators across all four students and 10 concepts to run a linear regression. The result, including weights of $W_n$, $W_r$ and $W_{c,}$ from the regression is shown in Table 3. It is clear from the result that the number of evidence items carries very little weight compared to the relevance and clarity. To evaluate the usefulness of the weight values, a paired T-test was conducted with the fifth evaluator's judgments to compare the AOC value computed using equation 1 and equation 2. The result shows that the values computed from equation 2 using standardized $W_n$, $W_r$ and $W_c$ values are not significantly different from the AOC values defined by equation1. This means that the accuracy values computed by the model (based on the various factors) are not statistically different from observed accuracy levels. Thus, we can conclude that this model for the accuracy of the evaluation process is promising.

**Table 13: Result of the regression and paired T-test**

| | | | | $W_n$ | $W_r$ | $W_c$ | Constant |
|---|---|---|---|---|---|---|---|
| **Unstandardized Coefficiency (B)** | | | | -.004 | .045 | .207 | -.027 |
| **Std. Error** | | | | .009 | .09 | .027 | .09 |
| | | **Mean** | **Std. Dev** | **N** | **t** | **Sig.** | **Correlation** |
| **Paired T-test** | $P_{equation1}$ | .785 | .218 | 40 | -1.33 | .191 | .657 |
| | $P_{equation2}$ | .750 | .147 | 40 | | | |

The result shows limitations (large standard errors), which are possibly due to our small size of sample data and errors brought by the linear regression. A larger sample (more than 10 students) dataset would help run a more accurate linear regression in future work. To refine the linear regression model for a better equation, three curve estimations were conducted with the standard accurate value (AOC) and each of the three independent variables $NOE_c$, $R_c$ and $C_c$. The following tables and figures show the results from the curve estimations.

**Table 14: Curve estimation for AOC & NOE - model summary and parameter estimates**

| Equation | Model Summary | | | | | Parameter Estimates | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R Square | F | df1 | df2 | Sig. | Constant | b1 | b2 | b3 |
| Linear | .046 | 7.62 | 1 | 158 | .006 | .702 | .025 | | |
| Logarithmic(a) | . | . | . | . | . | . | . | | |
| Inverse(b) | . | . | . | . | . | . | . | | |
| Quadratic | .072 | 6.07 | 2 | 157 | .003 | .652 | .075 | -.006 | |
| Cubic | .074 | 4.18 | 3 | 156 | .007 | .636 | .102 | -.015 | .001 |

Table 14 shows the model summary and parameter estimates from the estimation for the dependent variable AOC and the independent variable NOE. The Logarithmic and Power models cannot be calculated because the independent variable (NOE) contains non-positive values and the minimum value is .00. The Inverse and S models cannot be calculated because NOE contains values of zero. Log transform cannot be applied because the dependent variable (AOC) contains non-positive values and the minimum value is .000000. From the result we can see the significance values for all three available models (Linear, Quadratic and Cubic) show the result was not computed by chance. The R-square values shows how close are the two variables. Thus we can conclude the Cubic modeller describes the relationships of our experiment data.

Figure 12 shows the visualization of these relationships.

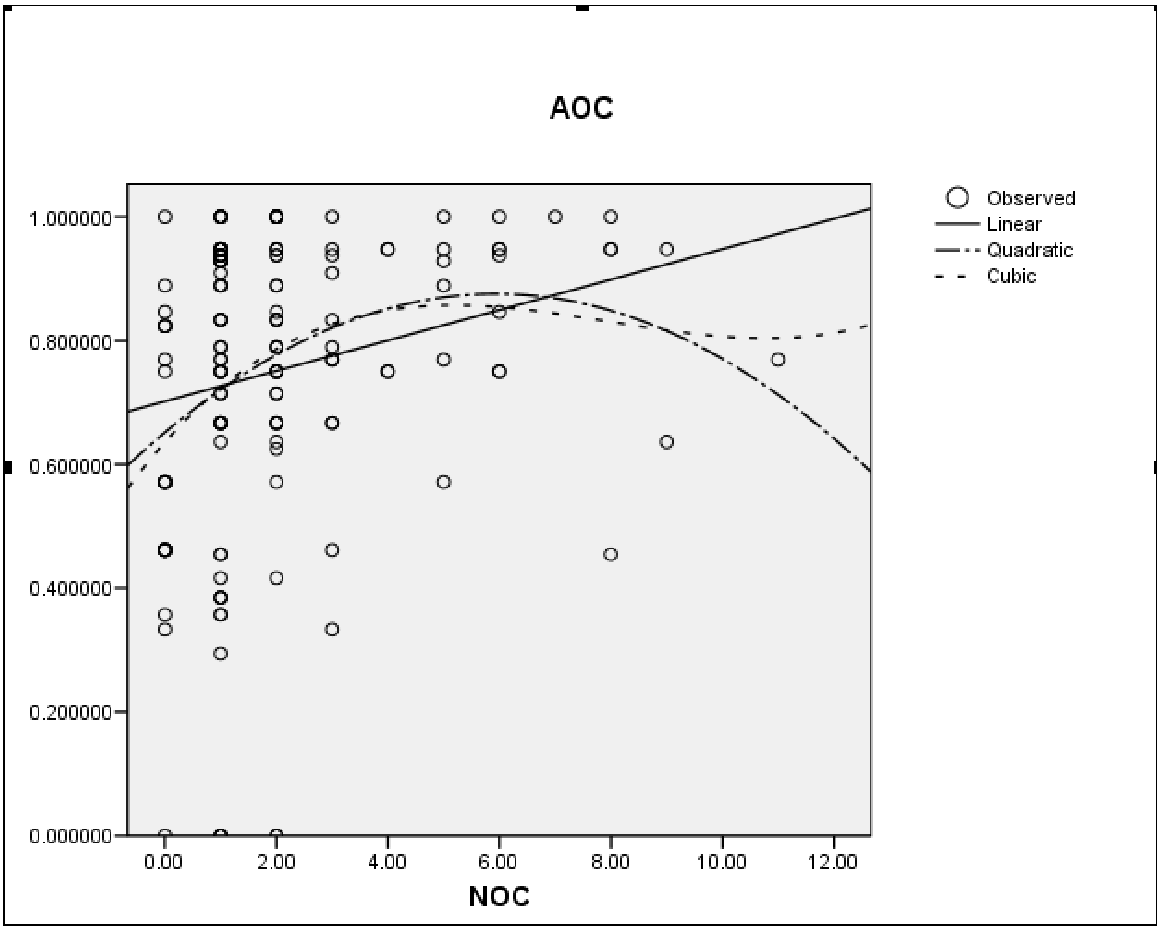



**Figure 12: Curve estimation graph for AOC and NOE**

**Table 15: Curve estimation for AOC & Rc - model summary and parameter estimates**

| Equation | Model Summary | | | | | Parameter Estimates | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R Square | F | df1 | df2 | Sig. | Constant | b1 | b2 | b3 |
| Linear | .140 | 25.63 | 1 | 158 | .000 | .623 | .356 | | |
| Logarithmic(a) | . | . | . | . | . | . | . | | |
| Inverse(b) | . | . | . | . | . | . | . | | |
| Quadratic | .214 | 21.38 | 2 | 157 | .000 | .544 | 1.03 | -.858 | |
| Cubic | .215 | 14.23 | 3 | 156 | .000 | .536 | 1.20 | -1.35 | .360 |

Table 15 shows the model summary and parameter estimates from the estimation for the dependent variable AOC and the independent variable Rc that represents the relevance. The Logarithmic and Power models cannot be calculated because the independent variable (Rc) contains non-positive values and the minimum value is .000000. The Inverse and S models cannot be calculated because the independent variable (Rc) contains values of zero. Log transform cannot be applied because the dependent variable (AOC) contains non-positive values. The minimum value is .000000. From the result we can see the significance values for all the three available models (Linear, Quadratic and Cubic) show the result was not computed by chance. The R-square values shows how close are the two variables. Thus we can conclude the Cubic model describe the relationships the best based on our experiment data. Figure 13 shows the visualization of these relationships.

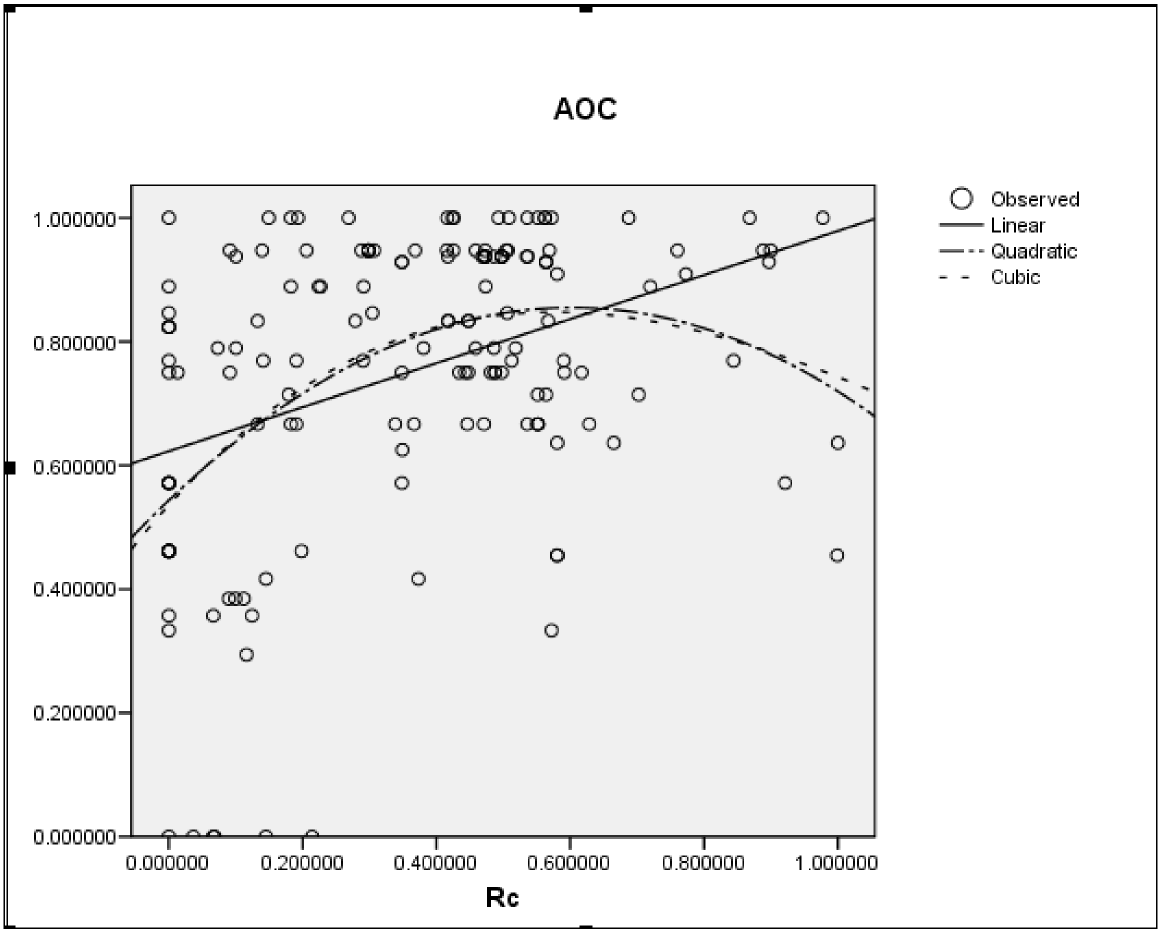



**Figure 13: Curve estimation graph for AOC and Rc**

**Table 16: Curve estimation for AOC & Cc - model summary and parameter estimates**

| Equation | Model Summary | | | | | Parameter Estimates | | | |
|---|---|---|---|---|---|---|---|---|---|
| | R Square | F | df1 | df2 | Sig. | Constant | b1 | b2 | b3 |
| Linear | .370 | 92.87 | 1 | 158 | .000 | -.038 | .212 | | |
| Logarithmic | .381 | 97.21 | 1 | 158 | .000 | -.181 | .721 | | |
| Inverse | .386 | 99.45 | 1 | 158 | .000 | 1.41 | -2.35 | | |
| Quadratic | .387 | 49.51 | 2 | 157 | .000 | -.881 | .725 | -.074 | |
| Cubic | .387 | 49.51 | 2 | 157 | .000 | -.881 | .725 | -.074 | .000 |

Table 15 shows the model summary and parameter estimates from the estimation for the dependent variable AOC and the independent variable Cc that represents for the clarity of the concept. Log transform cannot be applied because the dependent variable (AOC) contains non-positive values and the minimum value is .000000. From the result we can see the significance values for all the three available models (Linear, Quadratic and Cubic) show the result was not computed by chance. The R-square values show how close the two variables are. Quadratic, Inverse and Cubic models are very close. Thus we can conclude the Cubic model describes the relationships the best for all the three variables (NOE, Rc and Cc) based on our experiment data. However, the best option can vary in different contexts because these curve estimations were conducted only using our small size experiment data. We leave the work of combing the three variables in a more elaborate equation to future work.

Figure 14 shows the visualization of these relationships.

The above analysis has led us to believe the aggregation model of all the factors contributing to the accuracy of the determination of the learner model is more complex than the two questions that can be solved by linear regression estimations. To incorporate the proposed model in real systems, a pilot study needs to be conducted first in the defined environment/context for getting accurate variables that represent the weights of all the factors.  If the pilot data were to show that the model is valid and reliable, it could be used to predict the accuracy of evidence-based bootstrapping of learner models from e-portfolios.

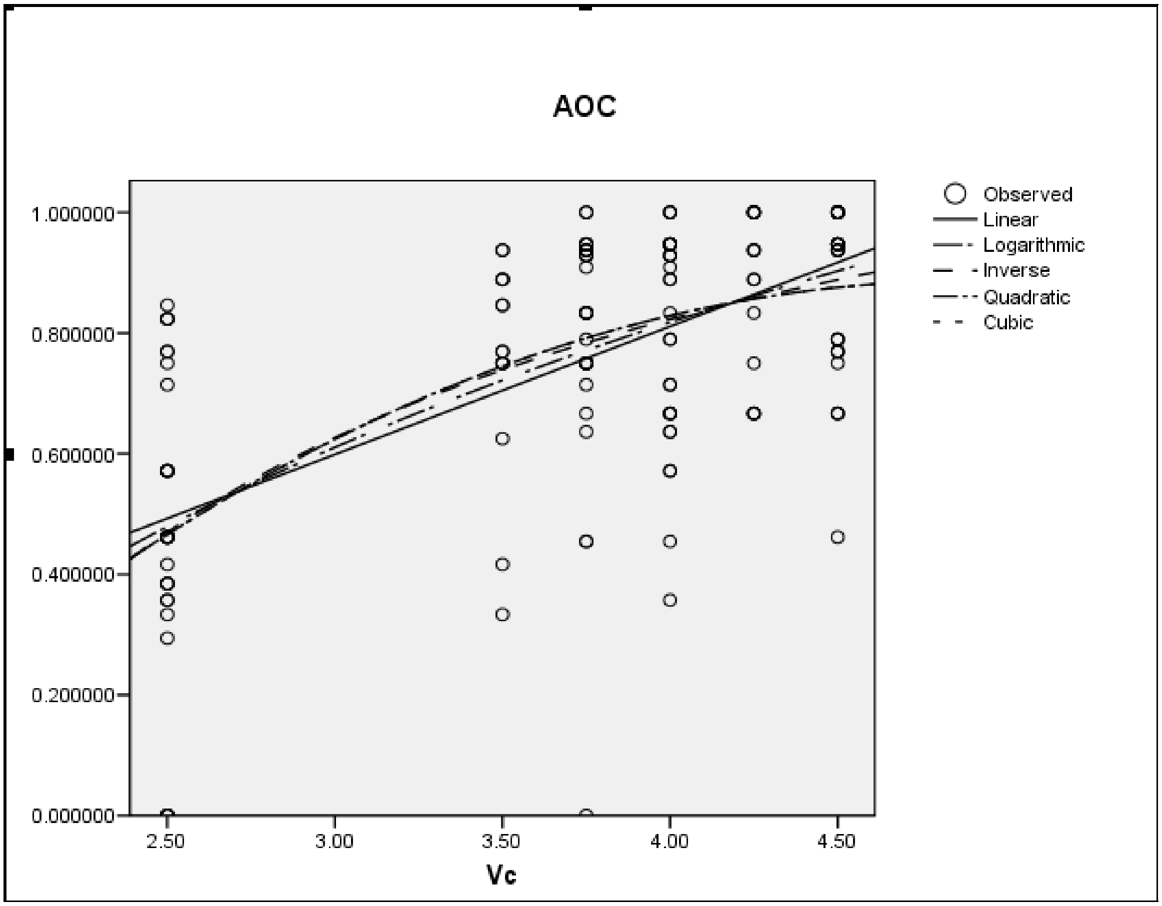



**Figure 14: Dependent variable: AOC &Cc**

## 4.5 Benefit for Reflective Learning

One notable benefit of the proposed method of learner model initialization for the student is reflective learning. Students can take the opportunity to review their prior learning activities and make connections that will be important for future learning.

The artifacts in an e-portfolio should be browseable in human-readable form and this leads to the requirement that learner models, in order to be useful e-portfolio artifacts, be inspectable by users. Research in open learner modelling has shown that inspectable learner models can bring benefits to students and teachers. After completing a session with a learning environment, the learner model could be transferred as a new artifact to the learner's e-portfolio. Attaching inspectable learner models to e-portfolios may provide another means for learner reflection. However, security and privacy issues for both user information and copyright protected course content need to be addressed.

### 4.5.1 How to Motivate Students to Reflect on Their E-portfolios

"Students will be motivated to reflect on their own learning because they know they are working for improving their marks. If their only job is to finish this class, they probably will never look back to what they did." –expert's quote

This e-portfolio based reflective learning process can be applied at different time points. For example, the instructor can have all the concepts/ skills marked before the final exam and return this to the students, and the students can send in new evidence to convince the instructor that a higher mark is appropriate. This would not only encourage students to benefit from reflective learning, but also motivate students to re-work the problems from the exam. It would be useful to have a system where students could challenge and potentially increase their marks through evidence.

The EP-LM system can be used by students to create learner models with learning evidence drawn from their prior learning experience. Some strategies could be implemented in motivating the users to reflect on their e-portfolios: 1. Provide the user an average learner model in the community, 2. Support group-based learner model initialization and learner model reviews.

### 4.5.2 Is the Reflective Goal Valuable Enough to Dismiss the LM Process

There are some tradeoffs between automatic information extraction from e-portfolios and manually creating learner models. Since standardized meta-data for e-portfolios and learner information is proposed and widely accepted, automatic extraction of learning information from e-portfolios is becoming more applicable and accurate. The automated learner model initialization may save time and reduce cost when being used in generate average learner models. However, having the learners participate in creating their own learner models and providing evidence from their e-portfolios can help them reflect on their prior learning activities. It seems that a fully automated learner model initialization is not good for the learner in terms of reflective learning. Is the reflective goal valuable enough to forget the learner model initializing and still have value? It is difficult to compare the importance between reflective learning and learner modeling when we have to choose only one of them. However, we are lucky enough to see no conflict to combine these two together in our EP-LM system. One important task for developers, instructors and administrative is to seek for the equilibrium of automatic information extraction and user learner model editing.

## 4.6 Other Issues

### 4.6.1 The Diversity of Evaluation Among Experts

Experts have wide disagreement on Q6 and Q10 mainly because of different understanding about the concept itself and the confidence level of making claims. Questions that are understood in different ways and questions that have no supporting evidence in the e-portfolio tend to cause bigger differences. A quote from the expert is as follows:

“I typically give them high scores because there are some evidences show that they know about it, but sometimes I wasn't really confident with the score I gave. For question 10, I had to give something, but I wasn't really confident about what I gave because there was no evidence to look at. For question 6, the other one with big standard deviation, I was actually very confident but I think I may have a misunderstanding on the concept that other people would judge." –expert's quote

This suggests that clear and accurate questions need to be addressed for generating good quality learner models. Some explanation at the beginning to clarify some relatively weak questions can be helpful. Experts agreed that detailed explanation with examples can be included. Excluding Q6 and 10, agreement reaches 81.25% (STDEV <1), and for the two students with marks over 80, we get 100% agreement (STDEV <1). Another reason that may cause the difference could be making the claims based on different artifacts. We analyzed the data to check if there are a few people who are outliers and if there is a common pattern among people who have not agreed with one another on a question, and we found two experts used later assignments and finals as evidence over 90% of the time and their claims are quite different from the other three.

We also compared the overall average of the expert-claimed knowledge level with the one claimed by the students. Question 8 and 9 are excluded because the students had not learned about the concepts by the time they were interviewed. It is not clear how close the average from the experts and average from the students we can get, because they look at the concepts from two different perspectives. However, an overall average of the differences is found to be approximately14% excluding Q8 and 9. Some other reasons involved can be seen from the following expert discussion:

"Another issue is that the students did not know how they did on the finals because there wasn't a chance for feedback." –expert's quote

“Another example is assignments, students can get help with so many concepts that they may not understand at all. They may not feel confident but they have completed the assignment so it shows that they much know something.” –expert’s quote

“If the students had a chance to look at the marks, it would help them adjust their confidence level of claiming their own knowledge level on the certain concept.” – expert’s quote

### 4.6.2 Evidence Selection to Refine Recommendation

The EP-LM system provides an evidence-recommending feature when the user is asked to select some evidence in supporting their claims on a knowledge level. Some ontologically related artifacts are highlighted according to the analysis of the context. The experimental data can help refine the recommendation feature by suggesting a statistical rating on the level of relevance. For example, if we take a look at which evidence is selected for question 5, we can see the five highest picked artifacts are Final Exam, Assignment5, Assignment4 and Mid-term Exam. It may be helpful to mark the highlight color lighter for the less picked ones and darker for the ones picked more. However, the downside of this method is that some students may totally follow the high recommended artifacts and dismiss some less important ones, which may stimulate important personal learning outcomes.

**Table 17: Overall count of artifacts attached as evidence**

| ARTI_ID | DESCRIPTION | Count | Percentage |
|---|---|---|---|
| 1 | Assignment1 | 17 | 3.79 |
| 2 | Assignment2 | 23 | 5.13 |
| 2.1 | Assignment2Feedback | 1 | 0.22 |
| 3 | Assignment3 | 35 | 7.81 |
| 3.1 | Assignment3Feedback | 3 | 0.67 |
| 3.2 | Assignment3Self-Comment | 4 | 0.89 |
| 4 | Assignment4 | 60 | 13.39 |
| 4.1 | Assignment4Feedback | 1 | 0.22 |
| 4.2 | Assignment4Self-Comment | 1 | 0.22 |
| 5 | Assignment5 | 61 | 13.62 |
| 5.1 | Assignment5Feedback | 2 | 0.45 |
| 6 | Quiz1 | 8 | 1.79 |
| 7 | Quiz2 | 16 | 3.57 |
| 7.1 | Quiz2Self-Comment | 2 | 0.45 |
| 8 | Quiz3 | 13 | 2.90 |
| 9 | Quiz4 | 8 | 1.79 |
| 9.1 | Quiz4Self-Comment | 1 | 0.22 |
| 10 | Mid-termExam | 43 | 9.60 |
| 11 | LabExam | 23 | 5.13 |
| 12 | FinalExam | 126 | 28.13 |
| total: | | 448 | 100 |

Table 17 shows an overall count of artifacts attached as evidence by all five experts for creating the four student models. The result is not surprising as the final exam and later assignments carry more weight compared to earlier assignments and quizzes. However, the situation is highly dependent on the course syllabus and other context information.

The experimental data with 446 attached pieces of evidence (21.5% were attached as negative evidence and 78.5% as positive), shows that 140 of them were submitted with comments, 55 with negative support vs. 85 with positive support. The content of these comments are not fully analyzed in this thesis, but they are available for future interpretation and processing.

## 4.7 Summary

In this chapter we have presented the experimental data collected through the process of initializing learner models from e-portfolios. We analyzed the accuracy of the process of creating learner models and proposed an accuracy model that is validated in the same/similar context. We also discussed the benefits for reflective learning and possible refinement of the EP-LM system.

# CHAPTER 5

# CONCLUSIONS AND FUTURE WORK

The rapidly growing use of e-portfolios in higher education, especially in online learning, provides students a user-centered file management option. Many schools and universities have developed e-portfolio systems where students are encouraged to store and organize artifacts during their formal schooling and to further carry on with augmenting that e-portfolio during lifelong learning. It is possible in the not-too-distant future that teachers or students using ALE/ATS will make use of their access to students' portfolios, where detailed learner information could be used for initializing learner models. Meanwhile, students may also wish to retain some of the assertion and reflective information captured in learner models through their learning activity with the ALE/ATS and keep that information in their lifelong learning portfolios.

The general goal of this thesis is to investigate the process of using the information in e-portfolios to initialize learner models for adaptive learning environments. Discussions and analysis on e-portfolios, e-portfolio specifications are presented as the basis to support our system design and planned experiment. The general design and implementation of the web-based EP-LM system is described in chapter 3. In chapter 4, an experiment and the results are discussed to address the two research questions. An accuracy model for evaluating the process of bootstrapping learner models is also proposed based on the analysis of the experimental results.

## 5.1 Contributions

The EP-LM is a system that connects student course e-portfolios with learner models. It supports initializing learner models from e-portfolios by making claims about the skill level on various concepts and backing up the claim with evidence drawn from the e-portfolio. The main contributions around this project are:

- Creation of course e-portfolios based on in-class student learning material

This phase investigates how to build an appropriate student e-portfolio for assessment and to showcase learning outcomes after a student has finished a course. The sample e-portfolios created for this research are course e-portfolios that can be included as part of the learner's life-long learning portfolio. The sample e-portfolios contain all the teaching and learning materials shared by six student volunteers from an entry-level Java programming course taught over the summer of 2006. The e-portfolios carry authentic learning evidence that have been found useful in supporting learner assessment and generate learner models.

- Analysis of the standardized e-portfolio and learner model specifications

E-portfolio specifications and standards are the basis that assures robustness and usability of our data sources. A detailed analysis of the information model and relationships among different types of categories is presented as a hypothesis of the system input. A discussion about how to initialize a learner model in traditional methods is also presented in which categories can be mapped to standard e-portfolio classes. Possible mappings are also described in chapter 2 and 3 that show some general cases followed by a description of the proposed system that works with domain ontology.

- Design and implementation of the EP-LM System

EP-LM as a system for bootstrapping learner models from e-portfolios is the core of the project. The application has main modules as follows:

A web interface: designed following the HCI and Web design principles, the web interface was simple to serve the learner model bootstrapping task.

Portfolio browsing tool: The e-portfolio browser displays the artifact in an in-line frame that is controlled by a built-in back button and a forward button with situations where there are hyper links or links to multiple sub-files in the artifact being viewed. Users can input annotations such as supporting type (positive or negative) and comments. A drop-down list provides the user an option to attach the current artifact as evidence for other questions without having to browse the same artifact again. Two features are planned for the next version of the system: 1) visualization based on the relationships between two artifacts (portfolio parts), 2) a search function available in both key words and relationship search.

Learner model editor: working with the portfolio browsing tool together in the web interface, the main task is to provide a means for the user to enter values and information that contribute to the learner model.

- A prototype architecture that links the e-portfolios to other learning support systems

The EP-LM is prototype research software that indirectly interacts with other content management systems and learning support applications (eHandin and iHelp Discussions). It shows its potential use for portfolio-based formal assessment.

- Learner model evidencing vs. e-portfolio assessment

The learner model initialization using the EP-LM system could be deemed as a process of self-evaluation on a student's course e-portfolio or a subset of it. Some factors about the evaluation process have been identified when we investigated how accurately a learner model can be bootstrapped from an e-portfolio. An aggregation model of these identified factors with their relationship is discussed and tested. We claim that this model suggests valuable insights for self-evaluation activities using e-portfolio evidence, which may be useful as reference for research in e-portfolio assessment.

The e-portfolio assessment involves assessing the quality of artifacts in an e-portfolio, which includes the authenticity, accessibility etc. while the learner model initialization discussed in this research only focus on the process of the evaluation. The e-portfolio assessment is a larger issue and is more complex than this thesis work.

## 5.2 Future Work

The next step of the EP-LM system is to add automated learner information extraction feature that can assist the manual process of making claims about knowledge levels and providing evidence. Information that can be automatically attached includes system information (creation date, ownership, etc.) and personal information (name, address, etc.). Another extension of this research work is to further investigate the possibility of integration or co-operation with a larger course management system.

In general, a learner model represents the learner's knowledge of the domain. A model of related factors including learning style and navigation preference is also important. In the proposed system, learner models are built manually by the users, with the help of browsing and reviewing their e-portfolios, which may be beneficial for the students in terms of reflective learning. However, (semi-) dynamically extracting information from e-portfolios (data mining e-portfolios) of a group of students may be helpful for managing learning information and evaluation. A sample model of good learning style can be recommended to learners, which may help increase their learning efficiency.

This research activity is also connected with the larger issue of e-portfolio assessment as well as prior learning assessment. E-portfolio assessment involves evaluating learner achievements relative to pre-defined rubrics and utilizing the e-portfolio elements as evidence sources for achieving prescribed learning outcomes. This has some striking similarity to the method described in this paper for initializing learner models. It also bears some similarity to inspectable learner modelling. The use of e-portfolios allows qualifications to be changed to focus more on the actual core of what needs to be assessed, rather than peripheral efforts to record and administer assessment tests of students' work [Grant, 2005]. The same could be said of learner models! Student self-assessment and portfolio assessment included in the e-portfolios can be beneficial for learner information management in personalized and adaptive learning environments.

## 5.3 Conclusions

This thesis aims to address the interplay between e-portfolios and learner models. We report on the work of creating sample course e-portfolios based on real-world data. A method of initializing student models from e-portfolios is discussed, with both a learner model editor and an e-portfolio browsing tool. The EP-LM system was developed to initialize learner models from e-portfolios. This is accomplished by making claims about the skill level on various concepts and backing up the claim with evidences drawn from the e-portfolio. An experiment has been conducted aiming at testing whether accurate learner models can be created through this approach and if learners can gain benefit in reflective and personalized learning. The results are presented showing its promise in adaptive learning environments.

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# APPENDIX A: CONSENT FORM (FOR STUDENTS)

Approved by the University Advisory Committee on Ethics in Behavioural Sciences Research on Nov 27, 2001 (BSC# 2001-198)

1. **Title of the study.**
   An I-Help Evaluation Study: Simulating Electronic Portfolios Based on Real Student Learning Materials

2. **Name(s), institutional affiliation(s) and telephone number(s) of researchers.**
   Jim Greer, Professor, Computer Science Department; 966-8655

   Zinan Guo, MSc Student, Computer Science Department, 966-2666

3. **Purpose and objectives of the study.**
   This is a pre-study of developing a student electronic portfolio (e-portfolio) system. This study is part of the research being conducted by the ARIES Group at the University of Saskatchewan, Department of Computer Science.

   The goal of the study is to build a system that is able to simulate sample e-portfolios according to the IMS specifications, based on real student learning resources. The simulated e-portfolios will further be used in a continuous research that focuses on initializing learner models in adaptive learning environments using e-portfolios as evidences.

4. **The possible benefits to the participants** will be potentially an e-portfolio system/service for certain Computer Science courses such as CMPT 111.

5. **Data Collection Procedure**
   In this study, student participants will be asked to share versions of their assignments, quizzes, lab exam, mid-term and final exams from the CMPT111 class. In addition, students will be asked to participate in an interview session that will take about an hour after completing this module of study, in which they will also be asked to fill out a short questionnaire. During the interview session, students will be given more information about the purpose and goals of the study.

   The data collected from this study will be used in creating sample electronic portfolios with specification-based meta-data which will be used in bootstrapping learner models for adaptive learning environments. The outcome of this research project will be presented in articles for publication in journals and conference proceedings. As one way of thanking students for their time, we will be pleased to provide each participant a $50 honorarium, plus to make available a copy of their simulated portfolios and a summary of the results of this study once compiled.

6. **Risks or Side Effects**
   It is hard to envisage any risks or side effects of the usage of the system. However, if we become aware of any such effects during the study, we will inform immediately the participants.

7. **Each participant is free to withdraw** from the study at anytime and this withdrawal will not affect the participants' academic status. If appropriate, the researcher may choose to discontinue a participant's involvement in the study. In any case data related to students who withdraw will be deleted from the study and destroyed.

8. **The information about the students** None of the information collected will be shared with your instructor. None of the information collected will influence your grade in this or other courses.

9. **The anonymity** of the collected data and the privacy of the subjects would be completely protected and the information obtained from this data would be used only in theses, journal articles or conference publications written by the researchers. In any publication only aggregate data will be reported. Thus, the names and identities of the subjects would not be used after the initial data collection is completed, not would they be published in any form.

10. **The participants will be advised** of any new information that will have a bearing on the participants' decision to continue in the study.

11. If you want to acquire information on the results of the research once the study is completed, send a request to Zinan Guo at zig094@mail.usask.ca .

12. Should you have any questions with regard to the study or to your rights as a participant in the research study, call Professor Jim Greer, 966-8655.

The study and contents of the consent have been explained to me, I understand the contents, and that I have received a copy of the consent form for my own records.

Date:

Signatures:

| | |
|---|---|
| ______________________ | ______________________ |
| Participant | Researcher |

# APPENDIX B: QUESTIONNAIRE (FOR STUDENTS)

The goal of this survey is to help us refine the e-portfolio that has been simulated so that they become more realistic and meaningful to both students and reviewers. This survey contains three parts and will take about 45 to 50 minutes to finish.

**Part 1** Linking the e-portfolio artifacts to Java programming topics

In this part, you are expected to read through the e-portfolio and add comments or annotations about some artifact(s). You will be asked to fill the following table with “*” in which the name/link of your assignments, quizzes, exams and I-Help posts are mapped to relative topics or concepts.

| Topics | A1 | A2 | A3 | A4 | A5 | Q1 | Q2 | Q3 | Q4 | Mid | Your post/reply in I-Help |
|---|---|---|---|---|---|---|---|---|---|---|---|
| The Nature of OO Applications | | | | | | | | | | | |
| Introduction to java. | | | | | | | | | | | |
| Concept of objects and OOP | | | | | | | | | | | |
| Properties, methods, and events. | | | | | | | | | | | |
| Basic Principles of Algorithms | | | | | | | | | | | |
| Algorithms and algorithmic processes. | | | | | | | | | | | |
| Formulation, development and description of algorithms. | | | | | | | | | | | |
| Algorithmic concepts and structures. | | | | | | | | | | | |
| Elementary Programming Concepts | | | | | | | | | | | |
| Basic Program Elements | | | | | | | | | | | |
| Editing and running a program | | | | | | | | | | | |
| Syntax diagrams | | | | | | | | | | | |
| Conditionals | | | | | | | | | | | |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Procedures: parameter passing, scope rules, side effects, recursion. | | | | | | | | | | | |
| Input/Output: basic and text file | | | | | | | | | | | |
| Exception handling | | | | | | | | | | | |
| Introduction to Data Structures | | | | | | | | | | | |
| Basic Data Structures: arrays, vectors . | | | | | | | | | | | |
| Searching and sorting. | | | | | | | | | | | |
| Objects as data structures. | | | | | | | | | | | |

**Part 2** Make a claim of your knowledge level on the following programming concepts.

| Concept | How comfortable are you with the concepts? | Evidence in e-portfolio? |
|---|---|---|
| **Simple Data Types** | | |
| int, float, double | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| char, string | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| boolean | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Control Structures** | | |
| do, while, for | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| if, else, switch | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Object Concept** | | |
| Defining objects | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| built-in objects in Java | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| nested objects | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| packages | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| complex object or class with multiple data types | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Define Classes** | | |
| variables | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| methods | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| constructors | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| method parameters | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| return statement | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| visibility modifiers | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Basic String Operations** | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Algorithm** | | |
| recursion | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |

| | | |
|---|---|---|
| **Simple Arrays/Vectors** | | |
| create an array of nums | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| create a vector of strings | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| array list | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| search and sort array/vector | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **Abstract Data Type** | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| **More…** | | |
| Java doc | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| Pseudo code | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |
| Exception handling | □ None □ Poor □ Average □ Good □ Excellent | □Yes □No |

Part 3 Questions about the e-portfolio

Would you be willing to share your e-portfolio with future instructors in the continuous computer science classes? If you choose no, what are your concerns?

□Yes □No

Do you think this e-portfolio captures and describes your knowledge? If not, what should be added?

# APPENDIX C: CONSENT FORM (FOR EXPERTS)

Approved by the University Advisory Committee on Ethics in Behavioural Sciences Research on Nov 27, 2001 (BSC# 2001-198)

1. **Title of the study.**
   An I-Help Evaluation Study: EP-LM: A System to Initialize Learner Models from Electronic Portfolios

2. **Name(s), institutional affiliation(s) and telephone number(s) of researchers.**
   Jim Greer, Professor, Computer Science Department; 966-8655

   Zinan Guo, MSc Student, Computer Science Department, 966-2666

3. **Purpose and objectives of the study.**
   In this study you will be asked to create learner models that contain the student's basic programming skills with actual evidences using the EP-LM system. EP-LM is a system to initialize learner models from e-portfolios. This is accomplished by making claims about the skill level on various concepts and backing up the claim with evidences drawn from the e-portfolio. In addition, you will be asked to participate in an interview session to discuss the results. More information about the purpose and goals of the study can be found at the instruction page at http://pigeon.usask.ca:8080/question/index.jsp .

4. **The possible benefits to the participants** will be potentially an e-portfolio system/service for certain Computer Science courses such as CMPT 111.

5. **Data Collection Procedure**
   The data collected from this study will be used in testing how accurate a model can be built and how beneficial this approach can be for reflective and personalized learning. The outcome of this research project will be shown in articles for publication in journals and conference proceedings. As one way of thanking you for your time, we will be pleased to provide you $50 honorarium, plus to make available to you a summary of the results of this study once they have been compiled.

6. **Risks or Side Effects**
   It is hard to envisage any risks or side effects of the usage of the system. However, if we become aware of any such effects during the study, we will inform immediately the participants.

7. **Each participant is free to withdraw** from the study at anytime and this withdrawal will not affect the participants' academic status. If appropriate, the researcher may choose to discontinue a participant's involvement in the study. In any case data related to students who withdraw will be deleted from the study and destroyed.

8. **The information about the students** None of the information collected will be shared with your instructor. None of the information collected will influence your grade in this or other courses.

9. **The anonymity** of the collected data and the privacy of the subjects would be completely protected and the information obtained from this data would be used only in theses, journal articles or conference publications written by the researchers. In any publication only aggregate data will be reported. Thus, the names and identities of the subjects would not be used after the initial data collection is completed, not would they be published in any form.

10. **The participants will be advised** of any new information that will have a bearing on the participants' decision to continue in the study.

11. If you want to acquire information on the results of the research once the study is completed, send a request to Zinan Guo at zig094@mail.usask.ca .

12. Should you have any questions with regard to the study or to your rights as a participant in the research study, call Professor Jim Greer, 966-8655.

The study and contents of the consent have been explained to me, I understand the contents, and that I have received a copy of the consent form for my own records.

Date:

Signatures:

______________________________ _______________________

Participant Researcher

# APPENDIX D: QUESTIONNAIRE (EXPERT MEETING)

Section 1: Learner Model

1. Diversity of claims about students' skill levels
    - Agreement, disagreement, and explanation.

2. Comparison between overall expert's claims and the student's claim
    - Comment, suggestion

3. Selection of artifacts as evidences.
    - Selection of artifacts

    - Comment

    - Support type

    - Recommendation (the highlight feature)

- The time spent on creating the Learner Models

4. Benefit for reflective learning

5. Other issues

Section 2: Data source (the E-Portfolios)

1. Content

2. Authenticity and Quality

3. Usability

Name________________________

Date__________________________

# APPENDIX E: RAW DATA COLLECTED FOR THE STATISTICAL ANALYSIS

## 1. Knowledge Level Claimed by Experts and Students

| SID | Question | Expert1 | Expert2 | Expert3 | Expert4 | Expert5 | STDEV | ByStudent |
|---|---|---|---|---|---|---|---|---|
| Student 1 | 1 | 3 | 5 | 3 | 4 | 3 | 0.89 | 3.5 |
| | 2 | 4 | 2 | 4 | 3 | 3 | 0.84 | 2.3 |
| | 3 | 3 | 3 | 4 | 4 | 3 | 0.55 | 3 |
| | 4 | 5 | 4 | 4 | 2 | 2 | 1.34 | 4 |
| | 5 | 5 | 3 | 5 | 4 | 3 | 1.00 | 3 |
| | 6 | 5 | 1 | 1 | 1 | 3 | 1.79 | 3 |
| | 7 | 5 | 3 | 5 | 4 | 3 | 1.00 | 3 |
| | 8 | 2 | 2 | 2 | 2 | 2 | 0.00 | 3.3 |
| | 9 | 2 | 2 | 3 | 2 | 2 | 0.45 | 2 |
| | 10 | 3 | 2 | 1 | 3 | 3 | 0.89 | 1 |
| | | | | | | | | |
| Student 2 | 1 | 4 | 5 | 5 | 5 | 5 | 0.45 | 4 |
| | 2 | 3 | 5 | 4 | 4 | 3 | 0.84 | 3.63 |
| | 3 | 2 | 5 | 2 | 2 | 2 | 1.34 | 2 |
| | 4 | 3 | 4 | 4 | 4 | 3 | 0.55 | 3 |
| | 5 | 5 | 4 | 4 | 4 | 4 | 0.45 | 4 |
| | 6 | 1 | 1 | 1 | 1 | 4 | 1.34 | 4 |
| | 7 | 2 | 4 | 5 | 4 | 4 | 1.10 | 4 |
| | 8 | 4 | 3 | 3 | 5 | 5 | 1.00 | 3 |
| | 9 | 2 | 2 | 4 | 5 | 3 | 1.30 | 3 |
| | 10 | 5 | 2 | 1 | 1 | 4 | 1.82 | 2 |
| | | | | | | | | |
| Student 3 | 1 | 5 | 5 | 5 | 5 | 5 | 0.00 | 5 |
| | 2 | 5 | 5 | 5 | 5 | 5 | 0.00 | 4.95 |
| | 3 | 5 | 4 | 4 | 3 | 4 | 0.71 | 5 |
| | 4 | 5 | 5 | 3 | 5 | 5 | 0.89 | 5 |
| | 5 | 5 | 4 | 4 | 5 | 5 | 0.55 | 4.5 |
| | 6 | 5 | 1 | 1 | 1 | 4 | 1.95 | 1 |
| | 7 | 5 | 5 | 4 | 5 | 4 | 0.55 | 4 |
| | 8 | 5 | 4 | 5 | 5 | 5 | 0.45 | n/a |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 9 | 3 | 3 | 4 | 3 | 4 | 0.55 | n/a |
| | 10 | 5 | 1 | 1 | 1 | 4 | 1.95 | 1 |
| | | | | | | | | |
| Student 4 | 1 | 5 | 5 | 5 | 5 | 4 | 0.45 | 4.5 |
| | 2 | 4 | 5 | 5 | 5 | 5 | 0.45 | 4.62 |
| | 3 | 5 | 5 | 5 | 5 | 4 | 0.45 | 5 |
| | 4 | 4 | 5 | 4 | 5 | 3 | 0.84 | 4.5 |
| | 5 | 5 | 5 | 5 | 5 | 5 | 0.00 | 4 |
| | 6 | 5 | 1 | 1 | 1 | 4 | 1.95 | 4 |
| | 7 | 5 | 5 | 5 | 5 | 4 | 0.45 | 4 |
| | 8 | 4 | 4 | 4 | 5 | 4 | 0.45 | n/a |
| | 9 | 4 | 4 | 5 | 4 | 4 | 0.45 | n/a |
| | 10 | 4 | 1 | 1 | 1 | 4 | 1.64 | 1 |

## 2. Accuracy of Claim (AOC) Values Calculated from Equation1

| SID | Question | E1_AOC | E2_AOC | E3_AOC | E4_AOC | E5_AOC |
|---|---|---|---|---|---|---|
| Student 1 | 1 | 0.77 | 0.46 | 0.77 | 0.85 | 0.77 |
| | 2 | 0.64 | 0.45 | 0.64 | 0.91 | 0.91 |
| | 3 | 0.83 | 0.83 | 0.75 | 0.75 | 0.83 |
| | 4 | 0.33 | 0.75 | 0.75 | 0.42 | 0.42 |
| | 5 | 0.67 | 0.67 | 0.67 | 1.00 | 0.67 |
| | 6 | 0.00 | 0.57 | 0.57 | 0.57 | 0.71 |
| | 7 | 0.67 | 0.67 | 0.67 | 1.00 | 0.67 |
| | 8 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | 9 | 0.93 | 0.93 | 0.71 | 0.93 | 0.93 |
| | 10 | 0.77 | 0.85 | 0.46 | 0.77 | 0.77 |
| | | | | | | |
| Student 2 | 1 | 0.79 | 0.95 | 0.95 | 0.95 | 0.95 |
| | 2 | 0.71 | 0.57 | 0.93 | 0.93 | 0.71 |
| | 3 | 0.75 | 0.00 | 0.75 | 0.75 | 0.75 |
| | 4 | 0.77 | 0.85 | 0.85 | 0.85 | 0.77 |
| | 5 | 0.75 | 0.94 | 0.94 | 0.94 | 0.94 |
| | 6 | 0.82 | 0.82 | 0.82 | 0.82 | 0.29 |
| | 7 | 0.36 | 0.93 | 0.57 | 0.93 | 0.93 |
| | 8 | 1.00 | 0.67 | 0.67 | 0.67 | 0.67 |
| | 9 | 0.45 | 0.45 | 0.64 | 0.18 | 0.91 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 10 | 0.00 | 0.75 | 0.33 | 0.33 | 0.42 |
| | | | | | | |
| Student 3 | 1 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | 2 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | 3 | 0.67 | 1.00 | 1.00 | 0.67 | 1.00 |
| | 4 | 0.89 | 0.89 | 0.56 | 0.89 | 0.89 |
| | 5 | 0.89 | 0.83 | 0.83 | 0.89 | 0.89 |
| | 6 | 0.00 | 0.46 | 0.46 | 0.46 | 0.38 |
| | 7 | 0.89 | 0.89 | 0.83 | 0.89 | 0.83 |
| | 8 | 0.95 | 0.79 | 0.95 | 0.95 | 0.95 |
| | 9 | 0.83 | 0.83 | 0.75 | 0.83 | 0.75 |
| | 10 | 0.00 | 0.46 | 0.46 | 0.46 | 0.38 |
| | | | | | | |
| Student 4 | 1 | 0.95 | 0.95 | 0.95 | 0.95 | 0.79 |
| | 2 | 0.79 | 0.95 | 0.95 | 0.95 | 0.95 |
| | 3 | 0.95 | 0.95 | 0.95 | 0.95 | 0.79 |
| | 4 | 0.94 | 0.75 | 0.94 | 0.75 | 0.63 |
| | 5 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| | 6 | 0.00 | 0.46 | 0.46 | 0.46 | 0.38 |
| | 7 | 0.95 | 0.95 | 0.95 | 0.95 | 0.79 |
| | 8 | 0.94 | 0.94 | 0.94 | 0.75 | 0.94 |
| | 9 | 0.94 | 0.94 | 0.75 | 0.94 | 0.94 |
| | 10 | 0.36 | 0.57 | 0.57 | 0.57 | 0.36 |

# 3. Number of Evidence Attached to the Claims

| SID | Question | E1_Enum | E2_Enum | E3_Enum | E4_Enum | E5_Enum |
|---|---|---|---|---|---|---|
| Student 1 | 1 | 3 | 3 | 11 | 9 | 5 |
| | 2 | 2 | 8 | 9 | 9 | 3 |
| | 3 | 2 | 3 | 2 | 3 | 2 |
| | 4 | 3 | 4 | 6 | 3 | 2 |
| | 5 | 1 | 3 | 3 | 1 | 2 |
| | 6 | 1 | 0 | 0 | 0 | 2 |
| | 7 | 1 | 1 | 2 | 3 | 2 |
| | 8 | 2 | 2 | 3 | 3 | 1 |
| | 9 | 1 | 1 | 1 | 1 | 1 |
| | 10 | 0 | 0 | 0 | 0 | 1 |
| | | | | | | |
| Student 2 | 1 | 3 | 4 | 9 | 7 | 1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 2 | 2 | 5 | 5 | 5 | 1 |
| | 3 | 2 | 2 | 2 | 2 | 1 |
| | 4 | 3 | 6 | 2 | 4 | 1 |
| | 5 | 1 | 3 | 2 | 3 | 2 |
| | 6 | 0 | 0 | 0 | 0 | 1 |
| | 7 | 1 | 1 | 2 | 1 | 1 |
| | 8 | 1 | 1 | 1 | 1 | 1 |
| | 9 | 1 | 1 | 1 | 1 | 1 |
| | 10 | 1 | 0 | 0 | 0 | 1 |
| | | | | | | |
| Student 3 | 1 | 1 | 8 | 9 | 6 | 1 |
| | 2 | 2 | 7 | 8 | 5 | 2 |
| | 3 | 2 | 6 | 3 | 2 | 1 |
| | 4 | 1 | 5 | 6 | 4 | 1 |
| | 5 | 1 | 2 | 5 | 3 | 2 |
| | 6 | 2 | 0 | 0 | 0 | 1 |
| | 7 | 0 | 2 | 1 | 1 | 1 |
| | 8 | 1 | 2 | 4 | 3 | 2 |
| | 9 | 1 | 1 | 1 | 1 | 1 |
| | 10 | 0 | 0 | 0 | 0 | 1 |
| | | | | | | |
| Student 4 | 1 | 1 | 6 | 8 | 4 | 1 |
| | 2 | 2 | 6 | 8 | 5 | 1 |
| | 3 | 1 | 3 | 2 | 1 | 2 |
| | 4 | 1 | 6 | 6 | 4 | 2 |
| | 5 | 0 | 2 | 5 | 2 | 2 |
| | 6 | 1 | 0 | 0 | 0 | 1 |
| | 7 | 1 | 2 | 1 | 1 | 1 |
| | 8 | 1 | 1 | 1 | 2 | 1 |
| | 9 | 1 | 1 | 1 | 1 | 1 |
| | 10 | 0 | 0 | 0 | 0 | 1 |

# 4. Relevance of Claim (Rc) Values Computed

| SID | Question | E1_Rc | E2_Rc | E3_Rc | E4_Rc | E5_Rc |
|---|---|---|---|---|---|---|
| Student 1 | 1 | 0.59 | 0.20 | 0.84 | 0.57 | 0.51 |
| | 2 | 0.67 | 1.00 | 1.00 | 0.96 | 0.77 |
| | 3 | 0.42 | 0.57 | 0.62 | 0.49 | 0.28 |
| | 4 | 0.57 | 0.43 | 0.48 | 0.44 | 0.37 |
| | 5 | 0.18 | 0.63 | 0.37 | 0.28 | 0.45 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 6 | 0.07 | 0.00 | 0.00 | 0.00 | 0.18 |
| | 7 | 0.13 | 0.34 | 0.54 | 0.47 | 0.47 |
| | 8 | 0.56 | 0.56 | 0.57 | 0.56 | 0.54 |
| | 9 | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 |
| | 10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.14 |
| | | | | | | |
| Student 2 | 1 | 0.49 | 0.29 | 0.76 | 0.78 | 0.09 |
| | 2 | 0.70 | 0.92 | 0.90 | 0.90 | 0.55 |
| | 3 | 0.49 | 0.21 | 0.49 | 0.41 | 0.35 |
| | 4 | 0.19 | 0.30 | 0.51 | 0.11 | 0.29 |
| | 5 | 0.09 | 0.53 | 0.54 | 0.44 | 0.47 |
| | 6 | 0.00 | 0.00 | 0.00 | 0.00 | 0.12 |
| | 7 | 0.07 | 0.35 | 0.35 | 0.42 | 0.35 |
| | 8 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 |
| | 9 | 0.58 | 0.58 | 0.58 | 0.58 | 0.58 |
| | 10 | 0.15 | 0.00 | 0.00 | 0.00 | 0.15 |
| | | | | | | |
| Student 3 | 1 | 0.27 | 0.87 | 0.68 | 0.93 | 0.18 |
| | 2 | 0.43 | 0.98 | 0.87 | 0.99 | 0.51 |
| | 3 | 0.19 | 0.69 | 0.26 | 0.41 | 0.15 |
| | 4 | 0.18 | 0.72 | 0.35 | 0.60 | 0.22 |
| | 5 | 0.29 | 0.42 | 0.38 | 0.39 | 0.47 |
| | 6 | 0.07 | 0.00 | 0.00 | 0.00 | 0.09 |
| | 7 | 0.00 | 0.23 | 0.09 | 0.09 | 0.13 |
| | 8 | 0.43 | 0.46 | 0.47 | 0.50 | 0.46 |
| | 9 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 |
| | 10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.11 |
| | | | | | | |
| Student 4 | 1 | 0.30 | 0.57 | 0.31 | 0.51 | 0.10 |
| | 2 | 0.52 | 0.89 | 0.42 | 0.90 | 0.47 |
| | 3 | 0.14 | 0.50 | 0.30 | 0.21 | 0.38 |
| | 4 | 0.10 | 0.59 | 0.42 | 0.44 | 0.35 |
| | 5 | 0.00 | 0.42 | 0.19 | 0.49 | 0.42 |
| | 6 | 0.04 | 0.00 | 0.00 | 0.00 | 0.10 |
| | 7 | 0.30 | 0.37 | 0.30 | 0.30 | 0.07 |
| | 8 | 0.47 | 0.47 | 0.49 | 0.01 | 0.47 |
| | 9 | 0.50 | 0.50 | 0.50 | 0.50 | 0.50 |
| | 10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.12 |

## 5. Clarity of the Concept/Question

| QID | Content | Clarity Value |
|---|---|---|
| 1 | Define Variables/Methods/Classes | 0.9 |
| 2 | Method parameters/Return statement | 0.8 |
| 3 | Constructors | 0.75 |
| 4 | Control Structures | 0.7 |
| 5 | Object Concept | 0.85 |
| 6 | Nested Object | 0.5 |
| 7 | Complex object(or class with multiple data types) | 0.8 |
| 8 | Simple Arrays/Vectors | 0.9 |
| 9 | Search and sort array/vector | 0.75 |
| 10 | Concept of Abstract Data Type | 0.5 |

## 6. Detail Numbers of Each Evidence Attached to Question 1 to 10 by All Five Experts

| ARTI_ID | DESC | Count | Percentage | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Assignment1 | 17 | 3.79 | 12 | 2 | 1 | 1 | 1 | | | | | |
| 2 | Assignment2 | 23 | 5.13 | 13 | 1 | | 9 | | | | | | |
| 2.1 | Assignment2Feedback | 1 | 0.22 | | | | 1 | | | | | | |
| 3 | Assignment3 | 35 | 7.81 | 10 | 13 | | 11 | 1 | | | | | |
| 3.1 | Assignment3Feedback | 3 | 0.67 | 1 | 2 | | | | | | | | |
| 3.2 | Assignment3Self-Comment | 4 | 0.89 | 2 | 2 | | | | | | | | |
| 4 | Assignment4 | 60 | 13.39 | 11 | 13 | 12 | 10 | 8 | | 6 | | | |
| 4.1 | Assignment4Feedback | 1 | 0.22 | | 1 | | | | | | | | |
| 4.2 | Assignment4Self-Comment | 1 | 0.22 | | 1 | | | | | | | | |
| 5 | Assignment5 | 61 | 13.62 | 11 | 5 | 9 | 11 | 11 | 4 | 8 | 2 | | |
| 5.1 | Assignment5Feedback | 2 | 0.45 | | | 1 | | | 1 | | | | |
| 6 | Quiz1 | 8 | 1.79 | 5 | 3 | | | | | | | | |
| 7 | Quiz2 | 16 | 3.57 | 4 | 10 | 1 | | 1 | | | | | |
| 7.1 | Quiz2Self-Comment | 2 | 0.45 | 1 | 1 | | | | | | | | |
| 8 | Quiz3 | 13 | 2.90 | 3 | 8 | | | 2 | | | | | |
| 9 | Quiz4 | 8 | 1.79 | | | | | | | | 8 | | |
| 9.1 | Quiz4Self-Comment | 1 | 0.22 | | | | | | | | 1 | | |
| 10 | Mid-termExam | 43 | 9.60 | 7 | 13 | 8 | 7 | 8 | | | | | |
| 11 | LabExam | 23 | 5.13 | 8 | 1 | | 10 | | | | 4 | | |
| 12 | FinalExam | 126 | 28.13 | 12 | 19 | 12 | 10 | 13 | 4 | 12 | 19 | 20 | 5 |
| total: | | 448 | 100 | | | | | | | | | | |

# 7. Statistical Analysis

Statistical analysis helps in validating the meanings of collected data (knowledge level, time spent, browsing activities), and in measuring the accuracy of the generated learner model. Inter-rater reliability is used to estimate the consistency reliability of the data across five expert participants. The T-test is used for assessing the significance of the difference between an expert's judgment and the student's own. Curve fitting testing helps estimate the regression statistic and finding a suitable regression model. The linear regression model is chosen in the data analysis process that is presented in Chapter 4.

## 7.1 Inter-rater Reliability

There are several different strategies for estimating internal consistency reliability. The most familiar are the split-half adjusted (i.e., adjusted using the Spearman-Brown prophecy formula), Kuder-Richardson formulas 20 and 21 (also known as K-R20 and K-R21) [Kuder, 1937], and Cronbach alpha [Cronbach, 1970].

The most frequently reported internal consistency estimates are the K-R20 and Cronbach alpha, Cronbach alpha is more flexible than K-R20 and is often the appropriate reliability estimate for language test development projects and language testing research [Brown, 2002]. Cronbach's alpha can be interpreted as the percent of variance the observed scale would explain in the hypothetical true scale composed of all possible items in the universe. Alternatively, it can be interpreted as the correlation of the observed scale with all possible other scales measuring the same thing and using the same number of items [Landis, 1977]. Put more simply, Cronbach alpha is used to estimate the proportion of variance that is systematic or consistent in a set of test scores. It can range from 0 (if no variance is consistent) to 1 (if all variance is consistent) with all values between 0 and 1 also being possible. For example, if the Cronbach alpha for a set of scores turns out to be .80, one can interpret that as meaning that the test is 80% reliable, and by extension that it is 20% unreliable. By convention, a lenient cut-off of .60 is common in exploratory research; alpha should be at least .70 or higher to retain an item in an "adequate" scale; and many researchers require a cut-off of .80 for a "good scale" [Landis, 1977].

## 7.2 T-Test

The t-test assesses whether the means of two groups are statistically different from each other. This analysis is appropriate whenever you want to compare the means of two groups. The formula for the t-test is a ratio of the difference between the two means or averages divided by a measure of the variability or dispersion of the scores. The t-value will be positive if the first mean is larger than the second and negative if it is smaller. The t-value needs to be large enough to say that the difference between the groups is not likely to have been a chance finding. To test the significance, a risk level, called the alpha level, needs to be set. In most social research, the "rule of thumb" is to set the alpha level at .05. This means that five times out of a hundred you would find a statistically significant difference between the means even if there was none (i.e., by "chance"). Another factor is the degrees of freedom (df) for the test. In the t-test, the df is the sum of the persons in both groups minus 2. Given the alpha level, the df, and the t-value, one can look the t-value up in a standard table of significance to determine whether the t-value is large enough to be significant. If it is, one can conclude that the difference between the means for the two groups is different (even given the variability). The Paired-Samples T Test procedure compares the means of two variables for a single group. The procedure computes the differences between values of the two variables for each case and tests whether the average differs from 0.

## 7.3 Curve Estimation

The Curve Estimation procedure produces curve estimation regression statistics and related plots for different curve estimation regression models available in the application (e.g. SPSS). A separate model is produced for each dependent variable. Significance values and R-Square values can be used to compare more than one curve estimation regression models and determine which model to use. Generally the variation by each model can be explained not due to chance if the significance value of the F statistic is less than 0.05. The R-Square statistic is a measure of the strength of association between the observed and model-predicted values of the dependent variable. The large R-Square values indicate strong relationships for both models. The curve estimation method is helpful in choosing the best model based on a group of dependant variables and a group of independent variables.

## 7.4 Linear Regression Analysis

Linear Regression estimates the coefficients of the linear equation, involving one or more independent variables that best predict the value of the dependent variable. For example, it can be used to predict a salesperson's total yearly sales (the dependent variable) from independent variables such as age, education, and years of experience. In general, the goal of linear regression is to find the line that best predicts Y from X. Linear regression does this by finding the line that minimizes the sum of the squares of the vertical distances of the points from the line. Linear regression does not test whether the data are linear (except via the runs test). It assumes that the data are linear, and finds the slope and intercept that make a straight line best fit the data.