# A Framework for Supporting e-Learning with Intelligent Features

## Abstract

In part 1, a proposed adaptive e-Learning model utilized different information systems for different e-Learning functionalities. In this paper, intelligent techniques are presented to empower the proposed adaptive e-Learning model. This paper presents nine intelligent services that can be utilized in different e-Learning systems. Presented intelligent services are categorized into three categories based on their aim to be: Instructor services, student services, and general services. Proposed services are considered a new motivation into utilizing intelligent techniques in the learning process. General services category include the Intelligent LO Classifier service. Instructor intelligent services are: Intelligent Time-to-Learn Topic Calculator, Intelligent Study Plan Advisor, Intelligent Online Lecture LOs Advisor, Intelligent Student Performance Tracker, and Intelligent Cheating Depressor. Student intelligent services are: Intelligent Agenda Study Time Planner, Intelligent Meeting Manager for Suspended Students, and Intelligent LOs Recommender. Intelligent Online Lecture LOs Advisor enables what is called Adaptive Online Lecture Model that presents different pedagogical aspects via: recommending the most suitable learning materials for students based on their learning profiles and preferences, involving students in the learning process from the very early beginning of the lecture, and preparing for the next/upcoming lecture, so students feel the personalization and customization of the lecture, and hopefully this model enhances the learning process and students’ online learning experience.

**Keywords:** Adaptive Online Lecture, Intelligent e-Learning Framework, Student Profiles, Group Learning, Intelligent Recommender, Supervised e-Learning

## Introduction

This paper focuses on utilizing intelligent technologies innovatively in e-Learning systems. Three different learning models are: traditional, distance, and blended learning. Depending on the type of learning provided in the educational institution, different scenarios for utilizing intelligent techniques can be presented. Adaptive and intelligent Curriculum sequencing for example has been widely discussed in research, and presented in some cases. Also personalized learning paths have been under research for a while. However, there are always doubts in students’ capabilities and abilities in identifying their learning path, and also in intelligent systems capability to identify personalized learning paths without the need for instructors to fine tune the learning process. Besides, group learning is a necessity.

Our proposed model utilizes different intelligent techniques and methods in empowering e-Learning with different intelligent services to form a proposed framework for supporting e-Learning with intelligent features. One of the main services supported by our framework is supervised intelligent curriculum sequencing to present adaptive e-Learning that is fine-tuned by instructor. Figure 1 presents the three proposed intelligent services’ classes. Characteristics of our proposed blended e-Learning model:

* Students are grouped. Each group is delimited by the same start date. Student who don’t catch this start date, are delayed to the next group which is 15 days later.
* Learning goals are identified by instructors. Based on those learning goals, instructors define learning paths. Instructors can make use of proposed Intelligent Study Plan Advisor Service. In this phase intelligent service is only advisory for the instructor.
* Intelligent Time-to-Learn Topic Calculator is the service that is used to advise instructor about the time needed for this group of students to study certain topic. Based on this group of students study time of previous topics, and the available Los for this topic, this service can intelligently advise instructor about study time issues.
* Students attend one or more adaptive online lecture within the same learning goal. Adaptive online lecture make use of the intelligent adaptive online lecture LOs advisor to recommend LOs for the instructor to use during the lecture based on students learning profiles.
* Intelligent Los recommender is the intelligent service that will recommend Los for students based on their learning profiles. Recommended Los list is approved by instructor. Recommended Los list is then reordered based on students’ preferences.
* Intelligent agenda study time planner is used to help students organize their time table and organize different activities. This agenda doesn’t just identify study times; however it also considers time for activities.
* Intelligent Student Tracker is the service used to track student performance during the online learning journey. Peaks in students’ performance need to be recorded and studied. Also, performance degradation needs to be recorded and studied.
* Learning path is marked by different learning checkpoints. At each checkpoint, students attend an online exam. Students who pass will continue the learning path, but those who don’t will re-attend the exam within 4 days. If they don’t pass again, they re-attend the exam within 2 days. If they don’t pass, they are suspended.
* Intelligent Cheat Depressor Service focus on utilizing intelligent techniques in prohibiting students from cheating. When combining both Intelligent Student Tracking Service, and Intelligent Cheat Depressor Service, combined with forecasting of students’ scores in coming exams, cheating can be identified. Different cheating prohibition mechanisms are presented in this paper.
* Suspended students drop behind their group. Intelligent meeting manager for suspended students is the service responsible for managing a meeting between an instructor and the suspended student to handle the learning issues that is preventing this student from coping with her/his group.

Figure : Different Proposed Intelligent e-Learning Services

## General Intelligent Services

This category includes services that can be utilized by both instructors and students. Based on the recent analysis of our proposed adaptive e-Learning model, this category includes the Intelligent LO Classifier. Different intelligent techniques can be utilized in classifying LO based on LO type. Classifying multimedia-based LOs can be ease via meta-data access. Different standards for LOs metadata are available, however the most widely accepted standard is SCORM (Rosen, 2009). SCORM 2004 4th edition is the latest SCORM standard specification, issued in June 2008 (ADL Press Release). Figure 2 presents an overall mapping from SCORM 2004 to relational database tables. Figures 3,4,5,6,7,8,9 presents SCORM 2004 closer looks on database tables. Figure 3 presents General Category tables that stores the general information that describes the resource as a whole. Figure 4 presents Classification category tables. Classification category describes where the SCORM Content Model Component falls within a particular classification system. Multiple Classification categories may be used to define multiple classifications. The Classification category is typically used to link to a controlled vocabulary or classification system. Figure 5 presents educational category specifications for each LO. The Educational category describes the key educational or pedagogic characteristics of the SCORM Content Model Component. This category allows for the description of the educational characteristics and is typically used by teachers, managers, authors and learners. Figure 6 presents lifecycle status of LO that groups the features related to the history and current state of the SCORM Content Model Component and those who have affected the component during its evolution. Figure 7 focuses on Meta-metadata category. Meta-metadata provides elements that describe the metadata record itself and not the SCORM Content Model Component the record is describing. This category describes how the metadata instance itself can be identified, who created the metadata instance, how, when and with what references. Figure 8 illustrates Technical category. The Technical category describes all of the technical characteristics and requirements of the SCORM Content Model Component. Figure 9 presents other table categories that are not part of the classification process in our proposed model. More details about SCORM specifications are available at ADL.

Text based LOs can be classified / categorized via the same algorithms used in document classification. Document classification is a problem in information science that focuses on the task of assigning an electronic document to one or more categories/classes, based on its contents. Text classification or categorization is the process of organizing information logically. It can be used in many fields such as document retrieval, routing, and clustering. The document classifier is used for classifying documents based on category (Kang, 2005). Document classification tasks can be divided into two sorts: supervised document classification where some external mechanism (such as human feedback) provides information on the correct classification for documents, and unsupervised document classification, where the classification must be done entirely without reference to external information (MOLE, 1999). There is also a semi-supervised document classification, where parts of the documents are labeled by the external mechanism.

Figure 10 presents Intelligent Document Classifier Class Diagram. Presented document classifier implements two of the Supervised Document Classification algorithms: Naive Bayes Classifier, and Term Frequency - Inverse Document Frequency (TF-IDF). Different document classification algorithms can be utilized and presented.

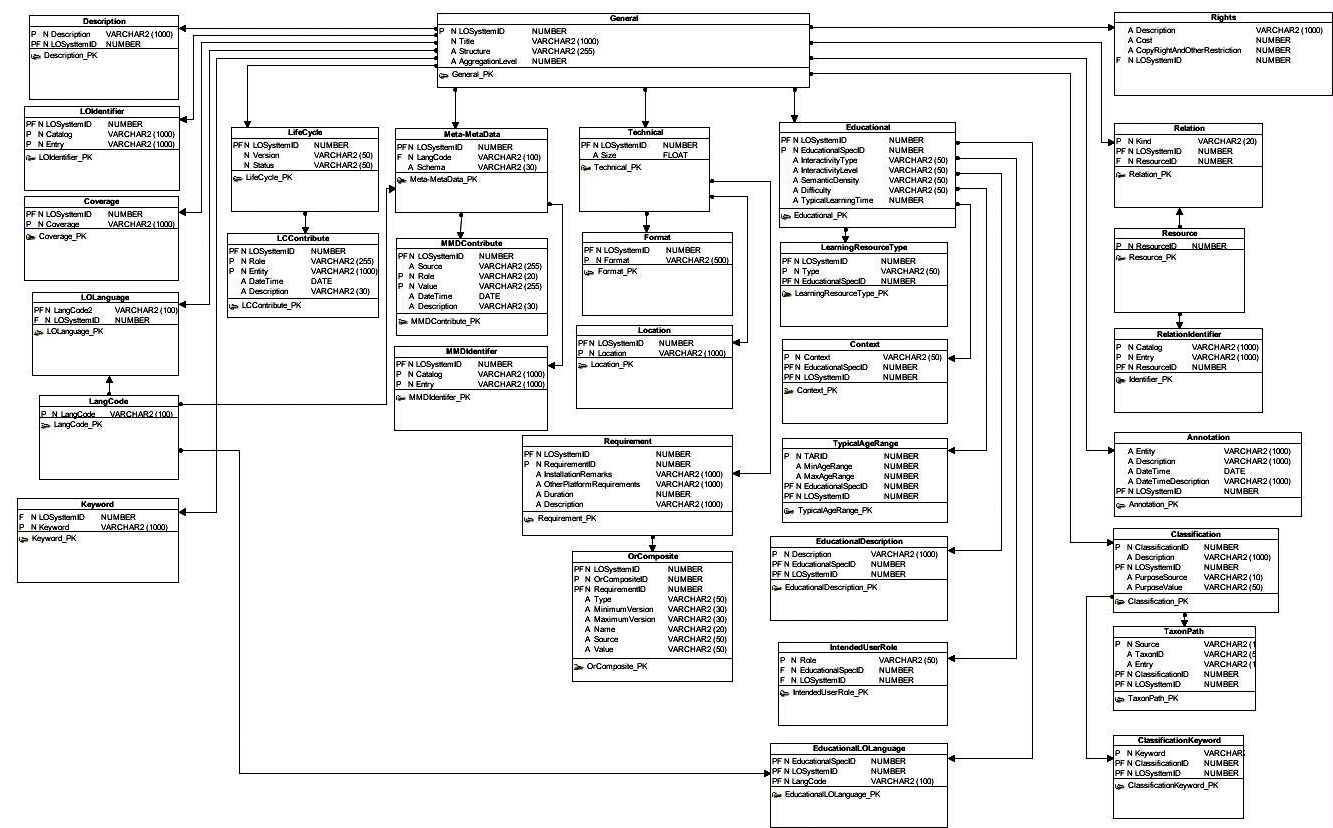


Figure : Complete SCORM - Relational Tables Mapping



Figure : LO SCORM Tables - General Category



Figure : LO SCORM Tables - Classification Category



Figure : LO SCORM Tables - Educational Category



Figure : LO SCORM Tables - Lifecycle Category



Figure : LO SCORM Tables - Meta-metadata Category



Figure : LO SCORM Tables - Technical Category



Figure : LO SCORM Tables - Other Category



Figure : Document Classifier Class Diagram

## Instructor Intelligent Services

Intelligent services aimed to help instructor through teaching are: intelligent time to learn topic calculator, intelligent study plan advisor, and intelligent adaptive online lecture Los advisor.

### Intelligent Study Plan Advisor

Intelligent study plan advisor is an intelligent advisory service used by instructor to help her/him identify points of strength and weakness in older study plan, and to identify different study plans for elder groups, so they can be used in recommending a study plan for current group. Students differ in their learning behavior and learning preferences. Intelligent study plan advisor service considers different students classes based on their learning preferences. Intelligent study plan advisor can be used in enhancing the Los repository content by being able to identify learning topics that don’t have efficient Los for different student classes. Table 1 presents intelligent study plan advisor specifications and figure 1 presents the detailed flow chart.

Table : Intelligent Study Plan Advisor Service Specifications

|  |  |
| --- | --- |
| Input | |
| Student Preferences | Proposed Model stores different learning preferences that identify student learning behavior. Those preferences are considered for identifying different study plans. |
| Learning Class | Students are grouped into Classes to ease some educational tasks. Classes include: Auditory, Visual, and other classes that are discussed in detail in Learning Profile section. |
| Related Los Specifications | Los satisfy students’ classes by percentage. The higher Los available that matches students’ preferences, the higher recommended this topic for teaching. |
| Study Plans for Previous Students | Instructor might need to take a closer look on previous instructor plans, grades that students scored by following certain plans, and other data. |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Summary Report | Recommended Study plan for current study group. |

### Intelligent Time-to-Learn Topic Calculator

Intelligent time to learn topic calculator is an intelligent service that provides an important adaptive feature to the proposed model. Each topic is the summation of Los for this topic. Instructors define learning time for each LO. By tracking different students’ learning progress, system can identify learning time shift between instructor identified learning time and the time student consumes learning. This time shift for current students and for elder group students is used in helping instructor identifying the time required for student to learn some topic. This time can help instructor during planning the course. Table 2 presents the intelligent time to learn topic calculator specifications and figure 2 depicts a detailed flow chart.

Table : Intelligent Time To Learn Topic Calculator Specifications

|  |  |
| --- | --- |
| Input | |
| Instructor Defined Learning Time | LO author defines learning time for each LO. This time is used as the standard time required for learning. Later, different instructors can identify learning times for the same LO. |
| Student Learning Time Shift | Tracking student learning progress helped the system to calculate the time to learn shift between the defined time and the student actual time to learn. Group consists of different students, average time to learn calculator will be presented. |
| Previous Groups Time To Learn Topic | Elder groups time to learn the same topic is used as an input in the calculation process |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Time To Learn Topic | Time estimation for current group to learn certain topic. |



Figure : Intelligent Study Plan Advisor Flowchart



Figure : Intelligent Time-to-Learn Topic Calculator Flowchart

### Intelligent Online Lecture Los Advisor

The need for conducting and attending lectures in learning is clear for both students and instructors, and can be managed effectively and efficiently when both exist in the same place and on the same time; “Traditional Learning Model”. Situation differs when students and instructors are experiencing either time and/or place differences/distances. Here comes “e-Learning” as the solution. Online meetings as a technology facilitate this objective by presenting the required audio and video communications between instructor and students side by side with the capability to share presentations, desktop activities, and transfer files. Different online meetings software and applications; in both Web and desktop forms are available, however their design and implementation was not aimed in the first place to be used for online lectures. Despite the tremendous advancement in technology that is witnessed by those applications, they still lack certain level of feedback from students to instructors that pushes students into more engagement within the learning process. Intelligent adaptive online lecture Los advisor accesses student profiles and learning preferences side by side with data from previous online lectures and course specification data. This service provides instructor with a recommended list of Los based on attending students. This list can be used during the lecture. Table 3 presents intelligent adaptive online lecture Los advisor specifications and figure 4 presents its detailed flowchart.

Table : Intelligent Adaptive Online Lecture LOs Advisor Specifications

|  |  |
| --- | --- |
| Input | |
| Student Preferences | Proposed Model stores different learning preferences that identify student learning behavior. Those preferences are considered for identifying different study plans. |
| Related Los Specifications | Los satisfy students’ classes by percentage. The higher Los available that matches students’ preferences, the higher recommended this topic for teaching. |
| Learning Topics Data | Proposed Model stores data about courses and topics to be pedagogically used in learning scenarios. |
| Previous Adaptive Online Lectures Data | Los that previous instructors used during online lectures for the same topic, and students feedback for those Los are important data for this recommendation process. |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Summary Report | Instructor can use this report for identifying strength and weakness points of utilizing certain LOs |

Preparing lecture is one of the instructor’s responsibilities that can be enhanced via utilizing new technologies. Different types of learning objects (LOs) media and formats exist, and the Web has turned into an open source for knowledge and sharing. While instructor has access to an enormous diversity of LOs, recommending LO over another can be helpful for instructor. This recommendation process needs to take place before the lecture “while instructor is preparing the lecture” based on students’ learning profiles and preferences, thus students becomes more attached to the lecture.

Engaging students in the lecture activities will enhance students learning experience. Technically, this is available via extensive utilization of technologies that exist nowadays. During the online lecture, students are encouraged to give continuous informal feedback about different lecture activities via the same Web 2.0 technologies they are used to. This feedback can be studied and analyzed later by instructor, and used as an indicator on how the lecture was moving, then utilized in enhancing the upcoming lectures. Formal feedback request can be initiated by instructor from time to time to test certain points that instructor needs to assure about; as a “check point” before moving on with the next lecture. Involving students in different assignments and activities during the lecture is welcomed, and needs to be recorded in students learning profiles.

Finally, preparing for the next/upcoming lecture is not only instructor’s responsibility. Pedagogically, instructor is supposed to define the upcoming lecture topics, and pre-requisites for learning those topics. Technically, LMS is supposed to check student’s learning profile and preferences to define to what extent student is familiar with those topics or not, then recommending the learning materials for student. It is student’s responsibility to study and examine those learning materials before next lecture.

### Phase One: Preparing the Lecture

Students' learning models are not the same, and that shall be considered while preparing and choosing the contents to be displayed during Online Lecture. In order not to lose student during the lecture, types of contents shall be mapped with both their direct feedback and learning profiles. Figure 13 presents the different activities required to fulfill this process.



Figure 3: Recommend LOs for Instructor based on Analysis of Learning Profiles Process

### Phase Two: During Online Lecture

Proposed Adaptive Online Lecture Model attempts to address different lecture aspects that are not available in current Video Conference Model. Those aspects are: Order of Contents, Assessments, and Assignments and Collaborative activities.

* **Order of Contents:** Displaying the video file before talking about it, or after talking about it or twice in the lecture is one of the decisions that instructors might not pay much attention to while it is important in keeping students focused on lecture activities. If students’ are given some capability to re-order the contents’ display and discussions, they will feel the personalization of the Online Lecture, and so deeply get involved in the lecture.
* **Assessments:** Instructors might need to conduct one of the on-the-fly assessments to ensure that students have reached a basic level of knowledge regarding one of the topics s/he was just talking about before moving to the next topic.
* **Assignments and Collaboration:** Students attending online lectures are already connected to the Internet via their laptops, have accounts on multiple Web 2.0 collaboration tools providers; like Microsoft and Google, so they can easily transform to those tools based on instructor’s directions. Their collaborative work can be marked, and discussed online as if they are in a traditional lecture.

Figure 14 presents the proposed Activity Diagram of the During Lecture activities that will allow students to submit informal feedback during the lecture. This feedback will be analyzed later by the instructor.



Figure 14: Formal and Informal Feedback Processes Synchronization during Lecture

### Phase Three: Upcoming Lecture

Identifying Next Lecture Topics based on Students' Learning Profiles and Feedback is one of the proposed Adaptive Online Lecture Model activities. Before Students leave current lecture, instructors shall ensure that they are familiar with the prerequisites of the upcoming lecture. Proposed Adaptive Online Lecture can facilitate so by conducting assessments from students and ask them clearly about the prerequisites. Besides, Proposed Adaptive Online Lecture Model is part of the learning institution and an important piece of enhancing the learning process. So, Proposed Adaptive Online Lecture Model can access the Student Profile and Online Preferences for data about their previous attended sessions, courses, specifications, and other details. In case one of the students doesn't satisfy requirements defined by instructor, a personalized content can be generated for that student via Intelligent Learning Objects (LOs) Recommender, and Student's interaction with those materials is tracked. Figure 15 presents the different system’s activities to support the adaptive LOs recommendation.



Figure 15: Recommend LOs for Students based on Upcoming Lecture Topics and their Preferences

Figure 16 presents a proposed IT architecture to support proposed adaptive online lecture model. Educational institutions differentiate between different components required to support the learning process, and are familiar with some technologies like UMIS and LMS. IT Architecture includes the following servers list:

* **Firewall:** The system’s entry point and responsible for providing security functions.
* **Active Directory (LDAP):** A Single Log-in point for the entire system. Helps avoid the repeated Log-in process between different applications and servers.
* **Collaboration, Assessments, and Assignments:** Main components of the Learning Process that are maintained separately to provide greater flexibility and the ability to utilize different technologies.
* **Students Data, Student Preferences, Learning Profiles:** Main asset of LMS that maintains students’ data to be utilized by different applications. Adaptive Online Lecture Model relies heavily on those data to present personalized recommendations.
* **Course Specifications and Instructors Data:** Data about Instructors and Courses are stored to enable automation of the communications between Course Management Systems (CMSs) and Recommenders.
* **Real-time Communication Server:** Responsible for providing communications functionalities between instructors and students, and students and each other. Manages Online Lecture file, desktop, text sharing, other activities, and Web 2.0 technologies that will be utilized in the Informal Feedback.
* **Analyzer and Report Generator:** Responsible for analyzing gathered data and generating appropriate reports that help instructors take the appropriate decision.
* **Middleware:** Responsible for managing Quality of Service (QoS) and directing messages between different components of the systems.



Figure 16: Proposed Adaptive Online Lecture Model IT Architecture

### Intelligent Student Tracker Service

Three different learning profiles will be available for each student:

1. General
2. Felder
3. ATLAS
4. Brain Works

#### General Learning Profile Manager

During registration and profile completion process, students are asked to complete their general learning preferences features. Incase student chooses more than one style, s/he is asked to rank her/his choice, so recommendation can define to what extent it is fulfilling student’s requirements. General Learning Profile Preferences are:

* Visual
* Auditory
* Tactile
* Logical
* Social
* Solitary



Figure : General Learning Profile Manager DB Tables

**Consumed Services:** Students Manager

#### Felder Learning Model

Felder learning model can be identified by promoting student to answer questions that help identify students’ learning preferences. Though Felder identifies that student is middle between different models, Felder model can help system identify student learning features, and prepare the most appropriate learning environment. Felder learning model categories are:

* Active and Reflective
* Sensing and Intuitive
* Visual and Verbal
* Sequential and Global



Figure : Felder Learning Model DB Tables

**Consumed Modules:** Calculate FelderCategoryRelevance

**Consumed Services:** Students Manager

#### ATLAS Learning Model

ATLAS learning model can be identified by promoting student to answer questions that help identify students’ learning preferences. ATLAS learning model categories are:

* Navigator
* Problem Solver
* Engager



Figure : ATLAS Learning Model DB Tables

**Consumed Modules:** Calculate ATLASCategoryRelevance

**Consumed Services:** Students Manager

#### Brain Works Learning Model

Brain Works learning model can be identified by promoting student to answer questions that help identify students’ learning preferences. Brain Works learning model categories are:

* Visual vs. Auditory
* Left vs. Right Brain Hemisphere



Figure : Brain Works Learning Model DB Tables

**Consumed Modules:** Calculate BrainWorksCategoryRelevance

**Consumed Services:** Students Manager

### Intelligent Cheat Depressor Service

One of the courses currently taught in Faculty of Computers and Information Sciences in Mansoura city University of Egypt (<http://csimu.mans.edu.eg>) in academic year 2008/2009 is “Information Systems Analysis and Design”. This course utilizes different features of learning and e-Learning activities. One of the utilized e-Learning activities is “Online Assessments”. Though Online Assessments is not the only criteria to qualify students, it is still an important feature to be activated because of the many advantages of enhancing learning experience, automated assessments marking, assessments and assessments’ items analysis, and students’ profiles features. However, one of the problems that prevent us from gaining advantages of online assessments is “Leak of Assessments”. Students search the WWW for assessments’ questions and answers, and unfortunately they can easily find them. Screenshots of questions, answers, final grade of those answers, and attendance date of assessment are the data available as search results. Of course it is students’ choice to follow those answers or not. No matter how close you are; as an instructor, to students, they will not confess “cheating”. Online assessments are not conducted in a secure and supervised environment in the Faculty. Argues that Distance Learning is based on providing different activities for away students convinced some professors to give students online assessments from home, typically as the case with distance learning students. During my analysis of the “First Assessment” and “Second Assessment” results, some facts became clear to me. One of the results that forced me to analyse assessments data was the noticeable number of students who finished the assessment in less than 10 minutes and acquired more than 30 out of 50 as a mark. Both assessments consist of 50 True/False questions. Those questions are very well prepared; some of them are available via the resources available from the book author(s), and the rest are prepared internally. It was shocking to find that number of students with high grades in an almost “not enough time to read the questions” is high. Luckily students do not know that the system records start-time, end-time, and can easily calculate duration or they would have spent longer times just pretending to be solving the assessment.

### 3.5.1 Problem Domain Analysis

This study holds the analysis results of first assessment; which is not so far different from second one. Figure 1 presents the percentage of students with variant assessment completion times. There are 223 students enrolled in this course with 209 online active users. Number of students attended the first assessment is 182.

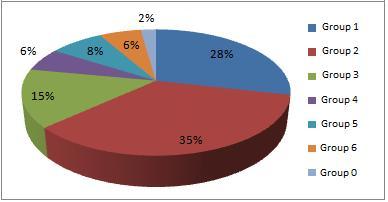


Figure 1: Percentage of Students Per Assessment Time

Students can be classified into 7 groups based on the assessment time as presented in table 1. The strange notice was that almost 2/3 of the students conducted the assessment in less than 20 min. and that indicates an alarm.

Table 1: Different Students Groups in this Study

|  |  |
| --- | --- |
| Group 1 | Students conducted the assessment in duration between 0 and 10 min. |
| Group 2 | Students conducted the assessment in duration between 10 and 20 min. |
| Group 3 | Students conducted the assessment in duration between 20 and 30 min. |
| Group 4 | Students conducted the assessment in duration between 30 and 40 min. |
| Group 5 | Students conducted the assessment in duration between 40 and 50 min. |
| Group 6 | Students conducted the assessment in duration between 50 and 60 min. |
| Group 0 | Students started but did not complete the assessment and will not be mentioned anymore in this study |

To verify the situation, the marks average of each group was calculated and again the results clearly indicate something that is not as “planned to be” situation. Figure 2 depicts the average of the six different groups with the notice that averages are almost the same. That means there are students who solved the assessment in less than 10 min. with marks close to; and may exceed sometimes, those who solved it in almost an hour.

Figure 2: Bar Graph of Marks Average Per Different Student Groups

To be sure about the grading issue, further analysis to the results was applied with the result that: no. of students from all groups who scored between 0 and 10 out of 50 is (zero), no. of students from all groups who scored between 10 and 20 is only (one). Figure 3 shows the different counts of different groups for marks between 20 and 30. Figure 4 and figure 5 shows the different number of students with marks between 30 and 40, and 40 and 50 respectively.

Figure 3: Bar Graph of No. of Students Achieving Grade Range from 20 to 30 Categorized by Group

Figure 4: Bar Graph of No. of Students Achieving Grade Range from 30 to 40 Categorized by Group

Figure 5: Bar Graph of No. of Students Achieving Grade Range from 40 to 50 Categorized by Group

### 3.5.2 Comments on Results

Here are some cheating tips I have witnessed myself or through students’ monitoring and feedback:

* **Access to Answers’ Files:** Open the pdf or document file of the assessment, search for keywords, and immediately apply answers. Most students have high memorable capabilities regarding mapping questions and answers.
* **Collaborative Solution:** Though collaboration is really important in the learning process, but this way of collaboration to cheat was really new to me. More than one student conducts the assessment. One holds the laptop, others hold different pages of the assessment answers; so they optimize the search time, and the one holding the laptop says the question loudly and of course students can find answers within no time. Of course in Non-Supervised e-Learning environment, there is no way to guarantee that students themselves attended the assessment.

Two categories of Students must not be neglected to assure certain learning quality level:

* **Careless Students:** They don’t really need to read the assessment questions. They only pick an answer and they don’t care about the results. There are students who answered 50 questions in less than 3 minutes, which gives them an average reading of 3.6 seconds for each question. Another form of careless was presented in the 4 students (out of 182 that is almost 2%) who did not finalize the assessment though they started it.
* **Not Interested Students:** Almost 23% of the course enrolled students (41 students out of total 223 students) did not attend any of the e-Learning activities. This percentage is huge, and in our course it is not acceptable at all. However, motivating students to attend   
  e-Learning activities is always a challenge.

### 3.5.3 Proposed Solution

Based on results presented in the introduction section, it is clear that there are issues that shall be considered before providing students with online exams. There must be a stronger way of controlling the Exam process; in order to make marks more trustable. Proposed Solution tips to this issue are many. More studies about efficiency and effectiveness of each one needs to be conducted and further analyzed and studied. Those actions can be categorized into two categories: educational and technical solutions. Solution include: Pedagogical and Technical aspects.

### 3.5.3.1 Pedagogical Proposed Solution Aspects

Educational Solutions include the attempt to present an unlimited Assessment Items Repository, and to track student progress during the learning process, so peaks can be determined and they might be a mark for inappropriate activity during the learning process. Also, a timed question is almost a must in the exam process. Timer shall not only start after the student sees the question, we are thinking about calculating time for both displaying and solving the question, so theoretically, students shall never find time to cheat.

This study proposes some tips that can be used as solutions that focuses on four aspects of the online assessment process and can be thought of as the integration of the four of them:

* **Questions Based Solution:** Assessments banks should consist from larger no. of questions with the chance to have ¼ or 1/3 of the assessment different for each student than others. Also, instructors shall work on updating assessments’ banks and keeping it out of student reach.
* **Environment Based Solution:** This solution is complimentary to the aforementioned suggested one. Supervised e-Learning environments are important and simply they are the only way to guarantee certain accepted level of learning quality. Students can find the time to search the answer files because they simply have the access to them. Hopefully when students don’t have access to such files, they might learn better.
* **Assessment Based Solution:** Timer that forces students to read questions before viewing the answers might be a good idea. Maybe by forcing student to wait for answers before s/he can choose one of them will be a catalyst for the student to read the questions and all the answers. Though this is not a guarantee, but it might be a good way to do so.
* **Student Based Solution:** Talking to students about the importance of e-Learning activities in the learning process and about the gains they can easily acquire and make use of via utilizing such activities is important. The attempt to qualify students’ culture with e-Learning is important to start gaining e-Learning advantages. Not all students yet believe in   
  e-Learning; only 182 out of 223 cared about attending the online course activities. The rest needs to be talked to; instead of just be neglected.

Most of nowadays students do their best to play it smart, even if they will not follow the rules. Solutions to guarantee learning efficiency and effectiveness for current situations must be thought of about regularly. Unfortunately students usually advance instructors in utilizing technology for their purposes; which might be “cheating”. We; as instructors, need to evaluate the situation regularly and rely more on student performance analysis tools to find facts that are not clear to us.

### 3.5.3.2 Technical Aspects of the Solution

Technical Solutions are a real challenge. There is no Web based assessment system that presented a clear solution to such a problem. Solution lies in a well-controlled desktop application that must be used in the Exam process. Desktop applications provide techniques that are not available via Web based systems. Those techniques include:

* **Keyboard Hooking:** Desktop application can control keyboard strikes on system basis; not on application basis. So, we can control which keys are available for students to click, and which are not. However, such solution is applicable for Microsoft Windows based Desktop Applications only; because Java Virtual Machine (JVM) doesn’t provide such control over Operating System, and that will stop authors from developing a platform independent Exam Desktop Application.
* **Operating System Log File:** Desktop application can check the Operating System Log file, and when it finds that student executed any of the non-authored applications during the exam, it exits the exam. However, students can be smart enough to use two computers during the exam: one for taking the exam, and another for cheating. Besides, checking the Log file will be a time based process that is not guaranteed to take place anytime.
* **Check Running Processes:** Desktop application will check the running processes on the system before and during the exam, and will exit any non-exam required process that is running during the exam. This technique seems to be the most appropriate one, however building this list of processes will take time and effort.

By combining the aforementioned techniques; both educational and technical, we might get a better circumstances during exams, and hopefully results will be available soon “after applying the exam to students, recording and analyzing statistics”.

## Student Intelligent Services

Student intelligent services are: Intelligent Agenda Study Time Planner, Intelligent Meeting Manager for Suspended Students, and Intelligent Los Recommender.

### Intelligent Los Recommender

Recommender system in an e-Learning context is a software agent that tries to “intelligently” recommend actions to a learner based on the actions of previous learners. Recommendation could be an online activity such as doing an exercise, reading posted messages on a conferencing system, or running an on-line simulation, or could be simply a web resource [Osmar R. Zaiane, 2002]. Table 4 presents intelligent Los recommender service specifications and figure 4 presents its detailed flowchart. Proposed intelligent Los recommender processes data in two phases: phase 1 where intelligent Los recommender actually recommends Los list based on student preferences and Los coverage for topics. Instructor approves recommended list, and when modifications are needed, instructors update weights causing the list to be generated not the list itself. This way, instructors are enhancing the system. Phase 2 includes reordering the generated recommended list based on students’ preferences. Users like to find their preferred material directly, and this phase is responsible for achieving this objective.

Proposed model presents LOs Recommender as a Service that makes use of different technologies and techniques presented by A. M. Riad et al. (A. M. Riad et al. (c)) in utilizing Co-Occurrence Matrix based recommender to present suitable learning materials to students. Modifications to previous recommender were required to fit the new recommendation scenario. LOs Recommender as a Service relies heavily on LO’s SCORM Meta Data presented in section 6. Figure 17 presents an overview of LOs Recommender as a Service recommendation process. Student; the main initiative of the learning process asks for suitable LOs that fits the learning objectives of the course topics. S/he finally gets three different lists of LOs: Ranked LOs list, list of LOs from Google Scholar, and an Instructor Recommended List.



Figure17: LO's Recommender as a Service Process

Student request can be identified either implicitly through LOs Recommender as a Service observation of students’ navigation through learning topics or explicitly through an ordinary search using Proposed Adaptive System Web site’s interface. On receiving a new request, LOs Recommender as a Service generates a set of recommendations; a list of ranked suggested LOs to view based on content similarity with student request side by side with results from Google Scholar.

At each request, LOs Recommender as a Service identifies the requested LO, Session ID, Student ID, and Referrer LO; that is the LO the student was viewing before the requested one. Based on students’ access behavior, Recommender as a Service updates the underlying Co-Occurrence Matrix as depicted in figure 18. Co-Occurrence Matrix is the mind of the Proposed LOs Recommender as a Service and it is reactive because it reflexes students’ access to LOs as it updates weight between LOs based on students’ navigation model between LOs. Co-Occurrence Matrix is a Matrix

M = N \* N

Where

N = No. of LOs in LCMS

Each element in the Co-Occurrence Matrix presents a Weight W(u,v). The equation used to update Co-Occurrence Matrix values is

W(u,v) = N(u,v) / Max (Nu,Nv)

Where

W(u,v) = Weight of adjacent LOs (u,v)

N(u,v) = Number of Students’ Sessions in which both LO(u) and LO(v) are visited

N(u) = Number of Sessions in which LO(u) is visited

N(v) = Number of Sessions in which LO(v) is visited



**Figure 18: Update Co-Occurrence Matrix Steps**

LOs Recommender as a Service relies on a Co-Occurrence Matrix that is stored in the database between different LOs. Building this Co-Occurrence Matrix is a student reactive process because it is mainly based on student navigation model between LOs. LOs Recommender as a Service gathers data required to recommend LOs to students from different data sources, and then builds Un-Directed Weighted Graph between the appropriate LOs based on the stored Co-Occurrence Matrix. The Clustering Algorithm is applied to this Un-Directed Weighted Graph to define different clusters and Generate the Recommended List of LOs. This list is then ranked based on the Ranking Algorithm and returned to the user.

1. **Building Un-Directed Weighted Graph**

The Un-Directed Weighted Graph is built programmatically based on the equation:

G = (V, E)

Where

V = Set of Vertices; that contains LOs Identifiers

E = Set of Weighted Edges between Vertices

An example of the Un-Directed Weighted Graph between LOs is the one presented in figure 19. Un-Directed Weighted Graph doesn’t highlight the order of viewing LOs; because this ordering will complicate the Clustering process.



Figure 19: Example of Un-Directed Weighted Graph between LOs

1. **Applying Clustering Algorithm**

LOs Recommender as a Service finds clusters based on Usage Data Analysis by Partitioning the built Un-Directed Graph to its Connected Components, assigning each component; that would be an LO into a different cluster based on a threshold value that is used to exclude poor correlated edges. The List of Recommended LOs contains LOs that coexist within the same cluster of the LOs of the requested learning topics. Proposed LOs Recommender as a Service utilized clustering algorithm is Depth First Search (DFS). DFS is an algorithm for traversing or searching a tree, tree structure, or graph, and it is used to find graph’s connected components. Threshold value shall be used to eliminate poor correlated edges. A start value of 0.4 is used in the beginning and it is a matter of change for later uses based on LOs Recommender performance.



Figure 20: Flow Chart of Implemented Depth First Search Algorithm

1. **Applying Ranking Algorithm**

Proposed Recommender as a Service uses a Content based Ranking Algorithm for ranking LOs; that is Term Frequency – Inverse Document Frequency (TF – IDF). TF – IDF is calculated as follows:

1. **Calculate Term Frequency (TF):** TF is the measure of how often a termi is found in a particular LOj. Each term in the input string is compared with each LO’s Meta-Data and Content if applicable.

TFi,j = Frequency of Termi in LOj / No. of Words in LOj

1. **Calculate Inverse Document Frequency (IDF):** The number of LOs in which the term occurs divides the toptal number of LOs in the database; resulting in *R*. The Log of *R* gives the IDF. IDF is calculated based on the formula

IDFi,j = Log (No\_d / No\_LOs\_Containing Termi)

Where

No\_d = Total No. of Retrieved LOs

No\_LOs\_Containing Term = No. of Relative LOs that contain Termi

1. **Calculate the Weight of Termi in Each LO:** The weight of the Termiis calculated indicating the importance of the query term in each document. The higher the weight of a term in a document, the more important is that document.

Weighti,j = TFi,j \* IDFi,j

1. **Google Scholar**

Google Scholar is a freely accessible Web search engine that indexes the full set of scholarly literature across any array of publishing formats and disciplines. Google Scholar is available online at <http://scholar.google.com> Released in beta in November 2004; the Google Scholar index includes most peer-reviewed online journals of the world’s largest scientific publishers. In terms of features, Google Scholar allows users to search for digital or physical copies of articles, whether they are online or in libraries. Through its “Cited By” feature, Google Scholar provides access to abstracts of articles that have cited the article being viewed. Through its “Related To” features, Google Scholar presents a list of closely related articles ranked primarily by how similar these articles are to the original result and how much relevance of each paper.



Figure : Intelligent Adaptive Online Lecture LOs Advisor Flowchart



Figure : Intelligent LOs Recommender Flowchart

Table : Intelligent LOs Recommender (Phase 1) Specifications

|  |  |
| --- | --- |
| Input | |
| Student Preferences | Proposed Model stores different learning preferences that identify student learning behavior. Those preferences are considered for identifying different study plans. |
| Related Los Specifications | Los satisfy students’ classes by percentage. The higher Los available that matches students’ preferences, the higher recommended this topic for teaching. |
| Learning Topics Data | Extract Topics related Keywords to match Los with topics. |
| Instructors Recommended Los list | Previous instructors’ recommended Los list for certain topics. In the beginning, instructors will need to approve generated lists every time to fine tune the system, then a database of approved lists will be used for approval. Instructor’s approval will be required from time to time. |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Los Recommended List | If this is the first time for the system to generate this list, Instructor’s approval is needed; otherwise system compares this list to previously stored lists. Matching percent less than 100% is allowed for systems adaptivity. |

### Intelligent Agenda Study Time Planner

Intelligent agenda study time planner presents an adaptivity feature to the proposed model. Table 5 presents the intelligent agenda study time planner specifications and figure 5 presents detailed flowchart. This service provides three main functionalities that are important to the student:

* General agenda that excepts vacations and holidays.
* Personalized agenda that takes into consideration time required to study a topic based on the time shift between instructor identified time to study and the actual time that student needs to study. An estimate is calculated and addressed on the agenda. This time varies from student to another. Bloom (1984) showed twenty-five years ago, as reported in his 2 sigma paper, that almost all students can learn to the mastery level, given the right learning environment (Bloom ,1984; Moursund, 2005). One of the important factors of the right learning environment is the "Time Factor". Bloom showed that all students reached mastery level for certain topics after different time intervals of learning.
* General agenda for different activities that is customized for each student based on their preferences. Students who prefer football are encouraged to participate in football games, and the same for other activities.



Figure : Intelligent Agenda Study Time Planner Flowchart

Table : Intelligent Agenda Study Time Planner Specifications

|  |  |
| --- | --- |
| Input | |
| Student Preferences | Proposed Model stores different learning preferences that identify student learning behavior. Those preferences are considered for identifying different study plans. |
| Related Los Specifications | Los satisfy students’ classes by percentage. The higher Los available that matches students’ preferences, the higher recommended this topic for teaching. |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Personalized Agenda | Personalized agenda for each student that help her/him organize their time between different activities and study. |

### Intelligent Meeting Manager for Suspended Students

Suspended students must meet one of the instructors to help them identify and work on solving their challenges. Table 6 presents the intelligent meeting manager for suspended students specifications, and figure 6 depicts its detailed flowchart.

Table : Intelligent Meeting Manager for Suspended Students Specifications

|  |  |
| --- | --- |
| Input | |
| Student Preferences | Proposed Model stores different learning preferences that identify student learning behavior. Those preferences are considered for identifying different study plans. |
| Related Los Specifications | Los satisfy students’ classes by percentage. The higher Los available that matches students’ preferences, the higher recommended this topic for teaching. |
| Processing | |
| By assigning different Weights to the different inputs, intelligent methods can be used to generate a weighted list summary report. | |
| Output | |
| Los Recommended List | If this is the first time for the system to generate this list, Instructor’s approval is needed; otherwise system compares this list to previously stored lists. Matching percent less than 100% is allowed for systems adaptivity. |



Figure : Intelligent Meeting Manager for Suspended Students Flowchar

This paper presented a proposed Adaptive Online Lecture Model that tends to utilize different technologies available to educational institutions, instructors, and students in an innovative way to provide deeper communication between instructors and students during online sessions needed to support e-Learning. Web 2.0 technologies enriched both instructors' and students’ lives with contents generated by Internet users, and the ability to provide real-time feedback, among other many different capabilities. Software Architecture and IT Infra Structure Architecture required to enable proposed adaptive online lecture model is presented, highlighting different challenges and presenting solutions for them.

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