GENERATING COMPUTER-BASED ADVICE IN WEB-BASED DISTANCE EDUCATION ENVIRONMENTS

By

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Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

University of Leeds
School of Computing

December, 2004

The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

Abstract

There is an increasing demand for distance education to be implemented nowadays by most educational organizations. The Internet has become the medium for course delivery, and Web Course Management Systems (WCMS) are widely used to deploy distance courses which need to provide appropriate support to both students and instructors. The instructors play a central role in managing the course, and their success in dealing with reported problems in distance learning, such as students' isolation and disorientation in hyperspace, depends on the understanding the instructors have about what is happening in distance classes. Based on tracking data, most WCMS provide statistical information to help instructors monitor their students. However, there is a lack of automatic features to guide instructors by pointing at important situations and highlighting possible problems. Such features may help instructors, and reduce the workload and communication overhead needed for managing distance classes effectively.

In this thesis, an approach is proposed where an artificial advisor is built to inform course instructors and facilitators about possible problems and needs of individuals and groups of students, as well as to suggest appropriate actions, when possible. A framework named TADV (Teacher ADVisor) has been developed to build fuzzy student, group, and class models based on the tracking data generated by WCMS. A taxonomy containing three main categories of advice related to the performance of individual students, groups of students, and the whole class is proposed, and an advice generator mechanism is developed. Important situations are highlighted to instructors and, when appropriate, possible actions are recommended.

A prototype of TADV is implemented and integrated within an existing WCMS. An empirical evaluation of the prototype has been conducted in a Discrete Mathematics course at the Arab Academy for Science and Technology, Alexandria, Egypt. The evaluative study has shown that TADV provides practical and effective advice. It allows advice generation and informing of instructors, which, in turn, made it easy to send help and feedback to distance students. The instructors confirmed the appropriateness of the generated advice and appreciated the knowledge they gained about their students. The students appreciated the feedback received from the instructors, which was a result of TADV recommendations. The study showed better overall satisfaction and social aspects for the students who used TADV advising features.

To My Dear Wife

Acknowledgments

Without the encouragement and support of many people the progress on this thesis would have been severely impeded. I would like to extend my sincere appreciation to them, even though this gesture is inadequate to measure my appreciation.

My deepest gratitude is due to my supervisors ***Dr. Vania Dimitrova*** and ***Prof. Roger Boyle*** for their continues support and true help throughout the various stages of this work. Their insights and suggestions have always been on target and timely. Their editorial skills greatly improved this final product. I owe a great debt of appreciation to them for the time, effort, support, and valuable guidance they offered.

Special and deep thanks to ***Prof. John Self***, my supervisor during the first year of my study. Thanks for his ideas, knowledge, and experience. Thanks for his continous advice even after his sudden retirement. Really, I got a great friend.

It gives me great pleasure to express my sincere appreciation to ***Prof. Gamal El-Din Mokhtar*** the president of Arab Academy for Science and Technology and Maritime Transport (AAST) - the sponsor of this work – for his sincere support and continues encouragement.

Thanks to ***Prof. Yousery El-Gamal*** my local supervisor for his great help and constructive advice. His valuable suggestions and support are gratefully acknowledged.

Dr. Khaled Mahar, the Discrete Mathematics domain expert, has had great influence on this thesis; he helped out with all tasks related to the course and metadata preparation, and the administration of the experimental study conducted. Many thanks.

My thanks are also presented to ***Engineer Amgad Neamatalla***, for his great help with the all tasks related to the implementation of the prototype examined in the experimental study. The list of thanks should be extended to include all members of AAST information centre especially ***Engineer Tarek El-Kalioby***, ***Mr. Mohammed Metwally***, and ***Mrs Azza El-Shaar*** for their kind help in preparing many parts of the prototype.

Last, but not the least, thanks to ***my wife and sons*** for their absolute support and encouragement with patience and love.

Abbreviations

AAST	Arab Academy for Science and Technology
AASTOLP	AAST On-line Learning Portal
AG	Advice Generator
AI	Artificial Intelligence
AIED	Artificial Intelligence in Education
CF	Certainty Factor
CM	Class Model
CSCL	Computer-Supported Collabourative Learning
DE	Distance Education
DKB	Domain Knowledge Base
DMK	Domain Meta Knowledge
GM	Group Model
GPA	General Point Average
HTML	Hyper Text Mark-up Language
IEEE LOM	Institute of Electrical and Electronics Engineer's Learning Object and Metadata
ITS	Intelligent Tutoring Systems
MB	Measure of Belief
MD	Measure of Disbelief
SDB	Student DataBase
SMB	Student Model Builder
TADV	Teacher Advisor
WBDE	Web-Based Distance Education
WBITS	Web-Based Intelligent Tutoring Systems
WCMS	Web Course Management Systems
WWW	World Wide Web

Conventions

The meaning of *learner* and *student* in this thesis is assumed equal. They refer to a person studying with a computer-based educational system. In the same line of thought, we assume that both terms *learner model* and *student model* are identical. They can be used in the same context to name the model built inside a computer system to present aspects of the knowledge of a person working with the system.

The meaning of *instructor*, *teacher*, and *facilitator* is assumed equal. They refer to a person teaching students via distance.

Throughout this thesis we will use male gender for the learner or the teacher, which is purely for convenience. In the exposition, he shall be taken to mean he or she and his shall be taken to mean his or her.

Throughout the whole thesis, *we* refers to the author and *our* refers to author's.

Publications

Some of the work in this thesis has been published prior to thesis submission.

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Chapter 1

Introduction

Advancements in computer and communication technologies have created great opportunities whereby educators can expand the educational process and deliver instruction to geographically diverse population of students. Consequently, distance education (DE) programs have been rapidly improved and conducted in different ways. Given the availability of resources, such as the Internet, computer networks, e-mail and other collaboration tools, it seemed feasible to enhance the educational outcomes of DE programs. Research in Education, Cognitive Psychology, and different areas of Computer Science has been carried out in order to create new educational models for student-student and teacher-student interactions, implement user friendly educational systems, and incorporate authoring and collaboration tools to improve the effectiveness of DE programs.

The Web-based implementation of distance courses allows delivering of these courses to a greater number of students, eliminates the problems of distributing software to individuals, and gives opportunities for designing tutoring systems with new pedagogical strategies. In addition, Web-Based DE (WBDE) offers many features that benefit the educational process over other DE delivery methods. However, some problems and barriers in distance courses delivered on the Web have been reported, such as the students' feeling of isolation and disorientation in the course hyperspace and the facilitators' communication overload and the difficulty in addressing the needs of each individual student.

WBDE environments led to changing the roles of students and teachers. Students need to know how to actively gain knowledge and fulfil their learning goals. They have to be able to effectively communicate and work together with teachers and other students. Teachers no longer follow a traditional teacher-centred education, instead, they become *facilitators* who support and guide the students' learning. Teachers need support to manage the learning process in distant classes. They are required to carefully monitor the students' progress through out the course, get an understanding of the problems that each individual student or a group of students faces, and provide appropriate help and guidance. The new, facilitating role of the teachers requires new competencies and skills. Furthermore, to be able to manage distance classes effectively, the teachers need to have appropriate information about the status and the behaviour of their students. Based on advancements in the technologies used to build educational software, especially the use of Artificial Intelligence (AI) techniques, we believe that Web-based distant courseware and the recent learning management systems can be enhanced to support students and facilitators to properly play their new roles within distance education environments. This, in turn, may reduce some of the problems and barriers existing in Web-based distance education. Most of the effort so far has been focused on supporting the students in WBDE environments, while, there is not much research on how to *support facilitators* in such environments. Providing appropriate support for facilitators in WBDE is the primarily goal of our work. This thesis will examine the application of AI techniques to provide such support.

Web Course Management Systems (WCMS) are popular tools designed to support authoring, delivery, and management of WBDE programs. They are now used by many educational organisations (universities, schools, training agencies, etc.) to deliver Web-based distance courses. WCMS provide efficient support for courseware authoring and delivery, however, they provide limited support to the facilitators to monitor what is happening in distance classes. Usually, WCMS keep a vast amount of data collected through the tracking of the students' interactions, such as the students' logins, visited pages, time spent on course pages, scores achieved in quizzes, postings to discussion forums, etc. This tracking data is used by the reporting features of WCMS to generate some statistical reports to provide facilitators with information about the students' interactions. However, these reports are usually presented in a complex format, which is often incomprehensible and difficult to use. The facilitators are required to carefully analyse data presented in these reports in order to reach some conclusive information about the cognitive, social, and behavioural status of their distant students. This task, in turn, requires additional effort and may significantly increase the facilitators' cognitive load. Tracking data is rarely used by WCMS to *automatically* guide or advise either the students or the facilitators. This thesis argues that this data provides rich information about students in WBDE and can be used to automatically generate some help to facilitators, which may reduce their workload and empower their management of distant classes.

In WCMS environments, the facilitators often face difficulties in monitoring and understanding cognitive and social problems experienced by students. The majority of the available WCMS are not equipped with intelligent mechanisms to allow instructors to monitor the students' performance. Even by using the statistical reports of WCMS, it is difficult for the instructors to find an automatic way to guide and advise students. Accordingly, facilitators usually receive many enquiries from distant students, e.g. through e-mails, chat rooms, and discussion forums. Often, the facilitators may fail to guide or advise distant students effectively due to insufficient information they have about the students' behaviour and the current knowledge status of both individual students and groups of students. Moreover, the facilitators often do not have enough time to handle the vast amount of student enquiries. The main research question in this thesis is: How can the students' tracking data collected by WCMS be used to generate advice automatically to facilitators in WBDE environments, so that they are able to help and guide distance students effectively?

Employing advanced AI techniques in educational software enables computer-based instructional systems to monitor and reason about the students' activities, and to provide support for both students and teachers. *Intelligent Tutoring Systems* (ITS) aim at providing individualised instruction in one-to-one computer-student interactions, based on the availability of some *student modelling* components. The major strength of ITS, compared to traditional educational systems such as Computer-Based Training and Computer-Assisted Instruction, is their ability to adapt to the knowledge and needs of each individual student. Many Web-based courses are designed with intelligent capabilities, which led to a new category of computer-based instructional systems called *Web-Based Intelligent Tutoring Systems* (WBITS). The majority of ITS and WBITS are developed with the aim of providing individualised feedback and guidance to students, however, there are few systems developed to support teachers in their practice.

Supporting teachers to effectively guide and help their students in the intelligent distance educational environments (e.g. WBITS) is an achievable goal because these systems usually constitute several intelligent modules, which can be employed to monitor the students' activities and decide about the students' knowledge levels with respect to different course topics. Accordingly, we argue that it is necessary to employ some intelligent features in order to enhance existing distant courseware developed in WCMS with an additional component that can play the role of an advisor and provide support to students and course facilitators. This extension can be achieved through the integration of ITS technologies within WCMS platforms. This integration should be handled using relatively simple and straightforward techniques which do not affect negatively the popular use of WCMS platforms.

In this thesis, we explore the idea of applying AI methods to support facilitators in WBDE environments developed with WCMS platforms through providing facilitators with computer-based advice of the problems and needs of individuals and groups, as well as with recommendations of possible actions that may improve the management of distance classes. Thus, facilitators will be provided with an *artificial advisor* that monitors what is happening in a distance learning class, infers the problems that may occur, and recommends possible interventions. Such an advisor may reduce the cognitive load of facilitators, may enable them to better understand the needs of their students and provide more effective guidance; which, on the other hand, may lessen the students' isolation and increase the effectiveness of WBDE. The proposed approach considers distance courses built with conventional WCMS, which are believed to provide rich data from tracking the students' actions. A framework called TADV (Teacher ADVisor) will be developed to use the tracking data generated by WCMS to build student, group, and class models. Based on these models advice will be generated to facilitators to help them manage distance classes effectively.

The framework presented in this thesis is a novel architecture for an advice generation system in WCMS environments. It comprises two main modules whose main goals are as follows:

- A *Student-Model Builder* (SMB) to use the WCMS tracking data to build individual student models, group models, and class models. These models should hold knowledge required to generate appropriate advice and to highlight useful information to facilitators.
- An *Advice Generator (AG)* to investigate and analyse the constructed student models and to generate appropriate advice to facilitators.

In order to appropriately achieve the main goals of our research, the following **methodology** was followed:

- **A study to investigate the content of WCMS tracking data:** Contents of the tracking data generated by some conventional WCMS were investigated through the examination of data previously generated during some courses implemented (e.g. using WebCT and Centra Knowledge Centre). Interpreting the meaning of this data and how it reflected the students' interactions with the course was crucial for designing the proposed student models, the Student Model Builder and the Advice Generator.
- **A study to investigate the facilitators' needs in WCMS platforms:** The facilitators' needs when they managed distance course in WCMS platforms were investigated through the analysis of problems with Web-based distance courses as

discussed in the literature and through several interviews conducted with some Web-based course instructors in Leeds University – UK and Arab Academy for Science and Technology - Egypt. After understanding the requirements, a proper taxonomy of advice types were then formulated.

- **Design of the TADV framework:** The TADV framework was designed, including Student Model Builder, Advice Generator, and other software modules based on AI techniques, specifically, fuzzy sets and certainty factor theories, in order to extend the existing WCMS with intelligent features. It aimed to provide support directly to facilitators and indirectly to students in a more teacher-controlled process. Generality, domain independency, and simplicity of the framework were considered.
- **Implementation of the TADV prototype:** A prototype was implemented for a Discrete Mathematics course. A conventional WCMS, called Centra, was extended by student modelling and advice generating modules according to the approaches defined by the designed framework.
- **Evaluation of the prototype in realistic distance learning environment:** Evaluation of the prototype in realistic distance learning settings was held to validate the framework and identify its impacts, strengths and limitations. The prototype was evaluated using formative and summative techniques. An experimental study with control and experimental groups was conducted and data were collected through qualitative and quantitative methods. Data were analysed and conclusions were drawn.

The tasks carried out to achieve the work presented in this thesis have demonstrated some original contributions to the fields of:

- Web-Based Distance Education, in particular, developing a framework for generating advice to support facilitators to manage Web-based courses delivered with WCMS.
- Artificial Intelligence in Education, in particular, using student modelling and advice generation techniques to support facilitators in WBDE environments.
- Intelligent Learning Management Systems, in particular, developing intelligent modules to extend the capabilities and the effectiveness of conventional WCMS.

The thesis is organised in eight chapters. Chapter 2 justifies the need for generating computer-based advice to facilitators in the WBDE environments. We will briefly define distance education showing some reasons for its growing popularity.

Web-Based Distance Education will then be introduced as one of the most important and successful implementations of distance education. Some problems of WBDE are presented together with possible solutions suggested in previous studies. The use of WCMS platforms in WBDE environments is discussed, and some problems of monitoring the students' activities in such environments and the ineffective use of student tracking data are pointed out. A brief summary of common metadata standards used by WCMS to describe the attributes of different types of learning objects, which will provide crucial information to reason about the students' activities, is presented. Computer-based advising is then discussed focusing on factors that facilitate advice giving in educational systems. The chapter also discusses the issue of supporting teachers in Web-based intelligent tutoring systems showing the teachers' need for more support to effectively manage and guide their distance classes. Recent ideas concerning intelligent learning management systems are discussed to put the approach presented in this thesis within the relevant context and to highlight its importance. The issue of supporting teachers in existing Artificial Intelligence in Education systems (AIED) is discussed in relation to this work.

An important feature in the proposed framework of advice generation is modelling students. The goal of Chapter 3 is to review existing student modelling approaches in order to justify the choice of an approach for building models of students and groups to be utilised in an intelligent teacher advisor. This chapter reviews relevant student modelling approaches, techniques, and systems. Student models constructed from tracking data captured by WCMS are characterised by their high level of uncertainty. Therefore, the focus of the review is directed to student modelling in uncertain environments and fuzzy student modelling. Since this thesis considers generating advice not only about the behaviour of individual students, but also about groups of students and the whole classes, some modelling of the status of groups and classes is needed. Hence, a brief review of relevant approaches for modelling groups of students is also presented.

An in-depth description of the proposed TADV framework for advice generation in WBDE implemented with WCMS environments, which is the core of this thesis, is presented in chapters 4 and 5. In Chapter 4, the overall architecture of TADV and its main components are described. The proposed courseware structure and metadata required to describe the course material is then presented. The chapter also gives a detailed description of the student modelling features, which form the basis of the advice generation process. The mechanisms used by the Student Model Builder (SMB) to interpret the students' interactions and construct individual student, group, and class models are also discussed.

Another crucial component in the proposed framework is the Advice Generator (AG). Chapter 5 addresses the issues related to what pieces of advice are needed and how to generate them. A taxonomy of advice types is proposed. The chapter describes the data model required for generating advice and the mechanism of advice generation in TADV.

Chapter 6 provides a prototype that implements the TADV architecture to extend an existing Web course management system, namely CENTRA. The chapter refers to technical aspects of the implementation based on the framework developed in chapters 4 and 5. Chapter 6 illustrates the main tasks carried out to extend a conventional WCMS by the Student Model Builder and the Advice Generator modules.

In order to facilitate the development of practical advice generation systems that follow the proposed approach, an empirical evaluation of the TADV is presented. The evaluation focuses on estimating pitfalls and outlining the potential of the framework so that it can be improved and employed in WBDE delivered with WCMS platforms. Chapter 7 gives a short review of relevant evaluation approaches to justify the methods adopted for the evaluative study of TADV. Then, the aims of the TADV evaluation are outlined and its two main phases - formative and summative - are reported. The results collected, together with a summary of the experimental study, are discussed and analysed with regard to the main evaluation issues: suitability of advice types in the proposed taxonomy and benefits of TADV to both facilitators and students.

Finally, Chapter 8 summarises the main aspects of this research, discusses the generality of the framework, points out the main contributions of this thesis, and sketches out directions for future work.

Chapter 2

Using Intelligent Tools to Support Teachers in WBDE

2.1. Introduction

Computer technology nowadays affects the educational process and makes a significant difference in the effectiveness of the instructional methods. The vision that computers can provide excellent instruction for a large number of students is supported by two groups of individuals (Larkin & Chabay, 1992): experienced teachers and educational researchers with strong background in their domains, and researchers in Cognitive Psychology and Computer Sciences who develop principles of learning and apply them in instructional software. Traditional computer-based tutoring systems require instructors to fully specify both presentation material (content), questions and their answers, and the flow of control through the course, allowing different branches to be taken upon the student's predetermined possible responses (Rickel, 1992).

The wide use of the Internet significantly affects the methods of computer-based education and training. The World Wide Web (WWW) gives attractive features to Web-based education, e.g. incorporation of distributed multimedia resources, self-paced learning, and multiple opportunities for instructors and students to communicate both synchronously and asynchronously. Moreover, since the Web is location independent, students and instructors can participate whenever and wherever it is more convenient. WBDE is becoming increasingly popular nowadays. However, there are some problems that affect the effectiveness of Web based education, which point at the need for further studies to enhance WBDE.

The aim of this chapter is to show the importance and the need for supporting teachers in WBDE environments and to present a comparative study of intelligent educational systems developed to support teachers. The discussion justifies the need for developing computer-based technologies that support instructors in Web-based courses delivered with course management systems, which is the focus of this thesis.

We will first discuss distance learning concepts showing the importance of effective communication between teachers and students in distant environments. Then, the necessity of providing teachers with appropriate information regarding what is happening in their distance classes and providing guidance towards the required communication are highlighted. We will then discuss the pros and cons of the Web as a medium for distance education and will point at problems brought by the teachers' new role as facilitators in WBDE. In line with studies conducted to increase the effectiveness of widely used WCMS platforms, the problem of insufficient support provided for the teachers in these environments will be examined. Also the concept of metadata standards, utilised by most conventional WCMS and which will be used in the teacher support approach proposed in this thesis, will be outlined.

The teachers need to be automatically supported through intelligent advising features is argued. In this vein, factors that facilitate advice giving in computer-based educational systems are reviewed. Then, the major components of Intelligent Tutoring Systems (ITS) are discussed in order to identify the components of a framework for advising teachers developed in this thesis. Adaptive techniques incorporated in Web-Based ITS (WBITS) are discussed to examine how they can contribute to solving WBDE problems. Some relevant studies concerning intelligent WCMS are also reviewed to show the importance of the problem addressed in this thesis and to highlight the significance within intelligent WCMS research. Furthermore, related AIED studies which aim to support teachers are reviewed to place our research within that field. Finally, the main approach followed in this study is elaborated.

2.2. Distance Education

DE opportunities are increasingly integrated into education and training programs in most of the countries around the world. The availability of DE programs that can effectively link teachers and learners separated by distance and time barriers offer new opportunities for learning. DE is an excellent method for adult learners because it offers them a high degree of flexibility to overcome challenging priorities, such as work, home, etc. Furthermore, the equity of educational opportunity is one of the most obvious advantages of DE: the distance mode offers study opportunities to students who would otherwise be unable to undertake a full-time course. Therefore, distant students are extremely diverse and may include a significant proportion of individuals with different goals, needs, knowledge, expectations, etc. (Wood, 1996).

There are many attempts to define distance education. For example, DE is defined as *the acquisition of knowledge and skills through mediated information and instruction, encompassing all technologies and other forms of learning at a distance* (Rockwell et al., 2000). Other researchers define DE as a *form of education in which* *there is normally a separation between the teacher and the student*; thus, some means such as, printed form, telephone, computer conferencing, teleconferencing, the Internet, etc. are used to bridge the physical gap (Spodick, 1995). Rumble (1992) stresses that the purpose of DE systems is to satisfy the needs of those who cannot attend a traditional school, college, or university, including persons of school age who live in remote areas in which it is difficult to provide face-to-face teaching, those who have been displaced, and those who move frequently. This means that DE programs can enable educational and training organisations to meet a wide variety of needs and to attract student categories that cannot be attracted through traditional educational programs.

There is a wide range of media available for DE programs. However, the most important issue is the selection of the medium that pedagogically works best. Communication between teachers and students, students and learning environments, and among students themselves are of the most important considerations that affect the quality and the integrity of DE. Without effective communication integrated into a DE program, students can become isolated, frustrated, and possibly drop out of the program (Sherry, 1996).

The problem of communication between teachers and students in DE environments is taken into account in this thesis. In order to be able to effectively communicate with their students, teachers need to have information about problems and needs of each individual student, as well as certain groups of students. Therefore, the medium used in DE should provide appropriate means for teachers to understand what is happening in distance classes.

2.3. Web-Based Distance Education (WBDE)

From the early days of the Internet, there were multiple efforts to use it as a medium for DE. The WWW offers the ability to easily distribute educational material around the globe. In the field of Education, there is an agreement between various domain experts and teachers that the Internet supports the design of novel approaches to teaching and learning, as well as cooperation among teachers who can share instructional material. It also offers opportunities for designing tutoring systems with diverse pedagogical strategies (Kinshuk & Patel, 1997). As reported in Alpert et al. (2000), Mitrovic (2000), and Peylo et al. (2000), there are many reasons for using the Web as a medium for DE, amongst which are:

- The Web enables reaching a greater number of students and much wider audience;

- Students are no longer constrained to where or when they can interact with the instructional system;
- Students can access tutoring material via Web browsers, and do not need to own a copy of the educational software.

Several advantages of WBDE have been reported indicating that there is a common acceptance from students and academics to use and develop WBDE courses:

- Students found the flexibility of online courses more suited to their personal life style, the fact that there is no need to be physically present at the university is considered by many students as a key advantage (Smith et al., 2000).
- WBDE was found to be more directed to the needs of individual students, and opportunities for faculty-student and student-student interaction were enhanced as a result of advanced computer mediated communication technologies (Smith et al., 2000). Furthermore, Jones (1999) considers the possibility to increase the interaction as one of the most successful aspects of WBDE.
- Academics from different disciplines found that the students' interests and motivation increased when the use of the Internet was an essential course requirement. Students appeared to be more active pursuers of knowledge and were keen to distribute findings to their peers (Smith et al., 2000).
- Smith et al. (2000) report also that academic staff considered the ability to create a student-centred environment to promote independent student learning as a major positive attribute of WBDE. Moreover, course management activities, such as collecting and distributing assignments, making class announcements, communicating with individual students and informing students of grades, were more efficient with WBDE than other media used for DE (Smith et al., 2000).

Although WBDE proves to be beneficial and many advantages and positive experiences are gained, there are still a number of problems and barriers that have to be resolved to ensure effective distance education. For example, Jerrams-Smith (2000) discusses that due to the fragmented nature of Web-based hypertext courses, the way to study is usually by browsing the various paths of a variety of hypertext documents. However, the browsing may not always be the most appropriate method of learning because of problems of *disorientation* and *cognitive overhead* (Jerrams-Smith, 2000). Disorientation or "getting lost in space" can occur if the student is uncertain about his location in the hypertext network and unsure of how this location relates to the student's learning goal. The probability of student disorientation is high because hypertext offers more dimensions in which the students can move. The problem of cognitive overhead occurs when a student is presented with a large number of links. In this case, the student may become distracted, leading to what is known as "information myopia" (Jerrams-Smith, 2000). Carro et al. (1999) also report that the determination of appropriate navigation paths in the hypermedia space is important to help students to effectively achieve their learning goals. In this line, Galusha (1997) points out that, students who *did not receive adequate feedback*, would be less likely to experience complete academic and social integration into the institutional life and, consequently, would be more likely to drop the course. Following this argument, the work in this thesis is based on the idea that *supporting facilitators to gain useful knowledge about their distant students will empower them to give more adequate feedback to the students.*

Another problem observed in WBDE relates to student *frustration*, which can be a major obstacle for learning, as it is linked to the pursuing goals and may influence the learning in cognitive and affective aspects (Hara & Kling, 1999). A study conducted by Hara and Kling concluded that the students' frustration originated from three sources: technological problems, ambiguous instructions both on the Web site and in e-mails, and *insufficient and ill-timed feedback from the instructors*. In order to *help giving appropriate and timely feedback to the students, WBDE should provide means to inform instructors of what is happening in their distance classes.* An approach to deal with this is examined in this thesis.

Usually, WBDE courses *increase the academic workload* compared to traditional classroom teaching. Activities, such as marking and commenting on assignments and the vast volume of online communication with the students require significant proportion of the instructor's time (Smith-Gratto, 1999; Smith et al., 2000). Organising communications with students is difficult, especially when the students are geographically located in different countries with different time zones (Smith et al., 2000). In this line of thought, we argue that *appropriate support for the instructors to help them compose well-suited and timed feedback to the students may lessen the increased communication overload and the overall academic workload.*

Different solutions have been proposed to overcome the problems mentioned above. Galusha (1997) argues that teachers in WBDE should play different roles. Teachers are no longer the sole source of knowledge but instead they have become *facilitators* who support the students' learning. The instructors should share instructional objectives with the students and explain why particular instructional activities, assignments, and projects are required. They should design assignments that include group work or group projects to be completed by peers. They should not monopolise the discussion and should allow time for students to respond to questions (Galusha, 1997). Rezabek and Weibel (1995) state that instructors can take advantage of technology to make themselves available to students. They should consider establishing "electronic office hours" which are reserved for communicating with students. Overcoming distant students' feelings of isolation is one of the most important contributions a teacher can make to add to the success of the WBDE course (Rezabek & Weibel, 1995). Smith-Gratto (1999) points out that, *instructors should evaluate students and provide corrective information and immediate planned feedback when necessary.* This raises an important question: in order for the facilitators to play this new role they have to have enough knowledge about their distant students. However, most WBDE courseware fail to provide teachers with sufficient knowledge about the students, their behaviour, and the problems they may face.

Galusha (1997) argues also that students should play different roles. They should actively participate in what and how knowledge is imparted. Students should be involved in some activities that encourage them to connect what they know to what is to be learned (Galusha, 1997). Smith-Gratto (1999) adds that students should be active rather than passive by requiring them to produce something that will indicate what they have learned. Following these claims, important questions can be asked: how can students know that they, or some of their peers, need help; how can a student find peers who can give him help; how can the facilitator know that there are some inactive students who have to be encouraged to actively participate in the course activities and should be given appropriate supervision.

Another way to overcome WBDE problems is to provide clear guidelines for instructors how to interact with their students (Graham et al., 2001). A study showed that the instructors wanted to be accessible to online students but were anxious about being overwhelmed with composing e-mail messages or bulletin board postings. This leads to the question: can appropriate support be provided so that both the number of students' enquiries sent to instructors and the instructor's workload needed for interacting with students be reduced while, at the same time, the facilitators can still maintain stimulating interactions with their students.

The discussion above highlights the difficulties and problems involved with the instructors' new role as facilitators in WBDE. In order to play this new role effectively, the facilitators need to keep track of each individual student (what the student knows, what he has not mastered, what feedback may be provided, etc.) and answer promptly the students' questions. A potential way to tackle these problems is to enhance the functionality of the software used in WBDE to play the role of an *advisor* that provides course facilitators with appropriate advice/help, which highlights important situations about the students' behaviour. The facilitators, in turn, can use the generated advice and help to monitor and guide distant students. Such an approach is examined in this thesis. It may be beneficial for the teachers and the students that facilitators be empowered with appropriate knowledge about distant students and be able to give more appropriate, effective, and individualised feedback to students. Students would then get regular and adequate feedback, their enquiries would decrease and this would lessen the facilitators' communication overload.

There are educational systems, specifically, the intelligent ones (which will be reviewed in Section 2.6), which are capable of helping and guiding students during their work on the system. However, less attention has been directed towards supporting the teachers in performing their tasks: such as monitoring, assessing, and guiding distant students and classes. Before reviewing the intelligent support in distance education (Section 2.6), the next section describes the most commonly systems used for delivering distance courses on the Web; namely, Web Course Management Systems (WCMS). Computer-based advising in educational systems is discussed in Section 2.5.

2.4. Using WCMS in WBDE Environments

The use of WCMS is rapidly growing within universities and other educational institutions. Nowadays, these systems are commonly used to build Web-based courseware. Similar to most WBDE environments, facilitators who manage courses using WCMS platforms do not get sufficient support to guide their students and manage their classes. This thesis addresses problems in the WBDE environments which use WCMS platforms. Therefore, this section presents a brief overview of WCMS, focusing on issues related to designing a framework for advising instructors who using WCMS.

With the advent of the Internet and adopting it as a teaching and learning medium, content authors, software designers and educators became interested in providing tools to facilitate efficient and effective education on the Web. Web-based tutoring has been classified into three groups (Capuano et al., 2000):

- *Static*, in which the teachers organise the material in interactive, linked, on-line HTML (Hyper Text Mark-up Language) pages, and students follow the path specified by the teacher.

- *Personalised*, in which WCMS is used to organise the course material and teachers perform *manual* tasks, such as monitoring the students' knowledge, assigning recovery material, and defining paths for different learning goals.
- *Adaptive*, similar to personalised tutoring but the teacher's activities are simulated using some AI techniques.

WCMS are specialised learning management systems, based on the state-of-the-art Internet and WWW technologies in order to provide education and training following the open and distance learning paradigm (Avgeriou et al., 2003). WCMS are either commercial products (e.g. WebCT[1], Blackboard[2], Lotus Learning Space[3], Centra Knowledge Center[4], etc.), internally customised by universities or educational organisations, or open-source projects (e.g. FLE[5]).

WCMS can serve all education and training stakeholders, i.e. students, instructors, and administrators. WCMS are now popular tools that support many tasks ranging from incorporating digital media of different types into the teaching and learning process to creating online assessment, managing group projects, and tracking student interactions. WCMS have been widely adopted by educational organisations and instructional designers in order to fulfil the increasing demand for pedagogically correct and effective education and training (Avgeriou et al., 2003). As discussed in Mann (2001), developers of WCMS have to ensure that their products require minimal technical skills and allow educators to follow their own way and criteria for effective management of Web-based courses. In line with this argument, we believe that research which aims at improving WCMS platforms by adding adaptive and intelligent features should consider factors, such as simplicity and intuitiveness of the new technology, and should encourage the involvement of teachers to ensure the successful deployment and adaptation to the practice of each individual teacher which can, in turn, reinforce the popularity of WCMS in distance education.

Chang (2003) predicts that WCMS, as distance learning tools, will be able to help high-level education to move toward another dimension of instruction in which DE is considered to be a trend of future education. Therefore, it is important to conduct studies to address the problems and propose solutions to enhance the effectiveness of WCMS platforms. Following this claim, this thesis examines the problem of the lack of

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[1] Web Course Tool, WebCT educational technologies, Vancouver, Canada. http://www.webct.com
[2] Blackboard Inc. Washington DC, USA http://blackboard.com/
[3] IBM Corporation, New York, USA http://www.lotus.com/home.nsf/welcome/learnspace
[4] Product of Centra Company located at Lexington, MA, USA http://www.centra.com/
[5] http://fle3.uiah.fi/

appropriate support given to the facilitators in WBDE environments who use WCMS platforms to manage distance courses, and proposes a way to tackle this problem through generating advice to teachers based on some analysis of student tracking data and supported by appropriate metadata added to the learning resources. The following sections describe the characteristics of student tracking data and learning object metadata, which will be used in the framework proposed later in the thesis (see chapters 4 and 5).

2.4.1. Student tracking data

One of the most important features provided by most WCMS is the ability to track student actions to monitor how students are progressing in the courses. For example, WebCT provides a *Track Student* feature which records the dates of each student's first and last access, counts the number of visits to specific types of pages and tools, and records the number of discussion messages that are read and posted by each student. It also enables course instructors to see how frequently a student has accessed content pages and which page a student has visited last. In Lotus Learning Space a comprehensive tracking and reporting function is as well implemented to record the student performance. Centra Knowledge Center also keeps tracking data of the students' interactions with the course. The facilitators can use this data through a *Report* facility to view and print information about the students' activities[6]. Some examples of these reports are:

- The number of students who browsed each assessment item and the percentage of students who answered it correctly.
- The list of the students who have worked with a learning resource. For each student, the instructor can view the date of assigning the learning object to the student, on which date the student has started the learning object, and the date when the student has completed the learning object.
- The learning hours spent. For a selected student, this report provides the facilitators with a summary of the number of learning hours completed to date and a detailed list of the learning objects completed by the student.

While most WCMS provide rich information from tracking the students' actions, this information is *scarcely used* by the facilitators because it contains a vast amount of detail in an unprocessed form (Kosba & Dimitrova, 2004). Mazza and Dimitrova (2004) point out that tracking data is usually provided to instructors in a tabular format with a

[6] Centra Knowledge Center User Guide, Centra Software Inc. (2002).

poor logical organisation and is difficult to follow. This shows that WCMS store student's tracking data and provide reporting features to support the facilitators, however, these features are *not effective enough* to help the instructors in WBDE environments to play their new facilitating role (see Section 2.3.).

We argue that the effort, time, and concentration required to analyse and interpret tracking data and statistical reports provided by WCMS are behind the ineffectiveness of these features. Moreover, the tracking data in its raw format and the reports provided by the built-in reporting features of WCMS do not *automatically* provide instructors with information like: why a student is struggling with a certain concept or topic, who is delayed, who is progressing too slowly or fast, who is dominating the discussion forums, who is uncommunicative, etc. Partly, such information is embedded in the tracking data generated by WCMS. However, the facilitators are not usually able to interpret this vast amount of data, which is cognitively demanding and time consuming. We propose that it can be beneficial if this data is used *automatically*, without increasing the facilitators' cognitive overload, to *intelligently* generate appropriate advice and useful help information to support the facilitators to manage effectively their distance classes delivered with WCMS. In order to reason about the student's actions, we will rely on the metadata attached to the learning objects, widely used recently to ensure sharing and reuse of both educational tools and teaching material.

2.4.2. Learning object metadata standards

Adding intelligent features to computer-based educational systems usually requires information about the characteristics of the course parts and learning objects that describe the course. For example, to enable a system to identify why a student is struggling with a certain concept, it is necessary to provide information about how this concept is related to other domain concepts. Also, if it is necessary for a system to know whether a student has spent sufficient time to study a specific learning object, then information about the typical reading time of that learning object is needed. Such issues are addressed in the intelligent teacher advisor proposed in this thesis to analyse the students' actions and to identify possible student problems. Therefore, it will be required to define metadata that will enable the system to generate appropriate advice and help information (see Chapter 4). On the other hand, most conventional WCMS utilise one or more metadata standards to describe the learning objects published in its content repositories. These standards have to be taken into account when defining the metadata used by the intelligent teacher advisor. Accordingly, this section presents a brief review of learning material metadata standards.

Adding intelligent features to computer-based educational systems is not the main reason behind the introduction of metadata standards. The idea of development of metadata standards is a direct result of the increasing amount of educational learning material electronically available via the WWW. With this huge amount of information, locating and using the most appropriate learning materials becomes tedious, and often impossible. Metadata assists in solving this problem by categorising the documents with descriptive data which increases the likelihood of the learning materials being found and used by teachers and learners.

Wayne et al. (2002) define metadata as information about an object, be it physical or digital. Learning Object Metadata is used to provide quite a powerful functionality for the learning objects that represent the course contents in Web-based learning environments. Generally, and as stated by IEEE participants in the Learning Technology Standardisation Committee, the purpose of metadata standards is to *facilitate search, evaluation, acquisition, and use of the learning objects* by the learners and the instructors, and to facilitate sharing and exchange of learning objects (Wayne et al., 2002). Capuano et al. (2000) state that a learning object metadata standard defines the *minimal set of properties required to facilitate managing, locating, and evaluating of the learning objects*. While these definitions clarify the original motivations behind the use of metadata standards, we believe that adding intelligent features to the WCMS will emphasise the importance of the metadata schemes. This can be supported by Moodie and Kunz (2003) who stress that the availability of a "Learning Object Library" is one of the four major components of intelligent WCMS. Moreover, Moodie and Kunz (2003) point out two key issues for learning objects metadata standards suitable for intelligent WCMS:

- the possibility to be *edited and customised by the teachers*;
- standards *should be expandable* so that teachers can add new attributes upon their needs.

As described in Chapter 4, we follow the two issues stressed by Moodie and Kunz. In our work, the teachers are considered as *active* participants in creating the course metadata. Furthermore, the argument that standards should be expandable enabled us to add additional attributes required for the proposed student modelling mechanisms (see Chapter 4).

There are a number of metadata schemes proposed by some learning organisations and working groups. The most popular schemes are listed below:

- DCMI[7] (Dublin Core Metadata Initiative) has been widely accepted and used internationally for quite a few years. It is a fairly simple and straightforward metadata scheme, often used as a basis for newer, more detailed, schemes.
- EdNA[8] (Education Network Australia) has developed a metadata standard based on the DCMI Scheme. It provides in-depth metadata to learning documents for schools. Unlike DCMI, which is more general and applied to a wider range of documents, EdNA targets chiefly school educational settings.
- IEEE LOM (Institute of Electrical and Electronics Engineers' Learning Objects and Metadata) defines metadata scheme for learning objects (Wayne et al., 2002). More details about IEEE LOM are presented later in this section.
- IMS[9] metadata specifications are developed by IMS Global Learning Consortium of vendors and implementers who focus on the development of XML-based specifications. These specifications describe the key characteristics of courses, lessons, assessments, learners, and groups.
- SCORM (Sharable Courseware Object Reference Model) combines standards from IEEE LOM and IMS to provide complex metadata with a large number of elements requiring information. This scheme is quite complex to create but very powerful when searched. It is aimed at a wide range of learning objects. SCORM is developed by Advanced Distributed Learning[10].

In this work, we will follow the IEEE LOM because it is widely adopted by educational digital library projects (Qin & Hernandez, 2004) and because other organisations are gradually converging to this one (Capuano et al., 2000). Moreover, other metadata schemes, e.g. IMS and SCORM, have been based on IEEE LOM. To illustrate the meaning of learning object metadata standards, the description of IEEE LOM is summarised below. More details are available in Wayne et al. (2002). In IEEE LOM, data elements that describe learning objects are grouped into nine categories:

- The *General* category groups the information that describes the learning object as a whole (e.g. title, description, keyword, etc.).
- The *Lifecycle* category groups the features related to the history and current state of the learning object and those who have affected this learning object during its evolution (e.g. version, status, data, etc.).

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7 http://dublincore.org/
8 http://www.edna.edu.au
9 http://www.imsproject.org
10 http://www.adlnet.org

- The *Meta-Metadata* category groups information about the metadata instance itself (rather than those of the resource being described).
- The *Technical* category groups the technical requirements and technical features of the learning object (e.g. format, size, location, requirements, etc.)
- The *Educational* category groups the educational characteristics of the learning object (e.g. learning resource type, difficulty, typical learning time, etc.).
- The *Rights* category groups the intellectual property rights and conditions of use for the learning object (e.g. cost, copyright, etc.).
- The *Relation* category groups features that define the relationship between the learning object and other related objects (e.g. kind, resource, description etc.).
- The *Annotation* category provides comments on the educational use of the learning object and provides information on when and by whom the comments were created.
- The *Classification* category describes learning object in relation to a particular classification system (classification, classification purpose, etc.).

In the framework developed in this thesis, a subset of the IEEE LOM standard is used and extended with some additional learning object characteristics required for appropriate analysis of the students' actions (see Chapter 4) and for intelligent advice generation (see Chapter 5).

2.5. Computer-Based Advising in Educational Systems

Since the work presented in this thesis is aimed to generate advice to the facilitators in WBDE environments, we will review relevant work in the computer-based advising in educational systems to identify important issues that should be considered in preparing a framework for advising the teachers in WBDE environments.

Most software applications are equipped with help or assistance utilities to guide users. Matthews et al. (2000) indicate that traditional help approaches associated with software applications (e.g. command indexed systems and tutorials) are generally weak and are not adapted to the level of individual users. An empirical study conducted by Virvou et al. (2000) showed that active help or advising systems are required for the following reasons:

- Some users are not aware of their problematic situations.

- Some users may not know what their problem is; they need advice for their individual status.
- Frustration can result for some users when the system is not able to spot the obvious errors.

These reasons can be valid in educational courseware applications, especially when the students use these applications from remote locations through the Internet. Sometimes, the students may fail to realise that they misunderstand certain domain concepts. They may not even know the appropriate way by which to acquire and apply domain knowledge. Each individual student needs some form of customised help or advice depending on his status and learning needs.

In face-to-face education, the instructors carry out activities, such as analysing the students' behaviour and monitoring the students' learning interactions. Therefore, the instructors are able to make the necessary decisions, such as what to recommend, how to support learning, and how to motivate the students because the teachers are able to assess and monitor the students' progress. In DE environments students must undertake the activities related to interpretation and organisation of the course materials. Arshad et al. (1995) argued that the students do not often posses the knowledge necessary to take decisions related to their learning activities. Moreover, Arshad et al. found that when students feel they struggle, they are willing to seek advice from their teachers and are prepared to change their style of study, if properly advised by their teachers. This emphasises the need to study what support may be appropriate to help distant students during their interactions with the system, which can, in turn, lessen the amount of questions and enquiries directed to the facilitators.

2.5.1. Characteristics of computer-based advice

As indicated by Arshad et al. (1995), computer-based advising in educational systems has to offer advice to students on the setting of *study goals* (topic, sub-topic sequence and the types of related knowledge, e.g. conceptual, procedural, operational), the *choice of learning materials* to achieve the learning goals, and the particular *learning techniques* which best ensure that the chosen materials will deliver the study goals. The authors also argue that advice should be *comprehensible and understandable* (i.e. clear in its expectations of the student and supporting learning-how-to-learn), *convincing* (i.e. the student should realise what will be achieved in order to be motivated to undertake the tasks), and *co-operative* (i.e. adapted to the learner's intentions, capabilities and current focus of interest).

The work proposed here is intended to generate advice to the facilitators (not to students directly). However, in some situations the system will recommend feedback to be sent to the students according to the facilitator's interest. The advice characteristics mentioned above will be followed, as appropriate, in the preparation of the recommended feedback to the students. Considering that the facilitators usually have experience of how to advise their students, we suppose that they may wish to change the recommended feedback or completely send new feedback based on what situations have been highlighted to them. Chapter 5 gives more details about the feedback recommended to students, and Chapter 6 provides examples of how this feedback has been used by instructors.

2.5.2. Factors that facilitate advice-giving in educational systems

For an educational system to provide adequate advice it must have algorithms to get an understanding of the students' interactions and their knowledge level of the course topics. Matthews et al. (2000) point out that the general approaches used in help giving systems can be classified, depending on the way of interaction, into two categories: *passive systems,* which respond to user-initiated queries and *active systems,* which initiate the interaction at appropriate times in a more human-like way. The authors argue that to achieve active capabilities, online systems need to:

- Model individual students, i.e. keep track of their strengths and deficiencies.
- Determine the context of student activities and provide responses to their individual needs.

In line with Matthews et al, Virvou et al. (2000) point out that advising systems have to employ a rich model of the student's interaction to be able to make some generic assumptions about students (e.g. consistent, sometimes forgetful, alert, etc.). Accordingly, the process of providing effective advice must involve modelling the individual characteristics of each student. Modelling the students is, therefore, well considered in the proposed framework. Moreover, the critical issues claimed by these studies are discussed in the student models presented in Chapter 4.

On the other hand, Arshad et al. (1995) state that in order to be effective, computer-based advisors should have knowledge about the objectives and study goals, preferred study strategies of the individual learners, knowledge about the structure of the domain, and knowledge about advice giving. The authors argue that arranging domain knowledge in a hierarchy of topics is also important. Task analysis and arrangement of learning outcomes can lead to an efficient linear ordering of topics.

Assigning mastery level performance conditions to course components that defines progress to higher levels subject to understanding of prerequisites provides higher levels of understanding (Arshad et al., 1995).

Furthermore, Arshad et al. (1995) mentioned that selecting appropriate teaching resources should depend on the knowledge goals that the advisor is trying to help the student to achieve, and on the most appropriate types of learning interactions for the student. Learning materials should be classified in terms of both their educational functions and their content. Information about the material (e.g. estimated study time) would be placed in a database so that the advisor could justify its recommendations for the student (Arshad et al., 1995).

Following these claims, the framework presented in this thesis follows a hierarchal structure of the course topics and a metadata scheme extracted from IEEE LOM standards (discussed in Section 2.4.2) with added attributes required for student modelling mechanisms (see Chapter 4).

The above discussion shows that educational systems should incorporate *intelligent features* to be able to give appropriate advice. Consequently, the extent to which these features are available will affect the types of advice generated from the system. To summarise, the most important features that should be included to facilitate advice-giving in educational systems are: *student modelling*, *domain knowledge hierarchy*, and *information about course material* (meta-knowledge). These features are discussed in Chapter 4.

Intelligent features in Web-based distance education, in general, and those appropriate for effective help/guidance, in particular, are discussed in the next section.

2.6. Intelligent Web-Based Distance Education

With the introduction of the WWW as a medium for education, intelligence becomes an important feature used to improve the effectiveness of educational systems. Students working on the Internet need more help and more appropriate guiding.

The discussion above suggests that effective computer-based educational systems, especially distance learning systems, should include the following features:

- The ability to provide adequate guidance/advice/help to students based on their individual status. Educational systems should be able to supply information about the behaviour of students (as individuals and as groups) to the teachers to enable them manage any given distance courses.

- Intelligence should be incorporated in computer-based educational systems to facilitate individualisation of the learning process according to student's behaviour and status.
- It is preferable to implement computer-based educational systems on the WWW so that it is possible to benefit from this widely used media.

Accordingly, this thesis aims to support the facilitators in WBDE environments designed by WCMS platforms via *extending WCMS by providing some intelligent modules*. In this section, areas of research related to intelligent educational systems are reviewed, more specifically, Intelligent Tutoring Systems, and Web-Based Intelligent Tutoring Systems. The aim is to briefly discuss the major components of intelligent educational systems in order to identify the major components required in a framework for advising teachers. The section will also review the recently emerging area of research concerning the intelligent WCMS to show the significance of the problems addressed in our thesis as well as to compare this thesis to related studies within this new area of research.

2.6.1. Intelligent Tutoring Systems (ITS)

The use of AI techniques in the development of computer-based educational systems represented a very important step towards providing knowledgeable, individualised instruction in one-to-one interaction with a student. Intelligence adds two important dimensions to educational systems: firstly, fairly rich representation of domain knowledge allows systems to use their knowledge in ways unspecified by the course designers, and secondly, the modelling of students enables the systems to individualise their instruction and tailor the presentation to the level of the student's knowledge (Rickel, 1992). We think that these dimensions are important for monitoring, guiding, and facilitating students' learning. Intelligent educational systems have usually been developed to support students while they are working with these systems.

The defining characteristic of ITS is that they are systems that "care" about the students, i.e. they are able to adapt the instruction style, the feedback, and the support given to the level and needs of each individual student (Self, 1999). Therefore, to work effectively, these systems need domain knowledge, instructional knowledge, and knowledge of individual students. These knowledge bases usually give depth so that students can "learn by doing" in realistic and meaningful contexts (Murray, 1999).

Generally, ITS are designed to mimic the human teachers, therefore, the designers of ITS should understand the general tutoring process involving a human instructor and students. Stephen and Hopple (1992) stress the ability of ITS, upon observing that the student is making errors, to imitate a human teacher and provide student with suitable remedial materials. Zhou et al. (1996) discuss the tutoring process in some detail and show that an important part of the teacher's role, that should be also carried by ITS, is to find out the students' problems and to help the students when they have difficulties.

The ability of ITS to play the role of the teachers regarding issues like presenting the appropriate material, detecting students' misconceptions, providing suitable remedial actions, etc. is undoubtedly important. On the other hand, the availability of the human teachers as active participants in the educational process is crucial, especially for other issues like behavioural and social issues in DE environments. We argue that intelligent features should be provided not only to support students to improve their learning, but also to assist the teachers to appropriately guide and help their students, which is inevitably important in distance learning environments.

Most researchers in the field of ITS agreed upon the major intelligent components that usually constitute a typical ITS. These components as outlined in Wenger (1987) and described in more detail by (Burns et al., 1991; Clancey, 1992; El-Gamal & El-Maghraby, 1994; Rickel, 1992; Stephen & Hopple, 1992; Zhou et al., 1996) are: Domain Knowledge Base, Student Model, Teaching Strategy Module, and Intelligent User Interface (or communication module).

Domain Knowledge Base stores the subject or domain knowledge, skills, and procedures that the system intends to teach. It is responsible for generating test problems and evaluating the correctness of the student's solutions to the problems. A challenge for the ITS designers is to provide domain knowledge rich enough to support the desired level of understanding and the required flexibility in teaching (Rickel, 1992). This component generally reflects the same knowledge representation schemes known in other AI systems, such as Semantic Networks, Scripts, Production rules, etc. In the work proposed here, WCMS authoring capabilities are used to build the domain knowledge. A group of HTML pages, as it is typical in such environments, represent the course contents. A sophisticated expert model to represent the course is not a usual feature of the courses designed by conventional WCMS. Therefore, a simple hierarchical structure for representing the course and the relations between its parts is used (see Chapter 4).

Student Model represents a student's knowledge about the subject domain, i.e. what the student does and does not know. Student modelling aims to model individual students. The information captured in a student model is used to modify the system's behaviour to most effectively facilitate the student's learning. Student modelling includes the application of techniques related to AI, Cognitive Psychology and Instructional Science. In the framework presented here, modelling students in WBDE is considered as a critical component for advice generation, as discussed in Section 2.5.2. Therefore, this issue is discussed in more detail in the next chapter where relevant student modelling approaches are reviewed.

Teaching Strategy (pedagogical scenario) Module describes the tutoring or instructional strategies used by an ITS during the teaching process. Teaching strategies deal with selecting an effective presentation method, determining the balance of the student and tutor control, and choosing evaluation criteria with which to judge the student's competence (Rickel, 1992). There are many teaching strategies used by educational computer systems, e.g. frame-based, coaching, gaming, and Socratic. More details about these scenarios can be found in (Clancey, 1992; Merrill, 1992; Rickel, 1992; Woods & Warren, 1996). In the work proposed here, there is no specific learning strategy defined and modelled by the system. The proposed framework is applied to WCMS environments where the students can study at their own pace and the facilitators can optionally intervene at times they prefer. However, our ideas are based on the assumption that the students in such distance education environments should be monitored, supervised and guided through their teachers, according to the pedagogical expertise of each individual teacher.

Intelligent User Interface (Communication Module) is the module by which the actual presentation of domain contents and the interaction with each individual student is accomplished. Burns et al. (1991) state that defining and deciding about computer-student interactions is a major issue in designing ITS. The student interface must include the ability to understand the student's responses and respond to the student in a way that he will understand (El-Gamal & El-Maghraby, 1994). Several techniques are used to design the interfaces of ITS: text and graphics (El-Gamal & El-Haggar, 1993), graphical animations (Rickel, 1992; Woolf et al., 1986), multimedia (Fahmy, 1996), and natural languages (Brown et al., 1982; El-Gamal & El-Maghraby, 1994). The work presented in this thesis depends on the interface provided by WCMS to present course contents. The students' interactions will be captured and stored by the WCMS students' tracking features. Appropriate interface is proposed to provide advising features to both facilitators and students (see Chapter 6).

2.6.2. Web-Based Intelligent Tutoring Systems (WBITS)

WBITS are aimed to provide more effective, student-centred distance educational environments. WBITS is a research area based on ITS and Internet technologies. As stated before, ITS have the ability to individualise and customise the instruction and feedback in a flexible way. WBITS combine ITS technologies related to curriculum sequencing, student modelling, intelligent analysis of student's solutions, and interactive problem solving support with Internet technologies, such as the use of hypertext, hypermedia, and adaptive navigational techniques as an interface that link students to the educational systems.

Although thousands of Web-Based educational applications and courses have been made available on the Web, most of these systems are just a network of static hypertext pages (Brusilovsky, 1999). In WBDE, adaptivity and intelligence are important because students in distance classes usually work on their own and often do not receive effective personalised assistance from the teacher. Furthermore, Web-based courses are used by a much wider variety of students than standalone educational applications, which makes the adaptivity highly desirable (Brusilovsky, 1999; Brusilovsky et al., 1997). In the same vein, Virvou and Moundridou (2000) stress that the integration of ITS and Internet technologies is very beneficial for the purposes of education. Internet and ITS is an excellent marriage of advanced technologies: WWW browsers overcome most of the problems associated with traditional educational systems by affording platform independent, easily updated training materials, while ITS add the ability to provide individualised instruction (Goldstein, 1997).

In order to increase the effectiveness of Web-based courses, some studies (e.g. Brusilovsky et al., 1998; Danielson, 1997; Virvou & Moundridou, 2000) propose incorporating of adaptive techniques that provide guidance to students during their interaction with the system and prevent them from being lost in the course hyperspace. These studies reported that adaptive guidance is very important especially in Web-based courses where the learning system has to play the role of the teacher and has to be able to help the student navigate through the course.

One of the popular adaptive techniques is the *Adaptive presentation technique* by which the content of a hypermedia page changes to meet the student's goals, knowledge and other information derived from the student model (Brusilovsky et al., 1998; Brusilovsky, 1999). This technique is used, for example, in InterBook to provide adaptive warnings about the educational status of a page (e.g. not ready to be learned) (Brusilovsky, 1999).

Another technique is the *adaptive navigation support* which aims to support the students in the hyperspace orientation and navigation by changing the appearance of the visible links (Brusilovsky & Pesin, 1995; Brusilovsky, 1999) and to help students find an "optimal path" through the hyperspace of the learning material (Brusilovsky, et al., 1998). There are many forms for adaptive navigation support, e.g. the *direct guidance* technique used in InterBook and ELM-ART (Brusilovsky, 1999), and the technique of *visual annotation of links* used in ISIS-Tutor (Brusilovsky & Pesin, 1995).

Although these adaptive techniques appear useful, some studies report that they are insufficient to solve the problems raised in WBDE environments. The experiment performed by Brusilovsky & Pesin (1995) to evaluate the adaptive visual annotation technique showed that, in educational context, this technique could reduce the student's floundering in the hyperspace. On the other hand, the visual annotation technique cannot reduce the number of nodes visited in the process of learning and it can hardly improve the quality of learning (Brusilovsky & Pesin, 1995). Moreover, Stauffer (1996) reports that although a number of advanced navigational tools are used to prevent students from disorientation or becoming lost in the hyperspace, experimental studies have shown that many students still use the material in the same manner as they read a textbook.

These results show that even when adaptive tutoring features are provided some guidance from the teachers may be needed to overcome WBDE problems. As the discussion above illustrates, most adaptive techniques are directed to support students based on their cognitive status (derived from student models) on what the students see in the hypermedia pages. Although the students may not necessarily understand the reasons behind changing the colours or the order of links, these techniques did not show the students how to solve their problems. Moreover, the important information provided to the students through these adaptive techniques is hidden with respect to the teachers who need to monitor and guide the students, and answer their enquiries. Using adaptive techniques to support the teachers carrying their new role is still very limited. We argue that it is important to let students feel that the teachers know about them and that they are guided and supported by their teachers. It is also important to empower the teachers to be active participants and to provide the means to enable teachers to fully apply their educational experience. This justifies the need for providing the teachers in WBDE environments with appropriate help/advice to enable them to guide their students effectively.

2.6.3. Intelligent WCMS

Following the need to increase the effectiveness of distance education with WCMS platforms and in line with the findings which recommend the use of intelligent techniques to enhance student learning in these environments, the area of intelligent WCMS (alternatively called intelligent Learning Management System) has been established recently. This section shows the significance of the work presented in this thesis and places it within the area of intelligent WCMS.

The intersection of WCMS and WBITS can be one of the most important contributions that will empower education to create a quantum leap in teaching and learning (Yacef, 2003). This can be realistic if the intersection is achieved using simple and practical technology, which will not undermine the popularity of WCMS environments. Furthermore, it is important for the future intelligent WCMS to provide support to the students as well as to the teachers. We believe that giving the teachers the chance to be active participants in the distance education environments and increasing their satisfaction by supporting them reducing different overloads are very important success factors.

In order to improve the effectiveness of Web-based learning environments which use WCMS platforms, Capuano et al. (2000) extended one of the traditional WCMS (Macromedia Attain) via an intelligent tutoring framework called ABITS (Agent Based Intelligent Tutoring System). ABITS is able to support a WCMS platform with a set of intelligent functions providing both student modelling and automatic curriculum generation. The aim of ABITS is to support student learning by adapting the didactic materials to the students' skills and preferences. ABITS did not use tracking data generated automatically by WCMS, instead ABITS, generated its own log data which included all student activities performed during the learning experience, such as visited pages, times spent to read the pages, test results, etc. Although ABITS is designed to support students (not the facilitators), it shows the necessity of integrating intelligent techniques to WCMS platforms to change their learning and teaching capabilities from being personalised to being adaptive. In line with ABITS, we propose to build student models using the students' tracking data, however, the main objective is to support the teachers.

Regarding the main components of the future intelligent WCMS, Moodie & Kunz (2003) propose the necessity of four major components: (1) an Educational Activity Toolset (empty generic pedagogical shells); (2) a Learning Object Library which is based on standard database applications; (3) an Adaptive Intelligent Agent that connects the first two components by offering a powerful search tool; (4) a Learning Community Agent which supports learners as well as teachers to manage and gain the most of their community-based learning experiences. In line with this view, the work presented here proposes a metadata component based on a standard database (see Chapter 4). On the other hand, the components presented by Moodie & Kunz did not consider the issue of teacher support in monitoring and guiding. This thesis demonstrates an extension of Moodie and Kunz' architecture to include a teacher-advising component.

Brusilovsky (2003) proposes the KnowledgeTree architecture for adaptive e-learning based on distributed re-usable intelligent learning activities. KnowledgeTree integrates three kinds of servers: a learning portal (e.g. WCMS), activity server which constitutes reusable contents and services, and student model server which collects data about the students' performance from learning portals and activity servers (Brusilovsky, 2003). This architecture integrates the benefits provided by modern WCMS and educational material repositories with the power of ITS and adaptive hypermedia technologies. The goal of this architecture is to bridge the gap between recent approaches of Web-based education based on WCMS and powerful but underused intelligent tutoring and adaptive hypermedia technologies. Although the proposed architecture is not related to the goal of supporting teachers in monitoring and guiding their students, it stresses the importance of the availability of *student models* and *pedagogical metadata* for the adaptivity of WCMS platforms.

There are studies that focus on using intelligent techniques to improve the teaching strategies of conventional WCMS. Schaverien (2003) argues that intelligence in WCMS should refer to educational intelligence, which emphasises the importance of designing WCMS based on a practical theory of learning. In line with Schaverien, Sánchez et al. aim to develop an intelligent learning management system that can improve the quality of traditional learning strategies and facilitate the implementation of new learning methodologies (Sánchez et al., 2003).

The review suggests that in the near future more studies will be concerned with intelligent WCMS, which will play a key role in Web-based learning. This justifies the *importance* of the work undertaken in this thesis. Furthermore, we argue that integrating intelligent technologies and WCMS technologies should be accomplished using straightforward and simple approaches without adding more burdens on teachers and course designers, otherwise it may undermine the popularity of conventional WCMS.

This thesis proposes the use of intelligent features to support teachers in WCMS. Studies for supporting teachers in computer-based learning are discussed in the next section in order to place this work within the relevant context.

2.7. A Brief Review of AIED Systems that Aim to Support Teachers

There is a large number of computer-based educational systems, especially intelligent systems, which are built to support students interact with courseware and collaborate with the teachers and peers. However, the issue of supporting teachers is rarely considered. This might be explained in the light of student-centred approaches to learning and teaching. In the era of e-learning, teaching strategies are simulated inside the software systems and often the teachers' role is mainly limited to preparing course material. However, as discussed in Section 2.3, WBDE programs emphasise the new role of teachers as facilitators and the essential need for teacher support. This section presents work from different areas of AIED aiming at supporting teachers and highlighting novel approach of advising facilitators in WBDE environments.

IRIS (IRakaste-Ikaste Sistima; Teaching-Learning System) is an authoring tool developed to help human instructors to build intelligent teaching-learning systems in a variety of domains (Arruarte et al., 1997). Elorriaga et al. (2000) integrate a Lesson Planner Manager to the IRIS that allows the teacher to create specialised lesson plans for students, monitor their results in these lessons, and, accordingly, take the appropriate instructional decision. The main objective of IRIS is to facilitate teachers by increasing their participation in pedagogical decisions of an intelligent tutoring system. Although this work is developed in an ITS environment, the authors stress that the teachers are mainly responsible for the teaching process and, therefore, the teachers need to monitor the students' learning and decide about changes in the teaching plans whenever appropriate. In line with this claim, the work presented in this thesis stresses the importance of providing teachers with important information to monitor and guide their students. Furthermore, we think that it is important for teachers to monitor not only the pedagogical issues but also the behavioural and social issues.

Merceron and Yacef (2003) developed Logic-ITA, a Web-based Intelligent Teaching Assistant system with the aim of facilitating the teaching and learning process by helping both the teacher and the student. They applied data mining techniques to the student answers to extract common pedagogically relevant information (common patterns) and provide feedback to the teachers. Logic-ITA is based on Logic Tutor – a Web-based ITS designed to teach formal proofs in propositional logic. Similarly to

Elorriaga et al. (2000), Merceron and Yacef (2003) focus on supporting teachers by providing only pedagogically relevant information. Their work is related to our study with regard to two dimensions. The first dimension is the use of tracking data. While Merceron and Yacef used only student answers data, in our work the data generated from all type of students' interaction is used. The second dimension is the common aim to support teachers. While Logic-ITA provides only pedagogically relevant information, this thesis aims to provide cognitive, behavioural, and social relevant information to the teachers. Although Logic-ITA confirms the necessity of ITS technologies to enable WBDE courseware to support both students and facilitators, there are some problems with the approach used. Firstly, data mining techniques usually require large volume of data to locate relatively confident common patterns on which the teachers can take concrete decisions. This means that the effectiveness of using Logic-ITA in the classes with small numbers of students is not granted. Secondly, Logic-ITA mines all students' answers to find the common patterns, which means that the erroneous pattern performed by a single student will not be highlighted to the teacher. In contrast with Merceron and Yacef, we propose the use of individual student's interactions to advise the teacher about a specific student. Moreover, we propose the use of group interactions and class interactions to advise the teacher about a group or a class, respectively.

A software tool called Pépite was developed to help instructors diagnose their students' competencies (Delozanne et al., 2003). Like Logic-ITA, Pépite depends on data collected from students' answers to some Algebra exercises. The authors report the possibility to analyse students' answers to identify the status of knowledge the students have built (correct, partial, or inappropriate) and identify this information to the teachers to help them give appropriate tasks to the student to destabilise the inappropriate coherences and make them evolve. Most comments mentioned with respect to Logic-ITA can be valid in Pépite except that Pépite processes the data of one student at a time, whereas Logic-ITA combines data from all students.

Due to the great amount of students in Web-based courses, Santos et al. (2003) emphasised the need to help the teacher to correctly design and manage the collaborative activities in the learning community. The authors propose a scenario for a collaborative task to be carried out in a Web-based collaborative learning environment. This collaborative task can be used to build a collaboration model, based on machine learning multi-agent approach, from students' interactions, which can help the tutor to manage the collaboration activity itself. The work of Santos et al. is directed to helping teachers in managing solely collaborative activities whereas other activities, e.g. progress with course schedule, are not considered.

Mazza and Dimitrova (2004) developed an approach to support the facilitators in the WCMS environments. In their system CourseVis, they explored the use of information visualisation techniques (Card et al., 1999) to present the tracking data stored by WCMS using appropriate graphical manner. In this way, they help the facilitators to gain understanding of their learners. Instead of using AI methods, tracking data is processed and used to generate graphical representations to be interpreted by the facilitators to draw conclusions. CourseVis is regarded as a useful tool since it produces graphics, which are usually easier to grasp. However, using this approach, the facilitators are still required to study the produced graphs, find out any problematic situations, and discover explanations, before taking appropriate actions. The facilitators' interpretations are heavily dependent on their ability to read graphs and the clarity of the graphical representations. For courses with high number of students, many study units, or long duration, it may be difficult for the teachers to understand the graphical representations produced by CourseVis. Also, CourseVis does not consider a hierarchical structure for the course topics, so it may be difficult to justify, for example, why most students are struggling with a certain domain concept.

Supporting the teachers in quantitative evaluation of their distance courses is discussed by Chang (2003) who reports that most WCMS are not incorporated with a strategic evaluation mechanism to allow a quantitative analysis of distance learning courseware. In order to solve this problem, she proposes an evaluation mechanism and a multimedia tool based on Courseware Diagram. The courseware allows an instructor to choose different instruction sequences based on the outcomes of an exam. In addition, Chang proposes a revised influence diagram, for designing course structure, which organises both the instructional materials, as well as the tests. A well-constructed courseware should maintain an effective course structure, with an appropriate number of tests. It is important to maintain this course structure based on a proposed strategic method, so that the instruction can proceed in maximum efficiency. In Chang's approach, the courseware design is considered to be a kind of a decision problem aims to design the courseware in a way by which it is possible to select appropriate lesson plan to maximize students' learning capacity. Therefore, the instructor should be able to design a courseware similar to making a decision, which can be computed to justify the maximal efficiency (Chang, 2003). While evaluation results of this approach are not published yet, we believe that the proposed approach of course structure is not a straightforward task, which, in turn, may affect the applicability of the approach. On the other hand, the approach assesses distance learning only through the results of the exams on which the teacher can choose different instruction sequence (not clear –

during the same course or in the next courses). However, the approach does not consider other students' activities, such as reading, discussing, etc. that also reflect the students' learning.

The prime objective of this thesis is to intelligently help the facilitators in WBDE environment that use WCMS platforms. Help information will be generated *automatically* to the facilitators as pieces of advice that highlight important information about the individual students, the groups of students, and the whole class. Corresponding to each advice generated to the facilitator, in some situations, the system will recommend feedback that could be sent to the students upon the facilitators' preferences. The facilitators are *not required to compose feedback themselves*, instead they can simply send the system recommendations or just modify before sending. Furthermore, through the generated advice, the facilitators can easily *know what is happening in their classes*, who are struggling and why, who are delayed, who are uncommunicative, etc. Upon receiving appropriate feedback from the facilitators, students will *know the problems they face* and can try to solve them as recommended by the facilitator *without sending additional enquiries to teachers*. Moreover, students may *feel that they are supervised and guided by their facilitators*. This may, in turn, reflect positively on the students' affective aspects. Very simple and straightforward courseware structure is proposed. A taxonomy of advice is prepared including situations that should be highlighted to the facilitators. The advice types included in this taxonomy consider some cognitive, behavioural, and social aspects of the students. The system will use WCMS tracking data to build student, group, and class models. These models will be used by an advice generator to automatically construct advice to the facilitators and recommend feedback to the students. More details about the proposed framework are presented in Chapter 4 and Chapter 5.

2.8. Summary

In this chapter, we have discussed reasons for supporting teachers and advising them on various class conditions in WBDE environments. The main goal was to study how the problem of supporting teachers in WBDE, especially those developed using WCMS platforms, had been tackled in other studies. Problems that face WBDE have been outlined. The aim was to find out how our work could contribute to the solution of WBDE problems, especially those resulted from the insufficient support given to facilitators. The lack of facilitators' knowledge about their students in virtual classes brought up the idea of advising and helping the facilitators. The focus is then directed to examine the level of support offered to facilitators by WCMS, as a common platform for WBDE. The difficulty of analysing the students' tracking data and the ineffectiveness of the reporting features provided by WCMS has confirmed the need to develop methods to automatically generate advice to teachers in these environments. Accordingly, computer-based advising in educational systems was discussed, focusing on the characteristics of effective advice and the factors that facilitate advice giving in educational systems. This revealed a need for intelligent student modelling feature, hierarchal domain knowledge structure, and metadata for describing the course material. Therefore, the major ITS components and the functionality of each component were described. We also looked at WBITS, emphasising their importance and their potential role in improving the effectiveness of WBDE and solving some of their existing problems. In addition, we reviewed adaptive techniques used in Web-based intelligent courses and their effects on students. The review of these different areas showed that most research interests were directed to supporting students and only a few projects could recognise supporting the teachers in WBDE and WCMS.

Simultaneously, some ongoing projects that incorporate intelligent features in WCMS have been reviewed. The review showed the importance of the subject in question and the need to incorporate intelligence in WCMS in order to increase their effectiveness. However, the review still reflects that less attention is directed to support teachers.

Finally, we have discussed some related approaches focusing on studies aiming at supporting the teachers either in ITS environments or in WCMS platforms. We have also outlined our novel approach of advising facilitators in WBDE environments.

The discussion presented in this chapter, points out the main issues that could be considered in the development of an intelligent computer-based advice generation framework as follows:

- The structure of the domain (course) contents suitable for the standard WCMS and the potential advice generation process.
- The necessary metadata attributes required for describing the course contents.
- The approach and the mechanism of the required student modelling features.
- The types of potential advice and its generation mechanisms.

These issues will be considered later in the thesis as parts of a framework for advice generation in WBDE environments developed using WCMS platforms.

Chapter 3

Modelling Students under Uncertain Conditions

3.1. Introduction

The main objective of our work is to use intelligent techniques to advise teachers in Web-based distance learning classes. As discussed in Chapter 2, teachers need to get a better understanding of what is happening in distance classes, which includes problems and needs of individual students, as well as of groups of students and the class as a whole. Therefore, in order to effectively advise teachers, an intelligent advising system should be able to identify the problems and needs of both individual students and groups of students. Consequently, it should incorporate appropriate techniques for diagnosing students and extracting student, group and class models. This work relies on WCMS tracking data as the main source for diagnosing students, which implies some degree of uncertainty both in the student modelling algorithms and in the structure of the individual and group models.

The aim of this chapter is to review existing student modelling approaches in order to justify the choice of an approach used for building models of students and groups utilised by an intelligent teacher advisor. Therefore, at the beginning of the chapter, a brief overview of student modelling is given, focusing on most common approaches, techniques, and systems, which are relevant to our work. Student tracking data is recorded by WCMS following a student's interactions with the course through a Web browser. There is a high level of uncertainty of using such data to obtain student models. Therefore, student modelling in uncertain environments, in general, and fuzzy student modelling, in particular, is reviewed. The framework proposed in this thesis considers generating advice not only about individual students but also about the behaviour of groups of students and the whole class. This means that an appropriate mechanism for modelling the status of groups and class is needed. A brief review of relevant approaches for modelling groups of students is presented at the end of this chapter.

3.2. Brief Overview of Student Modelling

Student modelling can be defined as the process of collecting and representing relevant information about the student (e.g. cognitive, behavioural, and social information) in order to model the student's aspects and facilitate the achievement of individualised interaction between a computer-based learning environment and a student (Holt et al., 1994; King, 1998; Kumar, 1992; Paiva et al., 1995; Rickel, 1992; Stephen & Hopple, 1992; Tsinakos & Margaritis, 2000). In this work, student models are used to keep information about the students to enable providing the teachers with appropriate advice which highlight important information about the students.

There is no agreement of what information should be included in a student model. A student model would include the student's *prior relevant learning*, the student's *progress within the course*, the student's preferred *learning style*, as well as other types of student-related information. Implementing such a comprehensive student model would be a computationally challenging and time consuming task. For this reason, most developers of intelligent educational systems attempt to model the student only in relation to subject matter representation (Holt et al., 1994). Eklund and Zeiliger (1996) list five main student's features that should be kept in student models of adaptive hypermedia Web-based systems either alone or in combination. These are the student's *learning goal*, *knowledge on the domain presented*, *background* (profession, work in related areas), *experience with the current hyperspace*, and *preferences*. Most of these features are dealt with in the student models used in TADV, as discussed in Chapter 4.

Many researchers (e.g. Clancey, 1986; Kass & Finin, 1988; Rich, 1979; Self, 1987; Sleeman, 1985) have attempted to suggest criteria to characterise student modelling. They focused on the *content*, the *use*, and the *ways of building* a student model. Verdejo (1994) determines five kinds of features that should be distinguished in modelling the cognitive aspects of a student: knowledge (student beliefs about the domain and world knowledge), intentions (student goal), capabilities (cognitive style and intellectual abilities), preferences (interaction styles), and motivations (traits such as achievement motivation, anxiety, competence motivation, and locus of control). Nykanen (1997) stresses that a student model should be "at least partially transparent" because it will be used not only for adapting the student's interactions but also for studying student behaviour and the use of content material.

There are many barriers to student modelling resulting from the problem of inferring knowledge about a student from data about his behaviour with the system. Some of these barriers are listed by Holt et al. (1994), including:

- The student modelling process generally contains a large amount of *uncertainty* due to the interpretive nature of observations and the assumptions were sometimes needed (more detail in Section 3.4).
- Constructing explanations from students' behaviour is *computationally challenging*.
- Students are creative and inventive and frequently engage in *unanticipated, novel behaviour* that requires much sophistication to interpret.

In this work, we depend mainly on tracking data stored by WCMS, the data represents uncertain information about the students' interactions with the course. This points out the need for utilising a student modelling mechanism appropriate for interpreting these uncertain interactions, together with an appropriate way to fine tune the student modelling variables (see Chapter 4).

3.3. Brief Review of Student Modelling Approaches

This section presents a review of the common approaches used for student modelling in intelligent computer-based educational systems. The aim is to justify the selection of a student modelling approach appropriate for the problem presented in this thesis.

There are many approaches for student modelling, however, there is no one accepted classification developed to systematically compare these approaches. Few studies have attempted to classify student models (e.g. Brusilovsky, 1994; Djordjevic-Kajan et al., 1996; Elsom-Cook, 1993; King, 1998). These studies seem to agree that the most commonly used basic student modelling approaches are: *Overlay* modelling, *buggy* (error) modelling and *Learner-based* modelling. The definitions of these approaches are presented in the next subsections and followed by a short discussion.

3.3.1. Overlay student modelling

In this approach, the perceived student knowledge is matched against the domain knowledge base, and areas of student understanding are flagged (Rickel, 1992). This means that a student's knowledge is viewed in terms of a tutor's domain knowledge, or as described by (Holt et al., 1994; King, 1998; Kumar, 1992; Sison & Shimura, 1998), the student's knowledge is expressed as a subset of the teacher's knowledge. In an overlay student model, the student is represented by a relatively simple mechanism, which supports inferencing about the student's cognitive state relative to an ideal domain expert (Stephen & Hopple, 1992). This gives a chance for an easy comparison between what the student knows and what he should know. The overlay model works well for systems where the goal is to strictly impart the expert's knowledge to the student (Holt et al., 1994), and it is more applicable when the subject matter can be represented as a prerequisite hierarchy (Kumar, 1992). The overlay model can be constructed from scratch as a semantic net, with nodes and arcs added as they are taught, or by starting with the expert knowledge base as a student model and interpreting deviations that are subsequently detected (Rickel, 1992).

The overlay student model is domain independent, has an easy representation of both tutor's and student's knowledge, and facilitates student assessment (Tsinakos & Margaritis, 2000). Using an overlay model, student errors will be interpreted as a lack of knowledge (Stephen & Hopple, 1992), which means that there is no plan to account and correct the student's misconceptions. This can be considered as a major disadvantage of the overlay modelling because misconceptions are common amongst average students and intelligent educational systems must deal with them regularly.

There are many ITS that implement overlay models, for example, SCHOLAR - a geography tutor for South America (Carbonell, 1970), BIP – a problem-solving laboratory for introductory programming (Barr et al., 1976), WEST – an electronic board game to teach arithmetic (Burton & Brown, 1978), WUMPUS – an educational game for teaching probabilistic reasoning (Goldstein, 1982), GUIDON – a tutor built on the medical diagnostic system MYCIN for medical student tutoring (Clancey, 1983), and TRILL - The Rather Intelligent Little Lisper (Cerri & Elsom-Cook, 1990).

The overlay modelling approach is commonly used recently in WBITS. Generally, system developers implement the overlay model in the way that helps satisfy the objectives of the systems they develop. In the Virtual Campus PROLOG Tutor, concepts and skills are organised in a concept lattice to represent the relationships between concepts (Peylo et al., 2000). To facilitate intelligent problem solving, concepts are related to skills and skills may be either defined in terms of knowing the intention and extension of a concept or in applying a concept to a task. This approach enables adaptive presentation of learning material with respect to the student's knowledge (Peylo et al., 2000). If a student solves a specific problem with the strategies and techniques that are applied on a class of problems, then he has reached a specific goal. The student modelling component uses two information sources to judge the students' understanding: URL-tracking to detect the visited concepts and the results from the intelligent analysis of assignments (Peylo et al., 2000).

A Web-based authoring tool that aims to help teachers and students of domains that make use of algebraic equations is described by Virvou & Moundridou (2000). This tool performs intelligent analysis of the students' solutions and provides interactive support. It sorts and annotates the links that the students visit to facilitate adaptive navigation support (Virvou & Moundridou, 2000). The student model used is a combination of a stereotype and an overlay. The *stereotype* student model classifies students according to their knowledge of the domain and their mathematical skills. As a result, each student is assigned to a stereotype (beginner, intermediate, or expert). The overlay model is represented by a set of pairs "concept-value". It is assumed by the system that a student knows a concept if he enters the correct equation in a given problem which requires knowledge of this concept. The value for each concept is an estimation of the student's knowledge-level (poor, average, or good) of this concept (Virvou & Moundridou, 2000).

In the Web-based Adaptive Statistics Tutor (AST) a student model is built by monitoring the student's interactions with a domain model, interactive examples, and tests (Specht et al., 1997). The AST architecture consists of three modules. First, a domain expert module, which contains concepts of the domain, their text, examples, and tests and their interrelations and dependencies built as a conceptual network. Second, a pedagogical expert module, which contains both pedagogical strategies used to teach different parts of the course and diagnostic knowledge about the tests. Third, a conceptual overlay student model, which stores the preferred settings of a student and the domain units a student worked on, and can be used to adapt and individualise the teaching according to the student's level and preferences (Specht et al., 1997).

PAT Online is an algebra Web-based tutor designed to assists students in solving linear equation problems (Brusilovsky et al., 1997). PAT Online updates a student overlay model through the assessment of the student's progress during problem solving. Skills that the student needs to master are represented in a rule-based system. PAT Online assumes a two-state model of skill learning (mastered or not), and maintains the probability that the student has mastered the skill. At each opportunity to learn, there is some probability that the skill will go from an unlearned to a learned state. Two other parameters estimate the probability that the student will make an error even though the skill has been mastered, and the probability that the student will give the correct answer even though the skill has not been mastered (Brusilovsky et al., 1997).

3.3.2. Buggy (error) student modelling

Burton (1982) introduced the buggy modelling approach, which considers both *correct and buggy rules* that the student may follow. The buggy model attempts to represent the *erroneous beliefs* of the student in terms of a set of bugs or misconceptions (Kumar, 1992). The common technique for implementing a buggy model is to represent explicit knowledge of likely misconceptions beside the representation of the expert knowledge. To determine the buggy model of a student, the system requires a library of bugs. Depending on the incorrect answers of a student to a set of questions, it is possible to determine bugs in the student's understanding by mapping the student's behaviour to bugs in the library (Kumar, 1992). The inclusion of the bugs allows more sophisticated understanding of the student than the understanding accomplished with a simple overlay on the expert model (Holt et al., 1994).

King (1998) indicates that buggy models can be divided into two categories. The first is the *Enumerative model*, which models both correct knowledge and common misconceptions. This normally relies on the reliability of the bug library. In most cases, it is necessary to enumerate all the bugs based on some empirical analysis of students' errors (VanLehn, 1982). Other approaches for enumerating bug libraries are informed by studies of human learning, e.g. Dimitrova (2001) uses concept learning theories to define possible patterns of erroneous reasoning. The second category is the *Reconstructive model*, which determines misconceptions when a student improperly applies operators during some procedural task; there is no need for bug library since misapplied operators will determine misconceptions (King, 1998).

A buggy model is domain independent, and represents both a student's knowledge and some student-expert differences, defined explicitly. The utilisation of a bug library provides information that can be used to promote the students' self-reflection and to give hints on context comprehension (Tsinakos & Margaritis, 2000). Unfortunately, there are many disadvantages, for example, buggy models are difficult to design and implement (Stephen & Hopple, 1992), and in some cases, they do not explain why bugs have occurred (Verdejo, 1994).

Some examples of systems that use buggy models are LMS - a system for testing algebra skills (Sleeman & Smith, 1981), PROUST - a system for teaching PASCAL programming (VanLehn, 1982), ACM – Automated Cognitive Modelling system (Langley & Ohlsson, 1984), MALGEN – which attempts to determine common misconceptions by forming new problem-solving operators that represent incorrect knowledge (Ellery, 1990), and INSTRUCT – which models tasks where domain knowledge can be partitioned into a set of operators and a set of applicability conditions (Djordjevic-Kajan et al., 1996).

3.3.3. Leaner-based modelling

Learner-based models can explain *misconceptions* in the student's knowledge in terms of their *generation* process (Brown & VanLehn, 1980). This approach, alternatively called *genetic modelling* (Brusilovsky, 1994), is based on the idea that when students construct knowledge over time, they can gradually form misconceptions, which in turn prevent a student from progressing through the course (King, 1998). Using this approach, it is important to explain the mechanisms by which the student acquires knowledge to enable the tutoring system to understand more about a particular student's learning abilities and to justify the problems with his abilities (Elsom-Cook, 1993). Learner-based models are usually implemented using *machine learning* techniques (e.g. neural networks and genetic algorithms) to emulate the generation process. This approach, therefore, brings intelligent educational systems one step closer to human-like performance (King, 1998). A comprehensive review of using machine learning techniques in student modelling can be found in Sison and Shimura (1998).

Examples of systems that implement learner models are: DEBUGGY – a system that evaluates a student's subtraction performance and describes misconceptions by selecting predefined bug specifications and then iteratively removes, combines or forces elements of the evolving set until a student's answers to a set of subtraction training examples are explained (Burton, 1982); PIXIE/INFER – which attempts to form student models through operator specialisation and designed to model a student's problem-solving ability and to provide appropriate remediation to improve the student's performance (Ellery, 1990), and ASSERT – which attempts to determine commonalties between newly created knowledge bugs through the use of bug generalisation procedures (Baffes & Mooney, 1996).

3.3.4. Discussion

The three most common and relevant approaches of student modelling are reviewed to select one practical approach that is suitable to model students in order to generate advice to the facilitators in WCMS distance learning environments. Each of the modelling approaches discussed is applied in different intelligent educational systems and has its pros and cons. However, in this research, the following factors drove the selection of a student modelling approach:

- The selected approach should be able to build student models depending mainly on the tracking data generated by WCMS which usually contains information about the students' interactions with the course parts, assessment items, and communication activities (see Chapter 2). This means that, in our case, we do not have enough information about how a student has constructed his knowledge which implies the inapplicability of learner-based modelling approaches.

- WCMS are usually domain independent, i.e. they can be used to build courses in different types of domains (e.g. procedural, declarative, etc.), therefore, the selected student modelling approach should be applicable to a variety of domains.
- The selected approach should be relatively simple so that it can be easily applied in different WCMS with different domains. By simplicity we mean the easiness of applying the modelling approach. For example, using the error or buggy modelling approach requires the availability of bug libraries which are usually difficult to accumulate. Selecting a bug modelling approach would add significant overloads to the tasks of preparing and designing the courses, which are usually time consuming. It should be noted though that the simplicity of the potential student modelling approach to be chosen does not contradict with the necessity of that approach to be robust and effective in representing the students' status because it is necessary to deal with large quantities of uncertain evidence collected from the available tracking information.

Accordingly, we argue that the *overlay modelling approach* would be beneficial in this research for the following reasons:

- While it is a simple mechanism, it supports the representation of the students' cognitive state. The available tracking data can be used to determine the parts of the course visited by the student and also the times the student spent working with these parts. Moreover, it can be used to know which assessments were solved correctly and which were solved wrongly by the student. Therefore, it is possible to estimate the student's knowledge of different concepts represented in a typical course.
- Since most WCMS courseware developed in universities and schools aims mainly to impart course knowledge to the students, then overlay model should be appropriate in our case.
- Overlay modelling has been applied to a variety of domains, and this will allow the application of the proposed framework in any domain to support the generality of the framework.
- When using an overlay student modelling approach there is no need to build bug libraries. Moreover, there is no strong need to use sophisticated knowledge

representation methods (e.g. semantic networks, frames, etc.) to represent the domain knowledge.

- The overlay modelling approach is the most commonly used to model students in ITS and WBITS. Eklund et al. (1997) report that an overlay model is the most commonly used student modelling technique in adaptive hypermedia systems.

In this section, we have discussed the three most common approaches used to build student models. The overlay approach is chosen as the most appropriate approach to construct student models in our case. The next section, deals with the algorithms that should be applied to extract such models in terms of some specific conditions pertinent to this project: namely, extracting models of students from a vast quantity of tracking data collected by WCMS.

3.4. Student Modelling and Uncertainty

In this study, the addition of intelligent features to traditional WCMS is considered. Consequently, the input for the algorithms for student modelling should be based on information normally provided in WCMS. We will examine the utilisation of the student tracking data captured by WCMS to build student models. A student's interactions will be used as evidence to estimate the *cognitive status* of this student. For example, if tracking data indicates that a student has read one of the course pages for 10 minutes, then this will be considered as evidence for estimating the student's understanding level of the knowledge represented by that page. However, we cannot be fully confident that the student has spent the whole 10 minutes in actively working with the content presented in the page. There is a possibility, for example, that the student answered a phone call or was engaged in a conversation during these 10 minutes. This implies that the data collected by WCMS can not be taken as *fully reliable* for modelling students. This, in turn, indicates the high level of uncertainty when constructing student models. In our project, we consider every piece of the vast tracking data as some kind of evidence. Then, we try to find out what this data means with regard to modelling a student's knowledge, and try to extract some approximated model of this particular student. Therefore, in addition to the overlay modelling, we need a diagnostic approach that deals with uncertain student modelling.

In general, the student modelling task is fraught with uncertainty, especially when it mainly depends on the students' interactions with the course. Most of the information included in the models comes from *observations* and *guesses* about the students, which may be proven right or wrong from their later performance. Katz et al. (1994) report that ITS developers attempt to include adaptive functions like selecting the appropriate level of advice and explanations, determining readiness for advancement and dynamic planning of the student's curriculum, and giving student the proper feedback on his performance and progress through the curriculum. These functions are not easily tractable and cause many difficulties to the researchers. There are several sources of uncertainty in modelling a student's knowledge:

- *Ambiguity* - there is often more than one explanation for student's actions;
- *Multiplicity* - an error or inappropriate problem-solving action can often be traced to several misconceptions and deficiencies;
- *Idiosyncratic (distinctive) errors* - such as computational, mechanical slip-ups (typos), lucky guesses, and the fact that students often forget prior knowledge (Katz et al., 1994).

Many techniques are used in AI to reason in uncertain environments. Amongst the most popular techniques are statistical (probabilistic) reasoning and fuzzy logic, and both techniques are used widely to reason in uncertain environments. These AI techniques have been applied also to model the students' cognitive aspects. The using of these techniques for student modelling is discussed in the next subsections. The aim is to identify a suitable approach for estimating the students' knowledge status using the evidence available from WCMS tracking data.

The selected approach should be able to estimate the students' cognitive status (knowledge level) with respect to the domain concepts and justify the students' mastery levels so that appropriate advice is generated to teachers. Simultaneously, the required knowledge representation schemas and the metadata required to describe the domain concepts and how they are related should be made fairly simple and clear, then the metadata can be easily acquired from domain experts (teachers). In addition, the potential approach should not be computationally difficult. We stress the simplicity and intuitiveness because building courses using WCMS is very popular among teachers who are not necessarily experts in computing, let alone familiar with sophisticated AI techniques, and we expect teachers to participate actively in building the courses they teach.

3.4.1. Student modelling using statistical reasoning

Statistical reasoning in AI is usually based on the Bayes' theorem. The Bayes' theorem is a mechanism for combining new and existent evidence usually given as *subjective probabilities*. It is used to revise existing prior probabilities based on a new set of observation made (Turban & Aronson, 2001). The theoretical background and mathematical basis of the Bayes' theorem can be found in Turban & Aronson (2001) and Rich & Knight (1993). Turban & Aronson (2001) indicate that, using the Bayes' statistics, what is inferred about a proposition is represented by a single value for its likelihood. This leads to two criticisms of Bayesian statistics. Firstly, a single value does not tell much about its precision, which may be very low when the value is derived from uncertain evidence. Secondly, the single value combines the evidence for and against a proposition without indicating how much there is of each. Rich & Knight (1993) add that the Bayes' theorem is *intractable* for several reasons. The knowledge acquisition is somewhat difficult because too many probabilities have to be provided. In addition, there is substantial empirical evidence that people are very poor probability estimators (Kahneman et al., 1982; Tversky & Kahneman, 1974). However, as Rich and Knight (1993) indicate, the Bayesian statistics provides an attractive basis for uncertain reasoning systems, and several mechanisms for exploiting its power and making it more tractable have been developed, e.g. Bayesian Networks, and Certainty Factors.

Reasoning using Bayesian Networks

Bayesian networks are probabilistic models that combine *probability theory* and *graph theory* (Pearl, 1988). They represent causal and probabilistic relations among random variables that are governed by probability theory (Ling & Zhang, 2002). Bayesian networks are used to model students in many intelligent educational systems. They can be used to model relationships between observed student actions, student internal states, and outcomes (Mayo & Mitrovic, 2001). Bayesian networks have been proposed to relate, in a probabilistic way, a particular piece of a student's knowledge with the student's observable behaviour (Stathacopoulou et al., 2003). There are several intelligent systems that use Bayesian networks for student modelling, for example, OLAE (Martin & VanLehn, 1995), POLA (Conati & VanLehn, 1996), CAPIT (Mayo & Mitrovic, 2001), Andes (VanLehn & Niu 2001), and ACE (Bunt & Conati, 2003).

OLAE (Online Assessment of Expertise) has been chosen as a typical example to illustrate how Bayesian networks can be used to build student models based on student's interactions. OLAE is a Web-based tool which aims to help assessors determine what a student knows in introductory physics (Martin & VanLehn, 1995). It uses Bayesian nets to represent student's behaviour during the problem solving and compute the probabilities of the student's application of each of the rules in a given knowledge domain. The OLAE student model consists of a rule-based program that captures the way a student computes answers to the given problems, both correctly and incorrectly.

In this model a, Bayesian net has four types of nodes. One node represents whether or not a student knows a given rule of elementary physics. The second node represents whether or not the student actually has used the rule, given a specific problem. The third node represents whether or not the student believes a particular fact about the problem, and the fourth node represents whether or not a student has performed a particular action. The analysis involves a multi-step process, which starts with the domain model and a physics problem. The domain model is applied to the problem to produce a problem solution graph, which indicates all possible inferences that can be drawn from the problem's solution. The student model is then generated which is also based on the previous assessments of the student. Once this model has been connected to the problem solution graph, the data is processed from the interface. The resulting probabilistic assessment can be viewed by the assessors in different formats (Martin & VanLehn, 1995).

The approach followed by OLAE shows that Bayesian networks require considerable computational efforts and emphasises the need for sophisticated domain and expert models. Moreover, Conati et al. (2002) pointed out the problems resulted when Bayesian networks were used to scale up the student models used in Andes (a tutoring system for Newtonian physics whose philosophy is to maximise the student initiative and freedom during the pedagogical interaction). Andes used Bayesian networks for around a hundred physics problems. It was necessary to regenerate all these Bayesian networks every time the problem solvers' knowledge base changed. Although Conati et al. described that they were able to automate the network reconstruction so that it could be done with little human intervention, they admitted that the performance of the computer used became much slower and in some cases they had to direct Andes to use stochastic evaluation of the networks to stop the reconstruction process (Conati et al., 2002).

In conclusion, the Bayesian networks prove effectiveness when used to model students in many applications. However, Bayesian networks are not computationally simple. They still depend on the acquiring of conditional probabilities and sophisticated domain and expert models. Significant time and effort are needed to initialise the Bayesian networks and to provide all probabilistic parameters. This is not always a straightforward task because people are usually poor probability estimators. Therefore, we did not choose Bayesian networks for the construction process of student models in our case. A simpler, fairly intuitive, technique is required so that the majority of teachers who use WCMS can follow it easily or, at least, can participate effectively in providing the necessary metadata required for representing domain knowledge.

Reasoning using certainty factors

Standard statistical reasoning methods are based on the assumption that uncertainty is the probability that an event is true or false. In the certainty factor theory, uncertainty is represented as a *degree of belief*. The certainty factor model was introduced by Shortliffe and Buchanan as a method for representing and manipulating of uncertain knowledge in the rule-based medical expert system MYCIN. Turban & Aronson (2001) define Certainty Factor (*CF*) as a figure that expresses a degree of belief in an event, fact, or hypothesis based on evidence or an expert's assessment. Several methods can be used to handle *CF* in intelligent systems. Klein and Methlie (1995), Rich and Knight (1993) and Turban & Aronson (2001) agreed that the approach used in MYCIN (Buchanan & Shortliffe, 1984; Shortliffe & Buchanan, 1975; Shortliffe, 1976) is the most acceptable approach for calculating the certainty factors. In MYCIN, the numbers attached to certainty factors take values in the range (-1, 1). If the value is positive one believes that the fact is true; if it is negative one believes that the fact is not true, with complete knowledge or certainty at each extreme -1 and +1 (Klein & Methlie, 1995). In this approach, certainty factor $(CF[h,e])$ is defined in terms of two components:

1. $MB[h,e]$ - A measure (between 0 and 1) of belief in a hypothesis h given the evidence e; it measures the extent to which the evidence supports the hypothesis.
2. $MD[h,e]$ - A measure (between 0 and 1) of disbelief in hypothesis h given the evidence e; *MD* measures the extent to which the evidence supports the negation of the hypothesis.

Using these two measures, *CF* is defined as:

$$CF[h,e] = MB[h,e] - MD[h,e] \qquad (3\text{-}1)$$

When several pieces of evidence are combined to compute the *CF* of one hypothesis, the measures of belief and disbelief of a hypothesis given observations s_1 and s_2 are computed from:

$$MB[h, s_1 \wedge s_2] = 0 \qquad \text{if } MD[h, s_1 \wedge s_2] = 1$$

$$= MB[h, s_1] + MB[h, s_2] \cdot (1 - MB[h, s_1]) \quad \text{otherwise} \qquad (3\text{-}2)$$

$$MD[h, s_1 \wedge s_2] = 0 \qquad \text{if } MB[h, s_1 \wedge s_2] = 1$$

$$= MD[h, s_1] + MD[h, s_2] \cdot (1 - MD[h, s_1]) \quad \text{otherwise} \qquad (3\text{-}3)$$

This can be stated as: the measure of belief in h is zero if h is disbelieved with certainty. Otherwise, the measure of belief in h given two observations is the measure of belief given by the first observation plus some increment added for the second observation. This increment is computed by firstly taking the difference between 1, the complete certainty, and the belief given from the first observation. This difference is the most that can be added by the second observation. The difference is then scaled by the belief in *h* given only the second observation. Similarly, it is possible to give an explanation for the formula of computing disbelief (Rich & Knight, 1993).

The approach of certainty factors appears to mimic quite well the way people manipulate certainties (Shultz et al., 1989). In addition, Rich & Knight (1993) state that this approach makes strong independece assmuptions that make it relatively *easy to use*; at the same time these assupmtions create *dangers* if the important dependencies are not captured correctly. This will not affect the reliability of the approach especially when individual evidence (antecedent)/hypothesis (consequent) relationships are considered *independently* of the others. In other words, the reliability of the approach will be negatively affected if *chaining* of individual dependent evidences (which lead to a certain hypothesis) is considered while the relationships between these evidences are missed or not correctly defined.

Regarding the problem undertaken in this thesis, a student's interactions stored by WCMS can be considered as evidence for the student's cognitive state. Each individual interaction related to a certain domain concept can be considered as evidence (belief or disbelief) to determine the knowledge level of that concept. In addition, the low mastery level of a domain concept can be explained by the absence of some types of interactions (e.g. the interactions which indicate that the student has visited the learning objects related to the concept do not exist) or by the existence of some interactions (e.g. interactions which indicate erroneous solution of quizzes related to the concept). The necessary data (measures of belief and disbelief) required to initialise this approach is relatively easy to acquire when compared with data required by the Bayesian network approach. It is easier to ask teachers specifying their beliefs and disbeliefs than to ask them to state the probabilities of all outcomes. Moreover, certainty factor approach does not require sophisticated schemes to represent domain knowledge. These mentioned factors make the overall computational effort required to estimate a students' knowledge status relatively simple. Therefore, we argue that the approach of certainty factors can be used along with some ideas from fuzzy logic and fuzzy set theory (discussed in the next section) to reason about a student’s status. We will show that this approach can be beneficial if applied to the problem presented in this thesis (see more details in Chapter 4). The certainty factor approach is used widely in expert system domain and also used to model students in some intelligent environments, e.g. Anjaneyulu (1997) and Kosba & Dawoud (1999).

3.4.2. Fuzzy student modelling

The certainty factors approach described above can be used as a mechanism to compute a scalar value (from -1 to 1) to represent the knowledge level of any domain concept represented in the overlay student model. This scalar value depends on the values of measures of belief and disbelief. In some cases, the computing of these measures needs an interpretation mechanism so that it can be reasonably estimated. For example, if the understanding measure of belief assigned to reading a page for five minutes is 0.4, what will be the value of this measure if a student read the page for only two minutes or for 15 minutes? Another issue to be considered is the determination of the knowledge levels of different concepts. For example, if the certainty factor of a concept is 0.3, what will be the status of that concept (i.e. learned or unlearned)? These issues show the need for some concepts of fuzzy logic and fuzzy set theory.

Fuzzy logic is a superset of conventional or Boolean logic that has been extended to handle the concept of *partial truth*, i.e. truth-values between “completely true” and “completely false”. Lotfi Zadeh introduced fuzzy logic in the 1960’s as a means to model the uncertainty of natural language (Turban & Aronson, 2001). Traditional set theory defines set membership as a Boolean predicate, e.g. one is either tall or not and of course there must be a specific height that defines the boundary. Fuzzy set theory allows us to represent set membership as a possibility distribution, i.e. one’s tallness increases with one’s height until the maximum boundary is reached. The techniques of inexact reasoning uses the theory of fuzzy sets to simulate the process of the normal human reasoning by allowing the computer to behave less precisely and logically than conventional computers do. The thinking behind this approach is that decision-making is not always a matter of true or false; it often involves grey areas and the term “may be”. Turban & Aronson (2001) point out many advantages of fuzzy logic, e.g. providing flexibility, giving options, and allowing for observation. More details about fuzzy logic can be found in Turban & Aronson (2001) and Rich & Knight (1993).

In conclusion, fuzzy set theory attempts to capture the notion that items can have varying degrees of membership within a set, as opposed to the standard view that an item either belongs or does not belong to a set. For example, a student might have partial membership within the set of students who are expert in a particular skill, as reflected in teacher comments, e.g. “student S is *fairly good* at two-column multiplication”.

Fuzzy student modelling approach was originally proposed by Hawkes and Derry and their colleague (Katz et al., 1994). Hawkes et al. (1990) state the following rational for applying fuzzy set theory to student modelling:

> *"The use of fuzzy terms, e.g. rather high, possibly, not likely, etc. allows for imprecision and vagueness in the values stored in the database. This provides a flexible and realistic representation that easily captures the way in which the human tutor might evaluate a student. Also, many tutoring decisions are not clear-cut ones and the capability to deal with such imprecision is a definite enhancement to ITS" page 416.*

The appeal of fuzzy logic to manage the uncertainty in student modelling is justified by Jameson (1996) for the following two reasons:

- People often reason in terms of vague concepts when dealing with uncertain situations. For example, the statement "This student is *quite* advanced" reflects uncertainty about how advanced the student is. Many systems take advantage of fuzzy logic's techniques for representing and reasoning with vague concepts to mimic this human style of reasoning. This approach of reasoning is easy for users and designers to understand and modify.
- When students supply information about themselves to a system, they may express this information vaguely. For example, a student's vagueness in "I don't know very much about the WWW" leads to uncertainty in the system. Fuzzy logic provides means to represent and process such uncertainties.

Several studies have been conducted to experiment imprecise student modelling approaches (Chin, 1989; Derry & Hawkes, 1992; Greer & McCalla, 1989; McCalla & Greer, 1992). These studies concluded that the incomplete and inaccurate models produced were useful for carrying out the system's knowledge assessment and pedagogical functions. A very crude categorisation of student ability into discrete knowledge levels worked quite well in guiding the system's decisions about the level of details to provide in hints. This is not surprising because there is an increasing body of evidence that human tutoring decisions seldom involve precise details about misconceptions or bugs that motivate student errors. In low-risk decision-making situations, such as tutoring, where new information is constantly being made available for modifying diagnostic hypotheses, imprecise student modelling appears adequate (Derry & Hawkes, 1992; Katz et al., 1994).

Fuzzy logic techniques have been used to improve the performance of intelligent educational systems due to their ability to handle uncertain information, such as students' actions, and to provide human descriptions of knowledge and of students' cognitive abilities. In most intelligent tutoring educational systems, students' interactions with the system are considered as the main source for judging the students' knowledge status. Different approaches have been used to get useful interpretation from students' interaction in order to build fuzzy student models. For example, Anjaneyulu, (1997) presents a framework for concept level modelling in a hypermedia application. Based on concept modelling, the system is able to determine the concepts the learner can go through. The students' answers to questions related to each concept are solely used to evaluate the students' performance. The students' interactions with course material are not considered in the evaluation process. Following the same approach, Grigoriadou et al. (2002) propose a fuzzy logic-based, decision making model which stores and analyses uncertain information regarding the various characteristics of the student and also evaluates his knowledge status and skills. The evaluation of a students' knowledge and cognitive abilities is based only on his answers to pre-stored questions.

SHERLOCK II is an intelligent coached practice environment developed to train technicians to diagnose faults in a complex electronic testing system (Lesgold et al., 1990). SHERLOCK II employs techniques for representing and updating fuzzy student knowledge variables. Each knowledge variable (skill) is associated with a "fuzzy probability distribution" that has been upgraded or downgraded at different rates depending upon the type and strength of the evidence that appears in a student problem-solving trace. For example the skill known as "the ability to interpret test results" receives a strong upgrade each time a student tests the input signals to a circuit card when a previous test shows that the card's output signals are faulty, but receives a weaker upgrade if the student performs the input verification after receiving system advice to do so.

In ABITS, discussed earlier in Section 2.9, when a student has read a learning object (e.g. lesson) with a given set of concepts included in it, the system forecasts a slight increase of the student's knowledge of these concepts with a large degree of uncertainty. When the student answers a test related to the same set of concepts correctly, the system again increases the knowledge degree of these concepts but with a lower degree of uncertainty (Capuano et al., 2000). In InterBook, information about the student is gained by tracking user actions in dimensions like reading text, looking at examples, or solving multiple-choice tests. Its overlay user model describes the user's current state of knowledge about a certain concept by a *score* on any of these dimensions. These multiple scores are finally projected, by applying some simple linear equations, into a scalar value used to estimate the educational state of any concept (Brusilovsky et al., 1997). As described by Brusilovsky et al. (1998), this overlay model is powerful and flexible since it can independently measure the student's knowledge of different topics. Weibelzahl & Weber (2003) point out that some adaptive systems, for example AHA (de Bra & Calvi, 1998), assess the users' current knowledge by just looking at the pages visited by the users, and argue that this source of knowledge is *insufficient* and it is necessary to employ explicit assessment with a set of test items to provide much more reliable user models.

In the proposed approach (described in detail in Chapter 4), two main sources of information for evaluating a student's performance are dealt with. The first is the *plausibly certain information* derived from the student's answers to assessment quizzes that test domain concepts. Based on the correctness of a student's answer, measures of belief and disbelief about the student's understanding of the considered concept are assigned. These two measures are taken into account when calculating the overall student's knowledge status. The second is *uncertain information* derived from the student's interactions with the learning objects designed to teach domain concepts. The main reason behind the uncertainty of this information is the inability to verify that a student has read or worked effectively with the learning objects. However, we argue that the students' interactions with learning objects should not be ignored when diagnosing the students' knowledge because these materials, examples, presentations, etc. are the main source from which the students build their domain competence. On the other hand, it is not cogent to grant significant understanding measure of beliefs as a result of vague interactions made by the student. The student modelling method proposed in Chapter 4 provides a fine-tuning effect of these uncertain interactions according to a defined fuzzy membership function, depending on the time a student has spent working with any specific learning object.

Fuzzy techniques are used in combination with different approaches for building student models. For example, in ATS (Adaptive Tutoring system), the student modelling component uses machine-learning techniques to emulate a student's learning state combined with fuzzy methods to represent uncertainty (Gurer et al., 1995). The Brilliant Scholar Series 1 (BSS1) is used by several thousand home and school users in the learning of curricular subjects such as mathematics and sciences (Warendorf & Taso, 1997). BSS1 uses heuristics to interact with users and monitor their progress. Fuzzy logic techniques have been used to improve the performance of BSS1. A general fuzzy logic engine was designed and implemented to support development of intelligent features for BSS1 (Warendorf & Taso, 1997). Tsaganou et al. (2002) present F-CBRDHTC, a Fuzzy Case-Based Reasoning method for modelling student's Historical Text Comprehension. The fuzzy Case Based Reasoning algorithm handles the uncertainty in the acquisition of the expert's knowledge regarding the student's observable behaviour during historical text comprehension. Finally, Stathacopoulou et al. (2003) proposed an approach for student modelling based on both neural networks and fuzzy modelling approach. Fuzzy logic is used to handle the subjective judgments of human tutors with respect to student observable behaviour and their classification of the student's knowledge. The student's knowledge is decomposed into pieces and assessed by combining fuzzy evidence, each one contributing to some degree to the final assessment (Stathacopoulou et al., 2003).

Most of the researchers who have used fuzzy student modelling have found that, although imprecise, the extracted student models are adequate for carrying out the system's assessment and pedagogical functions, since human tutoring decisions seldom involve precise details about misconceptions that cause student errors and since new information is constantly being made available for modifying diagnostic hypotheses. In line with this argument, we select to use fuzzy techniques along with certainty factor theory (discussed in Section 3.4.1) to build models of individual students, as well as groups and classes of distant students based on analysis of the information supplied by WCMS about the students' actions in Web-based distance courses.

3.5. Group Modelling

In this research, one of the important requirements is to generate advice to the teachers to enable them monitor the progress of groups and classes (class is considered as a big group). For example, a teacher may need to monitor the progress of groups of students with a certain nationality or age range or be informed about the topics in which most of the students in a group or the whole class are struggling with. Therefore, it is necessary for an intelligent advising system to model the status of groups and classes in order to facilitate discovery of any common problems that might encounter the majority of the students in such groups or classes.

In the early stages of intelligent educational systems, researchers focused their efforts to create individualised student models. With the advent of WWW and the increasing demand on collaborative learning, the need to model and support students working in groups became important. In a networked learning computing environment, Computer-Supported Collaborative Learning (CSCL) provides support to a group of students working in a collaborative learning environment (Koschmann, 1992). Collaborative learning benefits a student through facilitating participation in group discussions and active contributions to a group project (Edelson et al., 1996). CSCL systems usually provide tools to facilitate online interactions, such as chat, bulletin boards, and discussion forums. These tools are good mechanisms for supporting conversations among students, but they do not provide any guidance or direction for the students during or after the dialogue sessions (Soller, 2001).

Most WCMS include many types of communication tools to facilitate conversation and connection among distant students. However, WCMS are usually not directly concerned with the concepts of group or class learning, e.g. group problem solving or class assessment (although group activities can be assigned within distance courses). In this work, we will not tackle the process of collaborative learning, which is being extensively studied by a number of researchers [e.g. Hoppe (1995), Suthers & Jones (1997), and Reimann (2003)] but rather focus on how to model the knowledge status of groups and classes with respect to different course topics in order to provide facilitators with information and advice about cognitive and social aspects in distance classes. Nevertheless, some group modelling approaches from CSCL may be relevant.

Paiva (1997) discusses the use of collaborative student models in collaborative discussions from both an individual student model and a group model. Some systems attempted to support students by letting them work with simulated peers in order to promote effective discussion between the student and his peer (Goodman et al., 1997; Ragnemalm, 1996). Soller et al. (1999) also stress the importance of peers actively helping each other in a collaborative environment. In collaborative learning, the group is an active entity, therefore, the system must contain information that refers to the *group as a whole*. This information generates a group model. A CSCL system should extract a group model from the individual student models obtained from interactions between the students and the learning environment, as well as from the observation of the group as a whole (Jaques et al., 2002). Unlike these systems, observation of group interactions and modelling of the group learning processes are not the main concern in this research. Instead, given the interactions made by the students in this group our focus will be on how to judge the knowledge status of a group of students, i.e. the *knowledge model* of each individual student and of the group as a whole.

An effective group model is not simply the sum of the individual models; it certainly needs other sources of knowledge. The learning process in groups is by-and-large different from the learning process for individuals. Paiva (1997) lists the following components of the individual student model in a collaborative learning environment:

- *Student's beliefs*: Beliefs that the student has about the domain (conceptual beliefs) and beliefs that the student has about his colleagues.
- *Individual actions*: what the individual student does alone (task actions) and what he does with the group (communicative actions).
- *Goals (objectives)*: There are two kinds of objectives: individual and common. It is necessary that the individual objective isn't a danger to the rest of the group.
- *Misconceptions*: Individual student's mistakes.

In our case, based on WCMS tracking data, only some of the above components would have to be selected. For example, using only WCMS tracking data will make it difficult to obtain information about the beliefs a student has about his colleagues, or actions a student takes with other group members. Consequently, since our system is not directed to the problem of group learning, the proposed group models focus only on knowledge status and simplify the list of components suggested by Paiva (1997) including *global beliefs*, *group actions*, and *group misconceptions*.

Andrade et al. (2002) proposed an architecture of an intelligent agent that diagnoses group behaviour and offers some sequence of instruction and feedback (scaffolding tactics) to support the group members. The proposed group model is inspired by Paiva's work (Paiva, 1997) where the notions of beliefs, action and group skills are discussed. They consider the *individual as an instance of the group* and, hence, extend the same model for the individual and the group. The main attributes proposed in the group model are: group beliefs, social context of interaction, group skills, motivational and emotional characteristics, group difficulties and group relationships (i.e. assistance required and offered).

In conclusion, the group modelling mechanism proposed in this work (as described in Chapter 4) is not based on any type of collaborative learning between the students in the group (for example, group problem solving) because collaborative activities are not always included in traditional distance learning courses in WCMS platforms. Moreover, the tracking data reserved by WCMS might not be suitable to help building sophisticated group models that should reflect the detailed cognitive and collaborative aspects of the group. Therefore, group models proposed here are based on the idea that group model can be considered as an instance of a student model (Andrade et al., 2002; Paiva, 1997). The main difference is that an individual student model is dependent on the interactions of one specific student but a group model is dependent on the interactions of the group members. More details about group and class modelling in the TADV are given in Chapter 4.

3.6. Summary

Student models are usually implemented in intelligent educational systems to help tutors customise and adapt the learning process according to the student's knowledge and skills. In our research, the student model informs the facilitators of the kind of help and learning advice that is appropriate for each individual student through the process of learning. Then, it becomes feasible to use a student model that provides instructors with crucial knowledge about their students and classes so that they are able to remotely manage and assess their courses.

There is no formal classification for student modelling techniques used in intelligent learning environments, and there is no agreement about the information that should be kept in student models and the ways by which this information can be used to diagnose the students' errors and misconceptions. It appears that information kept in student models depends mainly on the domain being represented, the domain knowledge representation technique, and on the student modelling technique being used. Moreover, this information depends on the adaptive and individualisation features developers aim to implement in the educational system. Web-based intelligent educational systems use student models to support students in navigating through the course and preventing them from being lost in hyperspace. Most adaptive techniques and collaborative features used within these systems primarily depend on information from student models.

One way to simplify knowledge and software engineering tasks required for developing student-modelling components is to use techniques for imprecise diagnostic which have been used in many learning and educational systems. These diagnostic schemes allow system developers to build simple and computationally manageable reasoning modules, which are suitable especially in Internet environments.

In this chapter, we have justified the need to build student models in computer-based advising environments proposed in this work. A review of important student modelling concepts, approaches, and systems is presented. The issue of inexact student modelling and approaches used to deal with uncertainty in student modelling tasks are also discussed. Finally, group student modelling techniques are briefly reviewed.

We have argued that student, group and class models and appropriate diagnostic techniques are needed for the purpose of identifying the problems and the needs of individual students, groups of students, and the whole class so that appropriate advice to teachers might be generated. In order to select the proper approach for structuring the student models and diagnosing students based on WCMS tracking data, we have reviewed the existing techniques and argued that *overlay* individual and group models will be constructed using *fuzzy techniques* and the *certainty factors* approach. More details about student modelling approaches adopted for this thesis are presented in the next chapter.

Chapter 4

The TADV Architecture and Student Modelling Mechanism

4.1. Introduction

The main objective of this research is to use the student tracking data generated by WCMS to build student models, and then use these models to generate advice to distance-learning facilitators helping them to become more knowledgeable and effective in managing distance classes. A computational framework, called TADV (Teacher ADVisor), is defined. This chapter will outline the TADV framework, explain how it works and describe how its components are interrelated. In addition, the student modelling mechanism used in TADV will be described in detail. The overlay student modelling technique will be used to model individual students, and groups of students, as well as the whole distance class. In order to reason about the status of student knowledge, an approach of approximate student modelling based on fuzzy techniques and certainty factor theory is adopted.

The effectiveness of educational systems using the WWW depends on the quality of the underlying material and the pedagogical framework used in the development of systems (Anjaneyulu, 1997). Hence, the proposed framework takes into account the way in which course material should be organised and the meta-knowledge that should be kept about each part of the course knowledge. There are three major issues that have an impact on this project:

- The first is concerned with *generality*, i.e. the framework should be developed to be as general as possible so that it can be applied to a variety of distance courses maintained with WCMS.
- The second is related to *domain independency*, i.e. the possibility to apply the framework to courses in a variety of domains.
- The third is concerned with *simplicity of knowledge acquisition*, i.e. to appropriately reduce the complexity of the knowledge acquisition process for building the domain knowledge base and the required meta-knowledge. It is important to note that some simplification of the knowledge acquisition processes

in order to get more co-operation from the domain experts (human teachers and course facilitators) in building intelligent educational systems.

Although the above decisions may facilitate the deployment and portability of the proposed framework, there may be side-affects on the nature of the possible advice. For example, it will not be possible to generate advice types related to the detailed procedures in problem solving required which requires more tracking information than those kept by the current WCMS and the use of more sophisticated domain knowledge representation schemes.

Next in this chapter, the TADV architecture is presented along with a brief description of each of its parts. The proposed courseware structure and metadata used to describe course material are then discussed. Some of the critical components of the framework, namely the student, group, and class models, are described in detail and the mechanisms used to build these models are defined. Another critical component of the framework - the advice generator – will be discussed in the next chapter.

4.2. TADV Architecture

Figure 4.1 shows the TADV architecture. There are two main phases: *PART-I* (shown in grey background) represents the conventional procedure performed by an educational organisation to build and use a WCMS course; while *PART-II* (shown in white background) represents the architecture of the part proposed to model students and generate advice to the facilitators. In PART-I, the teacher or course designer is responsible for preparing the course material and designing it in the way he believes is suitable for the learning of the potential students. This material may contain HTML pages, presentations, glossary items, supplementary papers and articles, quizzes, etc. The material represents the whole course and is organised by the WCMS content (file) manager. This material builds the *Domain Knowledge Base (DKB)*.

Information about the students registered on the course is entered to the system through the teacher or course facilitators or uploaded directly to the WCMS from the information systems used for registration purposes in the educational organisation. Information about registered students may contain their student identifications, passwords, names, e-mail addresses, nationalities, educational backgrounds, etc. WCMS usually keeps such information in the WCMS *Student Database (SDB)*. Upon beginning the course, registered students can work on the course through normal Internet browsers. WCMS usually records information about different students' interactions in the SDB. This generated information is used by the reporting utility in

WCMS to generate statistical reports about the registered students on individual and group bases to the course teachers or facilitators. SDB is considered to be the main input required to the proposed second phase or PART-II.

There are five components in PART-II - *Domain Meta-Knowledge Base (DMK)*, *Student Model Builder (SMB)*, Individual *Student Models (SM)*, *Group and Class Models*, and *Advice Generator (AG)*. These components (except the advice generator, see Chapter 5), together with the DKB, are described in the following sections.

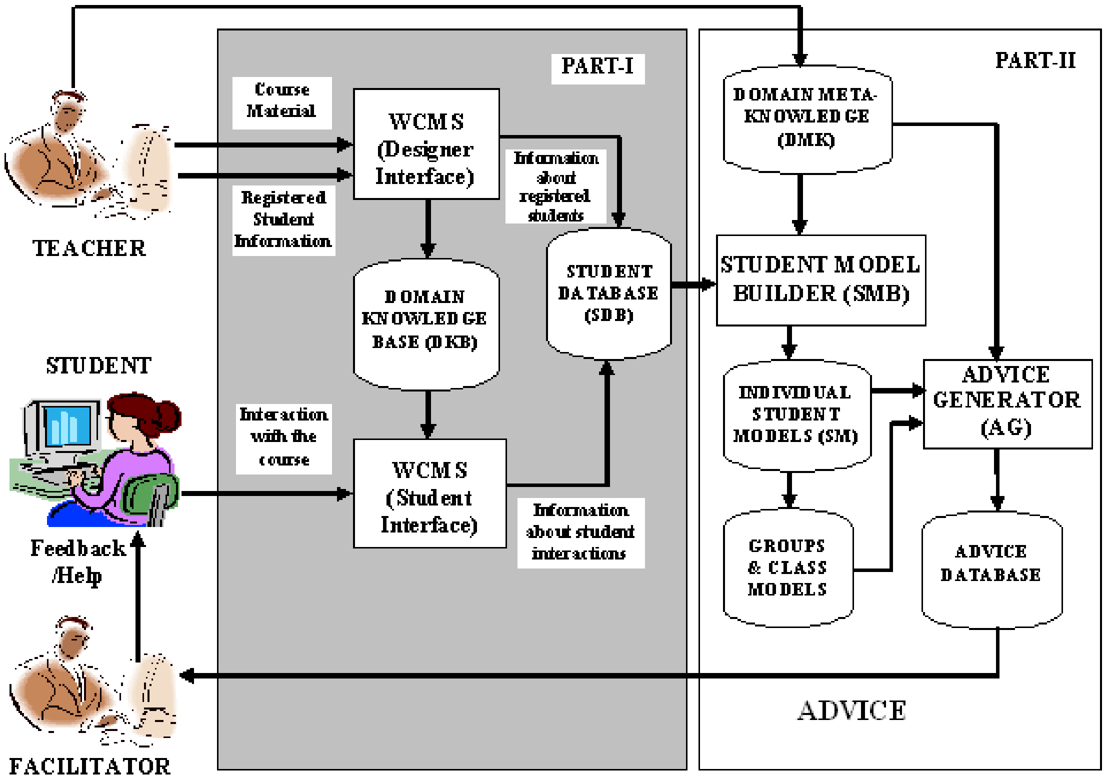

Figure 4.1 TADV Architecture. PART-I (with grey background) shows the componenets of a conventional WCMS. PART-II (with white background) shows the proposed components to extend a WCMS.

4.3. Courseware Structure and Meta-Knowledge

This section describes how course knowledge is created and organised in order to be used in the TADV framework, taking into account the three issues discussed above: generality, simplicity, and domain independence. In addition, this section describes the metadata that should be kept about the different knowledge chunks (pieces) that represent the course material.

4.3.1. Domain Knowledge Base

The Domain Knowledge Base (DKB) contains pre-stored course materials. These course materials are represented by a set of *learning objects* (HTML pages, presentations, video clips, simulations, etc.) that include the body of the knowledge representing the course. Some pages may contain materials that describe the domain concepts, while others may contain examples or practical cases. DKB contains also a set of pre-stored *assessment quizzes* used to evaluate the student's understanding and diagnose misconceptions. The assessment quizzes are usually in the form of Multiple-Choice or True/False problems (the quizzes types usually provided by most WCMS). The quizzes should be designed to help checking the level of student's understanding of domain concepts. The correct answer for each assessment quiz is predetermined together with the domain concepts that have to be mastered in order to correctly answer the quiz.

A course is defined in a hierarchical way as shown in Figure 4.2. The course is divided into a set of *lessons* (these can alternatively be chapters, sections, parts, etc.), each lesson can usually be decomposed into smaller units that comprise the knowledge building blocks, which are called *concepts*. There are three groups of items associated with each concept - the learning objects group, communication activities group, and assessment quizzes group. The learning object group contains the material used to explain the concept to the students. The assessment quizzes group contains the questions or quizzes used to assess the student's level of understanding of the concept. The communication activities group contains the discussion forums and/or chat rooms created to discuss and negotiate the concept.

The process of course structuring and dividing it into appropriate lessons and concepts is the responsibility of teachers (domain experts). Learning objects and assessment quizzes should be reliable and appropriate for respectively demonstrating (explaining) and assessing the candidate concepts.

The following notation will be used to describe and refer to the course parts:

L is the set of **L**essons belong to the course, i.e.

$L = \{l_1, l_2, \ldots, l_n\}$

C_i is the set of **C**oncepts belong to the ith lesson, i.e.

$$C_i = \{c_{i1}, c_{i2}, \ldots\ldots\ldots c_{ip_i}\}$$

The set of all domain concepts in the course will be denoted with C,

$$C = \bigcup_i C_i$$

O_c denotes the set of learning **O**bjects used to explain and demonstrate the knowledge of the concept *c*, i.e.

$$O_c = \{o_{c1}, o_{c2}, \ldots\ldots o_{ck_c}\}$$

Q_c denotes the set of assessment **Q**uizzes used to check student understanding level of the concept *c*, i.e.

$$Q_c = \{q_{c1}, q_{c2}, \ldots\ldots q_{cl_c}\}$$

Finally, D_c denotes the set of communication activities (discussion forums, chatting rooms, etc.) defined by course designer to **D**iscuss the concept *c*, i.e.

$$D_c = \{d_{c1}, d_{c2}, \ldots\ldots d_{cm_c}\}$$

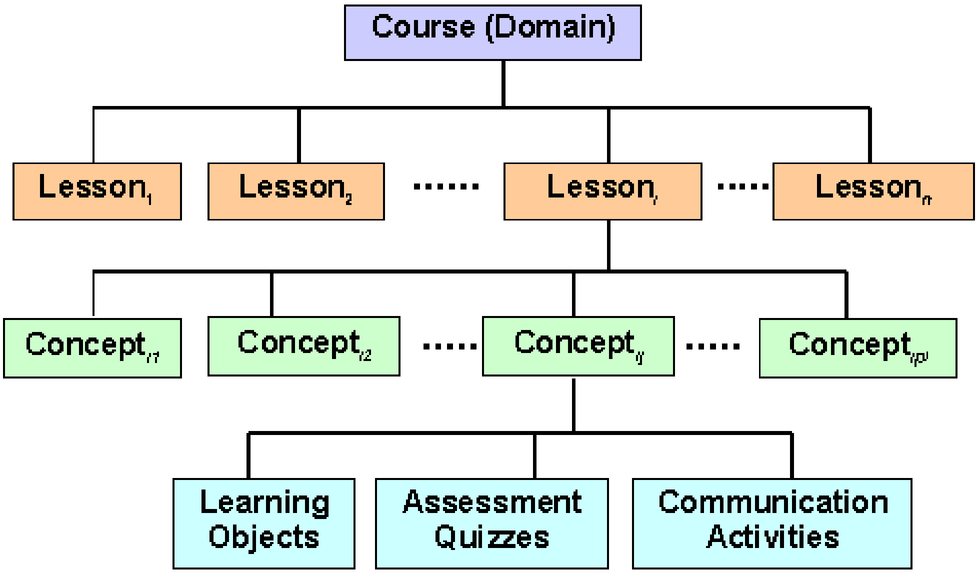

Figure 4.2 Course structure.

4.3.2. Domain Meta-Knowledge module (DMK)

DMK possesses the information that describes the course material and how it is inter-related. This section describes the DMK or the data that should be kept to describe the contents of DKB. An important feature about concepts in a domain is that they are not isolated but are related to one another in various ways. Therefore, it is necessary for tutoring system authors to formulate the knowledge concerning the relationship among domain concepts. There are many ITS and WBITS which use hierarchical structures to link the parts of the domain knowledge, see for example (Goodkovsky, 1996; Nykanen, 1997; Specht et al., 1997; and Capuano et al., 2000). Such links may be of the same type (e.g. prerequisite) or these may be more than one type of relationship (e.g. part of, type of, etc.). A semantic network is another scheme that can be used to represent a network of domain concepts and facilitate curriculum generation in intelligent educational systems. On the other hand, building such networks is not an easy task because it requires great effort especially for knowledge acquisition tasks.

Teachers and course designers who use WCMS to build Web-based distance courseware usually do not consider the tasks of defining and representing the relationships between domain concepts. This is because WCMS hardly allow intelligent features (Chang, 2003). In addition, it is unlikely that teachers can be familiar with knowledge representation techniques, which are usually difficult and time-consuming tasks. Our approach in TADV is to simplify this process by building a "concept map" that shows the relations among domain concepts in terms of the level of necessity of other concepts for understanding each separate concept. The concept map shows the prerequisite hierarchy between the course concepts. This approach is to some extent similar to the approach used by (Goodkovsky, 1996) to build the knowledge genesis model of the "Intelligent Tutor: Shell, Toolkit & Technology". TADV uses concept maps to represent relations between domain concepts in a hierarchical structure that shows prerequisite links between the domain concepts. Three types of relations are defined between domain concepts, Figure 4.3:

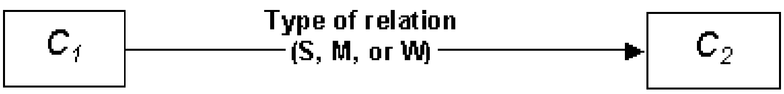

Figure 4.3 Types of relations between domain concepts; *S* (strongly related), *M* (moderately related), and *W* (weakly related).

- S - *Strongly related* - c_1 is strongly related to c_2, denoted by (c_1, c_2, *Strong*), if c_1 is a prerequisite of c_2 and to know c_2 the student should *completely understand* c_1.
- M – *Moderately related* - c_1 is moderately related to c_2, denoted (c_1, c_2, *Moderate*), if c_1 is a prerequisite to c_2 and to know c_2 the student should have *some understanding* of c_1.
- W – *Weakly related* - c_1 is weakly related to c_2, denoted (c_1, c_2, *Weak*), if c_1 is a prerequisite to c_2 and although the two concepts are related, the student can understand c_2 *without completely understanding* c_1.

Figure 4.4 shows part of the concept map for the functions lesson in a Discrete Mathematics course. The arrows show prerequisite relations that can be Strong (S), Moderate (M), or Weak (W). The concept map is used by the Advice Generator (AG) to infer why a student (or a group of students) may face problems with a specific concept. For example, if (c_1, c_2, *Strong*) and the system found that a student cannot understand c_2, then the system should check the status of c_1; if c_1 has not been learned by the student, then the system should generate advice to the facilitator and recommend guiding the student to study more about c_1. Otherwise, if the student has learnt c_1, then the system may search for other reasons and, if possible, recommend appropriate advice (see Chapter 5 for a description of the advice generator in TADV).

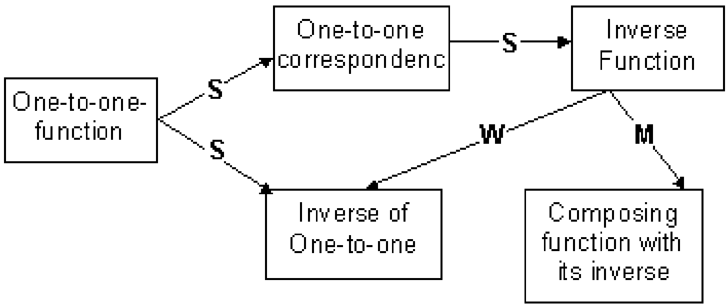

Figure 4.4 A part from the concept map of the "Functions" lesson in a Discrete Mathematics course.

There are four levels in the course structure (see Figure 4.2): course level, lessons level, concepts level, and content level. Each component in any of these levels should be specified in DMK by some information that can be used during student modelling and advice generation tasks to reason about students' knowledge status. Figure 4.5 illustrates the DMK data model, which shows the components of DMK and how these components are related to each other (the notation used and more detailed specifications are presented in Appendix-A). DMK contains metadata about the course, course calendar, course lessons, course concepts, and content material including learning objects, communication activities and assessment quizzes.

Course metadata include descriptive information, such as the course identification code, name, description, overall objectives, and start and end dates. Lesson metadata include the lesson identification, name, description, and objectives. For the course concepts, DMK includes information, such as concept identification, name, description, and weight. A concept weight stands for the percentage assigned to the concept as a part of the whole course. In other words, concept weight reflects how much the course is influenced by the concept in terms of the importance of the knowledge presented by the concept, the size of the concept as a unit of the course, the time and effort required from student to study the concept, and how the concept affects other course concepts. This is somewhat similar to the concept weight defined by (Chang, 2003) to develop courseware diagram suitable for applying an evaluation mechanism to assess student learning in Web-based learning environment. In general, concept weights are given by domain experts, who should be familiar with the course concepts and the effort a student should spend in order to study these concepts. In TADV, concept weights will be used by student modelling mechanisms to evaluate students with respect to a group of concepts, given that an evaluation for each concept is available. DMK also includes information that represents the types of relations between the concepts, as discussed above. The course calendar should be prepared by course facilitators to determine the interval of time assigned for each group of concepts and also the time dedicated for each individual concept. The purpose of including calendar information is to organise the course period to the distant students. It is used in TADV to identify delays in the students' progress.

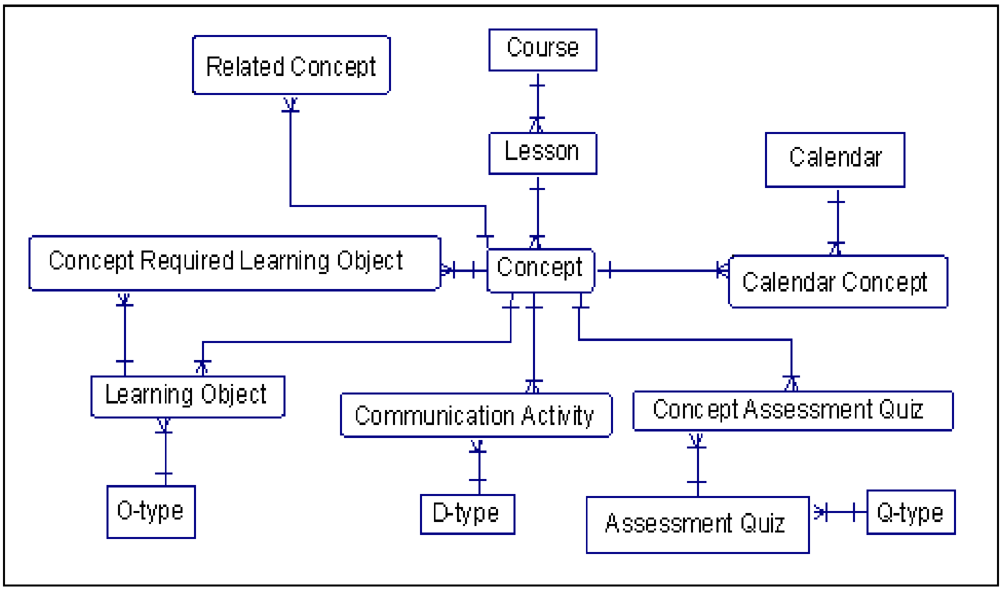

Figure 4.5 The components of the TADV Domain Meta-Knowledge Model. The shown entity relationship diagram is represented using Crow's foot convention (Hoffer et al., 2001). More detail about the convention used is shown in Appendix-A.

TADV follows the IEEE LOM metadata standards (IEEE 1484.12.1-2002), illustrated in Chapter 2, to describe the learning objects. The schema used proposes some attributes selected from three categories (General, Technical, and Educational), a subset of the nine categories defined by IEEE LOM standards, and some additional attributes required for the adopted fuzzy approach of student modelling (see below). There are two reasons for selecting a subset of IEEE standards in TADV. Firstly, we were driven by computational feasibility requirements. Assigning fuzzy values needed for the algorithms to run together with reasoning upon uncertain information in a Web-based environment is a challenging task. Therefore, the three most commonly used categories defined by the IEEE standards are considered. This will ensure that TADV does not add an unnecessary burden on the construction of the metadata and yet provides a general framework capable of dealing with the main IEEE standard categories. Secondly, TADV can be applied in a wide range of Web-based distance courses with minimum effort for adapting the metadata.

The additional attributes include information acquired from a domain expert to be used by the adopted fuzzy approach to reason about the students' knowledge levels, such as the minimum time required for the TADV to consider that a student has started the visit to the learning object, the limits of the typical learning time interval it takes to work on or through the learning object, the assigned understanding measure of belief if a student read the learning object in a time lies in the typical learning interval (i.e. up to what level the expert believes that student will understand a concept if he has read a learning object related to the concept), the assigned measure of disbelief if a student does not visit the learning object (i.e. up to what level the expert believes that student will not understand a concept if he did not read a learning object related to the concept), etc. More details about these metadata attributes are mentioned later in this chapter. Other metadata attributes are also required for assessment quizzes and communication activities groups.

There are cases in which many learning objects with different formats (text, presentation, video, etc) are used to discuss and explain a domain concept. In this case it is not necessary for the student to open and read all of these learning objects. Generally students will open the learning objects they prefer. What is required in this case is to ensure that the student will open at least the required learning objects that help him to understand the concept. DMK handled this situation by specifying the required learning objects through relating them by some logical operators. For example, suppose the learning objects o_1, o_2, o_3, o_4, o_5, and o_6 are designed to explain domain concept c; o_1, o_2, and o_3 carrying the same text required to discuss c with the formats HTML, word document, and presentation respectively while o_4, o_5, and o_6 are carrying an example to illustrate c with the format HTML, word document, and presentation respectively.

Then, in this case, it is possible to express the required learning objects for the concept *c* by: $(o_1 \vee o_2 \vee o_3) \wedge (o_4 \vee o_5 \vee o_6)$.

A comprehensive list of the metadata attributes used in TADV DMK and their descriptions are presented in Appendix-A for all domain levels specified in Figure 4.2. More details about the usage of metadata in TADV are clarified through the next sections of this chapter.

4.4. Student Model / Group and Class Models

As pointed out in Chapter 2, student modelling is critical for individualising the learning process. Some models of the students are required to automatically generate guiding information and advice to both students and teachers. A student model represents knowledge about the student and is used by an intelligent educational system to provide adaptive instruction to the student. In TADV, student models are required to ensure that facilitators are provided with appropriate advice about individual students, as well as groups of students and the whole class. To achieve effective advising, three levels of student modelling are proposed in TADV:

- ***Individual Student Models (SM)***: represent knowledge about each individual student.
- ***Group Models (GM)***: represent the knowledge status of a group of students. The course facilitator can optionally define groups of students according to the criteria he selects.
- ***Class Models (CM)***: represent the knowledge status of the whole class that accumulates the knowledge status of all students.

4.4.1. Student Model (SM)

The proposed individual student model (SM) contains four sub-models: *Student Profile Model*, *Student Behaviour Model*, *Student Knowledge Model*, and *Student Preferences Model*. Each of these sub-models is used to store information about the student. Most of the knowledge required for the student modelling process is extracted by the Student Model Builder (SMB) from the WCMS student database (SDB) which contains tracking data about student's actions while he is working with a Web-based educational system. It is important to note here that TADV relies upon two main sources of information to model the students' understanding and performance: the analysis of the students' interactions recorded by WCMS and the human-teacher (domain expert) judgments either represented in the DMK or embedded in the Advice Generator (AG). The variables derived from these sources of knowledge will be used to indicate some characteristics of the students' learning capabilities. Figure 4.6 shows the different parts of SM and how they are interrelated. It also shows GM and CM and how they are related to SM. The figure indicates that the building of these models is highly dependent on course information represented in DKM. The sub-models of SM are defined next and a more detailed description is given in Appendix-B.

- ***Student Profile Model:*** This part of the student model is designed to keep general information about the student. For example, some of his related personal information (student identification, name, contact information, etc.), educational background, general evaluation about his educational performance, etc.

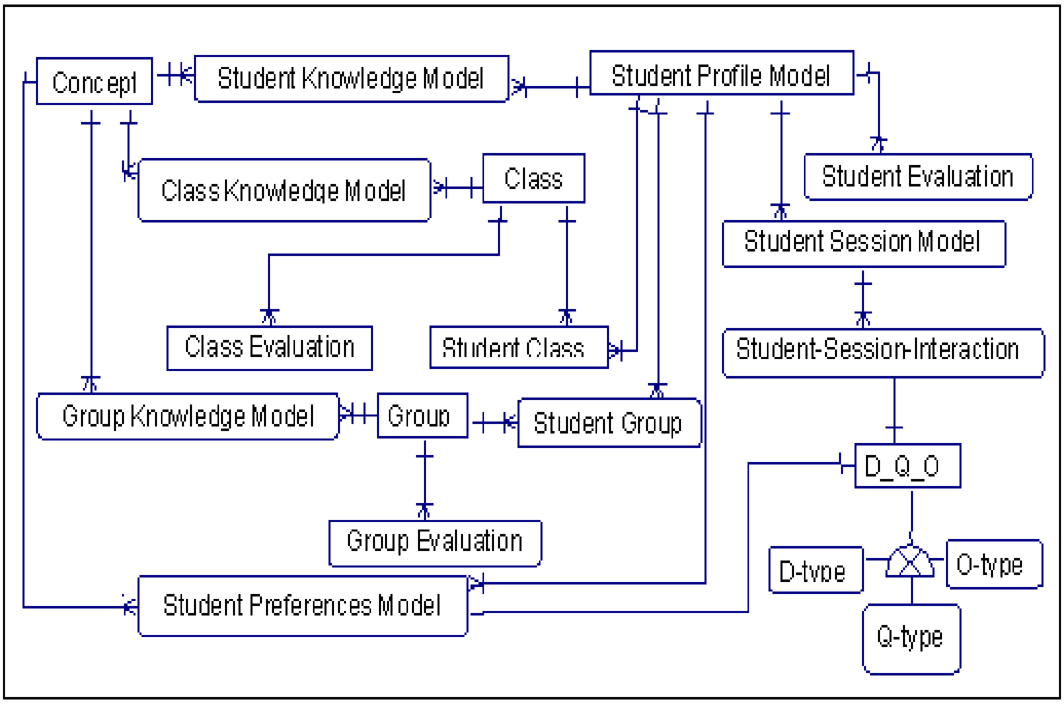

Figure 4.6 TADV Student, Group, and Class Models. The shown entity relationship diagram is represented using Crow's foot convention (Hoffer et al., 2001). More detail about the convention used is shown in Appendix-A.

- ***Student Behaviour Model:*** This part of the student model is designed to contain information that describes the student's learning actions. In other words, it contains information that describes how the student progresses throughout the course. This information is necessary to infer some cognitive characteristics and preferences of the student. There are two main parts to the student behaviour model - the *Student Session* part and the *Student Session Interactions*. The former contains information about the sessions a student has made with the system, including date and time elapsed in each session. The latter contains detailed information about the interactions made by the student during each of the sessions. Examples of this information include the type of the knowledge accessed during the interaction (learning object, assessment quiz, or communication activity), interaction elapsed time, interaction activity (reading text, solving problem, posting question or comment in a discussion forum, etc.), and score (only in the case of solving an assessment quiz).

- ***Student Knowledge Model:*** This part of the student model is used to determine the level at which the course concepts are mastered. This depends mainly on the information derived from the student behaviour model. An overlay modelling approach is used to evaluate students' knowledge. For each course concept represented in DMK, the student knowledge model keeps information that represents students' knowledge status in relation to that concept. The determination of this status is computationally based on certainty factor theory described earlier in Chapter 3. The approach used is an adaptation of the MYCIN model of reasoning in uncertain environments (Shortliffe & Buchanan, 1975) to handle uncertain student modelling in distance learning conditions. For each concept *c*, two values are defined: *MB* – the combined *measure of belief* that the student understands the concept and *MD* – the combined *measure of disbelief* that the student understands the concept. These two measures are used to calculate a certainty factor *CF* by subtracting MD from MB. The knowledge status of the course concepts is used to compute the general student evaluation with regard to the concepts studied. More details about the process of computing the variables representing student knowledge status in student knowledge model is presented in the Section 4.6.
- ***Student Preferences Model:*** This part of the student model contains information about the student's preferences. It is a summary of the student's activities throughout the course and presents the student's preferred types of learning objects, assessment quizzes, and communication activities. Note that student preferences considered in TADV can be related to learning styles (Arshad et al., 1995), but the latter considers much deeper cognitive characteristics of the students, which are beyond the scope of the student modelling in TADV.

4.4.2. Group Model (GM)

TADV gives the teacher the choice to specify groups of students to be monitored. Therefore, it is possible to model groups of students and generate advice to highlight existing group problems. Defining a group of students depends on the criteria selected by the teacher, for example the teacher can define groups according to nationality, background, course preference, etc. The group models generated in TADV are not based on any type of collaborative learning between the students in the group. Hence, TADV keeps a fairly general conception of distance learning and does not impose collaborative activities (which may not always be included in distance learning). It is assumed that each individual student will use the Web-based course on his own and at his preferred pace, and will be independently evaluated using the SM capability. The main goal of group modelling is to enable TADV to predict the common problems that might be encountered by the majority of the students in a group. Accordingly, it is possible to analyse how these problems are related to the common characteristics of the students in the group.

GM is derived through the aggregation of the individual student models of the group members. In other words, in TADV a group model is considered to be an instance of a student model (see Chapter 3, Section 3.5). The main difference is that an individual student model is dependent on the interactions of one specific student but a group model is dependent on the interactions of all students in a specific group. GM will keep information that represents the group's knowledge status in relation to each of the domain concepts. The determination of this status is also based on certainty factor theory and can be computed from the corresponding measures of belief and measures of disbelief of the same concept in the individual models of the students belonging to the group. The group model also monitors the communicative activities of group members and generally assesses the communication activities of the whole group.

4.4.3. Class Model (CM)

Analogous to the group models, a class model reflects the knowledge status of a group of students; in this case it is the whole class. A Class is considered as one big group of students but there are no predefined common characteristics amongst its members. In line with the group model, the class model is an aggregation of individual student models. Using the class model will make it possible to know what parts of the course are problematic to the majority of the students, which assessment quizzes are consistently difficult, what types of learning objects are preferred by the students, which communication activities are commonly/rarely used, etc. Such information may help the facilitators become more knowledgeable about their classes, to take prompt decisions during the course, and then to adapt their pedagogical activities to eventually achieve student satisfaction.

4.5. Student Model Builder

The Student Model Builder (SMB) is the module that reads student tracking data generated by WCMS and processes this data to be ready for recording in appropriate SM parts. SMB may be executed periodically (for example, daily or weekly) or when required by the course facilitator. This will depend mainly on the required interval of time between the sessions of advice generation. SMB contains three main modules: *Interaction Interpreter*, *Individual Model Builder*, and *Group & Class Models Builder*. Figure 4.7 shows the components of the SMB and their main inputs and outputs.

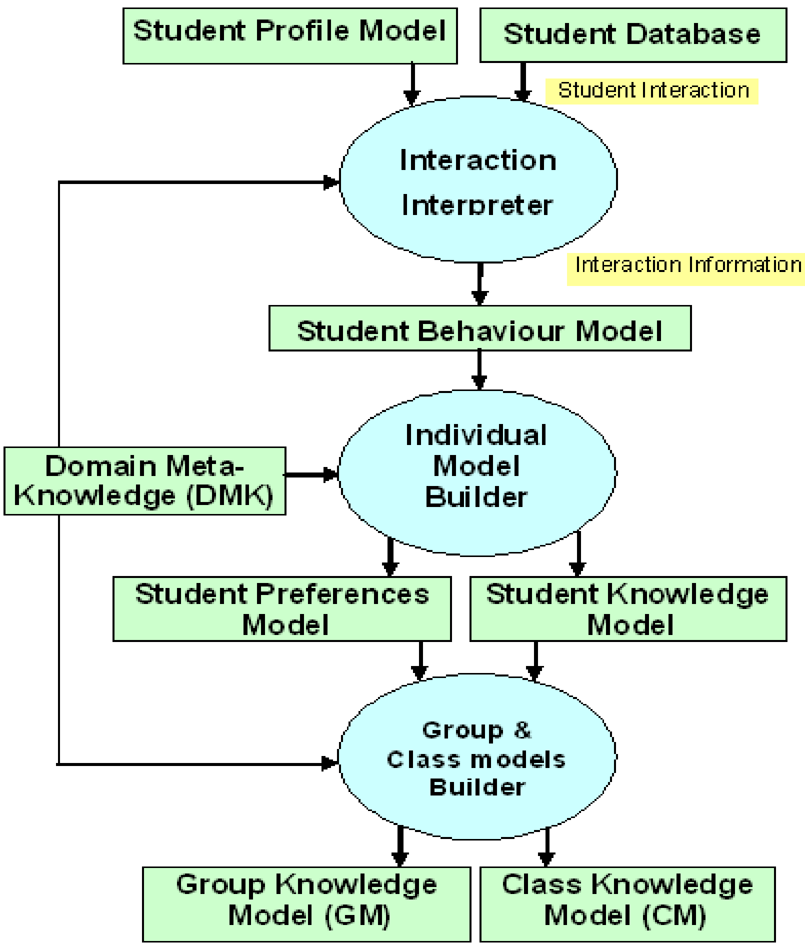

Figure 4.7 Structure of the Student Model Builder in TADV.

The main function of the *Interaction Interpreter* is to read student tracking data generated by the WCMS and process it so that it can be stored appropriately in the student behaviour model. The design of the Interaction Interpreter is highly dependent on the contents and the format of the information generated by WCMS. Some WCMS generate information about each student and save it in a group of text files kept in a single folder created for every individual student. Other WCMS, which use database management systems as a backend, keep tracking data for all students in one or more database tables. The design of the Interaction Interpreter requires detailed study of the structures, contents and formats of the generated tracking data and the way it is related to the course material stored by the WCMS content manager. The Interaction Interpreter should consult the student profile and the domain meta-knowledge to gather information about a student's interaction and the course material he has accessed.

The information gathered by the Interaction Interpreter is processed by the *Individual Model Builder* to make the necessary changes in both the student knowledge model and the student preference model. These changes depend on the interaction details, the part and type of domain knowledge to which the interaction is related, and on the relevant information extracted from DMK. Updating the student knowledge model according to the interactions stored in the student behaviour model is based on certainty factor theory and fuzzy student modelling; see Section 4.6 for a detailed description.

Group and Class Models Builder uses the information stored in the individual student models (specifically the knowledge and preferences parts) together with the information from DMK to build group and class models. Building group and class models depends on the aggregation of some modelling variables derived from the individual models of the students belonging to the group or the class. Again the aggregation criteria depend on the certainty factor theory presented in the next section.

4.6. Diagnosing Student Knowledge and Evaluation Mechanisms

The student knowledge part of the student modelling process in TADV is based on techniques from certainty factor theory and fuzzy sets described earlier in Chapter 3. The main justification behind adopting this approach is the high level of uncertainty that characterises Web-based learning environments and the difficulty with building precise student models by both human and computer tutors. Another reason is the adequacy of fuzzy techniques for intelligent Web-tutoring applications and their fairly simple application (see Chapter 3). The objective of TADV student modelling is to facilitate reasoning about both the students' cognitive status (i.e. the knowledge status achieved by the students about each domain concept) and the students' learning preferences (i.e. the students' preferred types of learning resources and communication activities).

It is important to point out here that the adopted fuzzy student modelling approach requires sufficient initial data to run the calculations. For example, metadata attributes of learning objects and assessment quizzes, measures of beliefs and disbeliefs, boundaries used to evaluate concepts' learning status, and boundaries used to generally evaluate students and their communicative status. Consequently, the method discussed here depends on important parameters and metadata attributes supplied by the teacher. Adopting different values for this data and parameters may significantly affect the system's beliefs about students' status. We have to acknowledge that the assigned values can be subjective and present the view of a particular teacher about the course material he has developed. Approaches like acquiring knowledge from group domain experts or performing some sensitivity analysis studies can be applied to determine the values of this data in a more reliable way. On the other hand, TADV provides a general framework for generating advice that is geared towards the needs of individual teachers who usually believe that their views about the courses they run should be taken into account.

The adopted approach of overlay student modelling contains a list of all concepts *C* represented in the concept map of the domain. For each concept *c*, there are two associated fuzzy values (ranges from 0 to 1) handled by the student knowledge model:

- *MB(c)* – the combined Measure of Belief that the student understands *c*.
- *MD(c)* – the combined Measure of Disbelief that the student understands *c*.

These two measures are used to calculate the certainty factor ($-1 \leq CF \geq 1$) for understanding concept *c* – $CF(c) = MB(c) - MD(c)$. The certainty factor of understanding *c* can then be used to judge a student's knowledge status of *c*. The mechanism used by TADV to diagnose the student's knowledge is presented in the following subsections.

4.6.1. Interpreting the student's interactions

When a student has performed some activities within WCMS (for example he has opened a learning object and has spent *t* minutes reading or working on it), TADV needs to interpret this tracking data and update the student model. In other words, there has to be a mechanism for assigning a value of the understanding measure of belief. To address this question it is necessary to define the *belief graph* or the *fuzzy membership function* used by TADV to interpret student interactions. Figure 4.8 shows the belief graph used to compute *MB* when a student interacts with a *learning object* (*o*), related to a domain concept *c*, for elapsed time *t*. The following attributes of *o* (which are given by the domain expert/teacher and presented in the DMK) are considered:

- *TMIN(o)* – minimum time required to consider that a student has visited the learning object *o* (this excludes situations when students browse through the material without reading it), e.g. a text with an example of ONE-TO-ONE FUNCTIONS may require *TMIN(o)* = 2 minutes for a student to gain some understanding of it.
- *T1(o)* & *T2(o)* – optimal time interval for a student to familiarise with the learning object o. This considers that the students' reading pace may differ, e.g. the above mentioned text about ONE-TO-ONE FUNCTIONS may have *T1(o)* = 5 & *T2(o)* = 10 min.
- *MB(o)* – measure of belief that a student may gain some understanding of *c* from the material in the learning object *o* when *t* is within the optimal time interval (this defines that a proper familiarisation with the course material increases the student's understanding of the concept presented in this material, e.g. a student's understanding of INVERSE FUNCTIONS may increase slightly after seeing an example of this concept, *MB(o)* in this case may be 0.1, while a learning object with a detailed explanation of INVERSE FUNCTIONS may have a greater impact on the student's understanding, e.g. *MB(o)* can be 0.4).

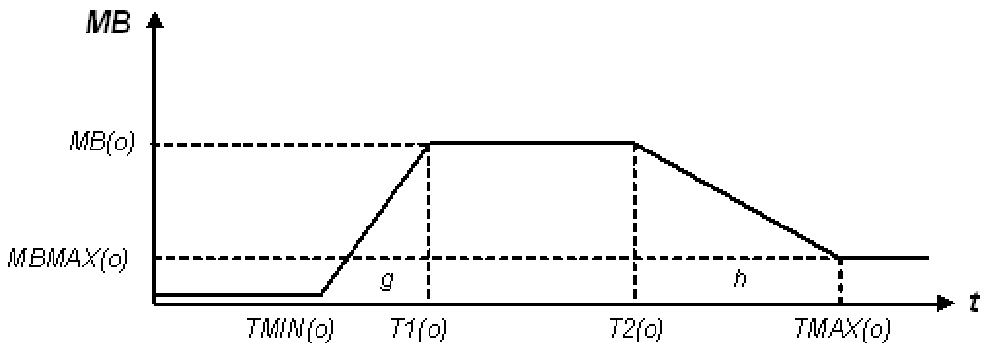

Figure 4.8 The TADV belief graph or the fuzzy membership function.

- *TMAX(o)* – maximum time for familiarising with the learning object *o*, i.e. it is assumed that there is no more impact on a student's understanding if he stays on *o* longer than *TMAX(o)* (this accommodates situations when a page stays open without the student working on it). For example, it may not be expected that a student should stay more than 15 min on *o*, which has one example of INVERSE FUNCTION.

- *MBMAX(o)* – teacher's belief about the understanding of *c* gained by a student who stays on *o* beyond the maximum time. The main justification for including *MBMAX(o)*, which corresponds to the belief at *TMAX(o)* and is normally less than *MB(o)*, is that a student spends longer time working with a learning object: either due to problems he faced in understanding the concept or that he might have opened the page without working on it effectively.

The proposed membership function indicates that the assigned value of *MB* should be zero if the student does not spend time greater than the defined minimum reading time ($t < TMIN(o)$). If *t* has increased so that it is greater than *TMIN(o)* but it is still less than *T1(o)*, then depending on *t*, a partial value of the complete understanding measure of belief defined for this learning object, *MB(o)*, should be assigned to the interaction. This means that TADV assigns the measure of belief to the interaction linearly and as *t* increases. If the elapsed time has increased so that ($T1(o) \le t \le T2(o)$), then the complete measure of belief, *MB(o)*, will be assigned to the interaction. Upon increasing of the elapsed time so that it become greater than *T2(o)*, TADV should start gradually to decrease the assigned measure of belief until reaching to *TMAX(o)* at which TADV should assign the understanding measure of belief *MBMAX(o)*, for any time beyond *TMAX(o)*. Considering these criteria and the belief graph shown in Figure 4.8, the assigned measure of belief, *MB*, is calculated according to the equations (4-1), (4-2), (4-3), (4-4), and (4-5).

$$MB = 0 \qquad \text{if} \quad t < TMIN(o) \tag{4-1}$$

$$= MB(o)(t - TMIN(o))/g \qquad \text{if} \quad TMIN(o) \le t < T1(o) \tag{4-2}$$

$$= MB(o) \qquad \text{if} \quad T1(o) \le t \le T2(o) \tag{4-3}$$

$$= (MBMAX(o) - MB(o))(t - T2(o))/h + MB(o) \tag{4-4}$$

$$\text{if} \quad T2(o) < t \le TMAX(o)$$

$$= MBMAX(o) \qquad \text{if} \quad t > TMAX(o) \tag{4-5}$$

where $g = T1(o) - TMIN(o)$ and $h = TMAX(o) - T2(o)$

When a student does not work on one of the main learning objects required to teach a domain concept *c* during the time interval specified in the course calendar, then TADV should automatically consider the understanding measure of disbelief, *MD(o)*, in the calculation of the combined measure of disbelief of the concept *c*, *MD(c)* which will be shown in Section 4.6.3.

It is important to mention here that according to the criteria described it is necessary to acquire seven metadata attributes from the domain expert for each learning object: *TMIN(o)*, *T1(o)*, *T2(o)*, *TMAX(o)*, *MB(o)*, *MBMAX(o)*, and *MD(o)*. This may require additional effort from the course teachers and designers. It appears feasible to simplify the process by considering actions like:

- Defining a constant value for *TMIN(o)* for all learning objects.
- Defining a formula to compute *TMAX(o)* as a function of *T2(o)* for all learning objects (e.g. *TMAX(o)* = 2* *T2(o)*)
- Defining a formula to compute *MBMAX(o)* as a function of *MB(o)* for all learning objects (e.g. *MBMAX(o)* = 0.5* *MB(o)*)

It is clear from the above explanation that in TADV, elapsed time is used to rationalise the system's interpretations of student's interactions with the provided learning objects. The assigned understanding measure of belief to an interaction with a learning object is computed as a function of the elapsed time. We have used elapsed time to provide evidence about the likelihood of student understanding after reading the available learning objects. For example, assume that, as recommended by the domain expert, a learning object (*o*) requires from 5 to 8 minutes to be read and the system got the following cases:

Student A – did not open *o*

Student B – read *o* for less than 1 minute

Student C – read *o* for 3 minutes

Student D – read *o* for 6 minutes

Student E – read *o* for 30 minutes

It is assumed that fuzzy reasoning based on these tracking data should result in different interpretations. The proposed membership function is used to rationalise the system's beliefs resulting from evidence such as those given above. It is important to mention here that interactions with learning objects, including those that lie in the optimal time interval, do not give significant evidence that a student has understood the concept. Therefore, the system considers a small value for the measure of belief in this case. The aggregation (combination) of small pieces of belief resulting from different interactions with learning objects and assessment quizzes related to a domain concept gives the measure of belief for the understanding of this concept.

To calculate *MB* or *MD* resulting from a student's interaction with an assessment quiz *(q)* related to a concept *c*, the following attributes of *q* (which are given by the domain expert/teacher and presented in the DMK) are taken into account:

- *MBC(q)* – measures the belief that the student understands *c* when his solution of *q* is correct;
- *MDW(q)* – measures the belief that the student does not understand *c* when his solution of *q* is wrong;
- *MDN(q)* - measures the belief that the student does not understand *c* when he has not produced a solution of *q* in the time interval specified by the course calendar.

Respectively, *MB* and *MD* are calculated as follows:

$MB = MBC(q)$ if *q* is correctly solved,

$MD = MDW(q)$ if *q* is erroneously solved, and

$MD = MDN(q)$ if *q* is not solved.

TADV considers the cases in which the student re-solves the available assessment quizzes. In this case the assigned *MB* or *MD* depends mainly on the result of the last trial the student made in solving the same quiz. The criteria will be as follow:

- If the answer is correct and the last answer is wrong – this gives evidence of potential understanding of the concept assessed by quiz and some understanding measure of belief should be offered. Therefore, the measure of belief of the correct answer should be assigned, i.e. $MB = MBC(q)$.
- If the answer is correct and the last answer is also correct – this means that student has already known the correct answer before solving the quiz and this gives no new evidence of more understanding. Therefore, no measure of belief is assigned, i.e. $MB = 0$.
- If the answer is wrong and the last answer is correct – this implies that either previous correct answer came accidentally through guessing it or might be the case that the student forgot the knowledge he previously gained. In either case evidence for misconception is implied. Therefore, understanding measure of disbelief of the wrong answer should be assigned, i.e. $MD = MDW(q)$.
- If the answer is wrong and the last answer is also wrong – this confirms the misconception previously revealed and it is more certain now that student is

struggling with the concept assessed by the quiz. Therefore, understanding measure of disbelief of the wrong answer should be assigned, i.e. $MD = MDW(q)$.

It is important to mention here that the changes in the values of the understanding measure of belief and measure of disbelief of a particular concept *c* (according to the interactions student made with learning objects and assessment quizzes) did not propagate any changes in the understanding measures of belief and disbelief of the concepts related to *c* in the concept map.

For the interactions that reflect student's communication activities, TADV will not assign any measures of belief or measures of disbelief. Instead, these interactions are used to update the Student Preferences Model, so that it is possible to know which type of communication activity the student prefers and decide whether the student is communicative. It is important to mention here that all interactions should affect or change the student preference model. For example, if an interaction related to learning object (*o*) occurred, then this will lead to incrementing the number of the student's hits to the type of knowledge (text, presentation, simulation, etc.) indicated by the definition of *o* in DMK. A student's interaction with an assessment quiz (*q*) is used to increment the number of hits to the assessment quizzes in the student preferences model. In the same way, posting a message to a communication activity (*d*) would increment the number of posts made by the student.

4.6.2. Initialising student, group and class models

Before discussing the criteria used to calculate the combined measures of belief and measures of disbelief of the student's understanding levels represented in the student knowledge model, it is necessary to know how to initialise the student model. The initialisation of a student model means assigning initial values to the modelling variables before the student starts working with the WCMS. In TADV, all concepts represented in the individual student models, group models and class model will have an initial value of zero assigned to all measures of belief and measures of disbelief, i.e. for each concept *c* initially $MB(c) = MD(c) = 0$.

Similarly, for group and class models:

$GMB(c) = GMD(c) = 0$ for every group and every concept *c*, where $GMB(c)$, and $GMD(c)$ are the combined understanding measure of belief and the combined understanding measure of disbelief of concept *c* for the group, respectively.

$CMB(c) = CMD(c) = 0$ for every concept c where $CMB(c)$, and $CMD(c)$ are the combined understanding measure of belief and the combined understanding measure of disbelief of c for the class, respectively.

Assigning zero values to all measures of belief and disbelief in the different parts of the student modelling components means that the initial certainty factors of the understanding levels are also zero which in turn means that initially TADV does not know anything about the students' understanding of the domain concepts.

4.6.3. Diagnosing knowledge status

In this section, the criteria used by the SMB to compute the combined concept understanding measures of belief and disbelief for individual students, groups, and classes are discussed.

Diagnosing an individual student's knowledge

At any instance during the course period, assume that for a particular student the current understanding measures of belief and disbelief of the concept c are $MB(c)_{curr}$ and $MD(c)_{curr}$ respectively. Assume also that MB is the assigned measure of belief to one of the student's interactions stored in his Student Behaviour Model. Now, according to equation (3-2) it is possible to calculate the new measure of belief of c as follows:

$$MB(c)_{new} = MB(c)_{curr} + MB[1 - MB(c)_{curr}] \qquad (4\text{-}6)$$

$MB(c)_{new}$ is now considered to be the current measure of belief of the concept c. The action taken by the equation (4-6) can be stated as: after reading or working on one of the learning objects related to the concept c, the concept understanding measure of belief is increased by some increment. This increment is computed by taking the difference between the complete (certain) belief, i.e. 1, and the current belief. MB, the assigned measure of belief of the new interaction, then scales this difference.

In the case where some understanding measure of disbelief is indicated by TADV (e.g. the student has not read or worked on one of the mandatory learning objects related to c) and $MD(o)$ is its measure of disbelief, then similarly to equation (3-3) it is possible to calculate the new measure of disbelief using equation (4-7).

$$MD(c)_{new} = MD(c)_{curr} + MD(o)[1 - MD(c)_{curr}] \qquad (4\text{-}7)$$

Equation (4-7) can be explained similarly to equation (4-6): if there is evidence that the student has not read or worked on the learning object (o), then the concept understanding measure of disbelief is increased by some increment. This increment is computed by taking the difference between the complete (certain) disbelief, i.e. 1, and the current disbelief. This difference is then scaled by the disbelief in the new evidence.

The criteria used to manipulate interactions with learning objects can also be used to manipulate interactions with the assessment quizzes related to the concept *c*. Equations (4-8), (4-9), and (4-10) are applied respectively in the cases when the student has solved the quiz correctly, wrongly, or has not solved the quiz.

$$MB(c)_{new} = MB(c)_{curr} + MBC(q)[1 - MB(c)_{curr}] \tag{4-8}$$

$$MD(c)_{new} = MD(c)_{curr} + MDW(q)[1 - MD(c)_{curr}] \tag{4-9}$$

$$MD(c)_{new} = MD(c)_{curr} + MDN(q)[1 - MD(c)_{curr}] \tag{4-10}$$

At any instance during the evaluation process, the concept's understanding certainty factor (-1 to 1) can be computed by subtracting *MD(c)* from *MB(c)*:

$$CF(c) = MB(c) - MD(c) \tag{4-11}$$

According to the value of *CF(c)*, TADV will assign the concept to one of the fuzzy sets defined to indicate the different mastering or understanding levels of the concepts. There are three fuzzy sets defined in TADV:

- *Completely Learned* set of concepts, which include the concepts that according to TADV are believed to have been completely mastered and understood by the student. No advice will be generated regarding improving the knowledge of those concepts; instead, TADV may advise the facilitator/teacher to motivate the student to help his peers who have problems with these concepts.
- *Learned* set of concepts, which include the concepts TADV believes are understood by the student but not completely. Some advice may be generated to the teacher about the mastering of these concepts, as well as some suggestions, if appropriate, to guide the student to enhance his level on these concepts.
- *Unlearned* set of concepts, which include the concepts TADV believes have not been understood by the student. Appropriate advice should be generated to the teacher informing that the student is struggling with these concepts, as well as suggesting possible actions to be taken by the teacher and/or the student to increase the student's understanding of these concepts.

In TADV, it is possible for the teachers or the facilitators to define the boundaries for each of these sets, for example one possible scheme is as follows:

$c \in$ *Completely Learned* set of concepts if $0.7 \le CF(c) \le 1.0$

$c \in$ *Learned* set of concepts if $0.4 \le CF(c) < 0.7$

$c \in$ *Unlearned* set of concepts if $-1.0 \le CF(c) < 0.4$

TADV can also evaluate the student in a comprehensive way by calculating his general evaluation in all studied concepts (determination of candidate concepts is guided by the course calendar) as a function of the certainty factors of the individual concepts. The approach of weighted average is used to compute *AVGCF(S)*, the average certainty factor for a student *S*, using the certainty factors of the individual concepts and corresponding concept weights, *W(c)*. Assume for example that TADV is going to compute *AVGCF(S)* for the concepts ranges from c_{11} (the first concept related to first lesson) to c_{xy} (the yth concept related to xth lesson), then AV*GCF(S)* can be calculated using equation (4-12), where y_i is the number of concepts in the lesson *i*.

$$AVGCF(S) = [\sum_{i=1}^{x-1}\sum_{j=1}^{y_i} W(c_{ij}) * CF(c_{ij}) + \sum_{j=1}^{y} W(c_{xj}) * CF(c_{xj})] / [\sum_{i=1}^{x-1}\sum_{j=1}^{y_i} W(c_{ij}) + \sum_{j=1}^{y} W(c_{xj})] \quad (4\text{-}12)$$

Where $\sum_{i=1}^{x-1}\sum_{j=1}^{y_i} W(c_{ij}) * CF(c_{ij})$ is the weighted summation of the certainty factors of the concepts related to the completed lessons, i.e. from lesson 1 to lesson x-1, $\sum_{i=1}^{x-1}\sum_{j=1}^{y_i} W(c_{ij})$ is the summation of their weights, $\sum_{j=1}^{y} W(c_{xj}) * CF(c_{xj})$ is the weighted summation of the certainty factors of the first y concepts related to lesson x, and $\sum_{j=1}^{y} W(c_{xj})$ is the summation of their weights.

The *AVGCF(S)* is then used to assign the student to one of the fuzzy student sets defined to categorise students according to their general evaluation. There are three categories defined in TADV; Excellent, Good, and Weak categories. TADV will give the course teacher the possibility to define the *AVGCF* boundaries for each category. For example, one can select the following schema to define the categories:

$S \in$ *Excellent* category if $0.8 \le AVGCF(S) \le 1.0$

$S \in$ *Good* category if $0.6 \le AVGCF(S) < 0.8$

$S \in$ *Weak* category if $AVGCF(S) < 0.6$

Diagnosing group and class knowledge

A group's concept understanding measures of belief, *GMB(c)* is calculated by the aggregation of individual student's concepts measures of belief in the same way as the aggregations of assigned interactions measures of beliefs, i.e.

$$GMB(c)_{new} = GMB(c)_{curr} + MB(c)_k[1 - GMB(c)_{curr}] \quad \text{for } k = 1, 2, \ldots, n \qquad (4\text{-}13)$$

where n is the number of students in the group. In the first use of (4-13), the initial value of $GMB(c)_{curr}$ is zero. In the same way, it is possible to calculate the group's concept understanding measures of disbelief, *GMD(c)* by the aggregation of individual student's concepts measures of disbelief as shown in equation (4-14).

$$GMD(c)_{new} = GMD(c)_{curr} + MD(c)_k[1 - GMD(c)_{curr}] \quad \text{for } k = 1, 2, \ldots, n \qquad (4\text{-}14)$$

The group's concept understanding certainty factor *GCF(c)*, can be calculated using (4-15).

The general evaluation of a group of students, *GEVAL(G)*, can be calculated by taking the average of the students' *AVGCF*. Equation (4-16) can be used to compute the general evaluation of a group *G* of n students ($S_1, S_2, \ldots, S_n$).

$$GCF(c) = GMB(c) - GMD(c) \qquad (4\text{-}15)$$

$$GEVAL(G) = [\sum_{i=1}^{n} AVGCF(S_i)] / n \qquad (4\text{-}16)$$

GEVAL(G) can be then used to assign the group to one of the fuzzy categories defined to differentiate between groups of students. An approach similar to one used to categorise students is also used to categorise groups.

Similarly, we can calculate the measure of belief of the class' understanding of a concept *c*, *CMB(c)*, by the aggregation of the individual students' measures of belief of *c*, i.e.

$$CMB(c)_{new} = CMB(c)_{curr} + MB(c)_k[1 - CMB(c)_{curr}] \quad \text{for } k = 1, 2, \ldots, m \qquad (4\text{-}17)$$

where m is the number of students in the class. In the first use of equation (4-17), the initial value of $CMB(c)_{curr}$ is zero.

In the same way, it is possible to calculate the class concept understanding measures of disbelief, *CMD(c)* by the aggregation of individual student's concepts measures of disbelief as shown in equation (4-18). It is possible to calculate the class concept understanding certainty factor *CCF(c)*, using equation (4-19). *CEVAL(C)*, the general evaluation of the class with m students ($S_1, S_2, \ldots\ldots\ldots, Sm$) can be calculated by taking the average of the students' *AVGCF*, equation (4-20).

$$CMD(c)_{new} = CMD(c)_{curr} + MD(c)_k[1 - CMD(c)_{curr}] \quad \text{for } k = 1, 2,.., \text{m} \quad (4\text{-}18)$$

$$CCF(c) = CMB(c) - CMD(c) \quad (4\text{-}19)$$

$$CEVAL(C) = [\sum_{i=1}^{m} AVGCF(S_i)]/m \quad (4\text{-}20)$$

4.6.4. Diagnosing communication status

To generate appropriate advice, TADV has to diagnose not only the students' knowledge status but also their communicative behaviour. A model of the communicative behaviour can be used to advise the teachers to encourage the uncommunicative students to contact their peers. It can also be used to generate advice that informs facilitators about highly communicative students and hence directing them to help their peers. This in turn may create a substitution for some social aspects missed in Web-based distance education, open the door for more peer-to-peer interactions, and lessen the communication overload required from facilitators.

Generally, WCMS offer many sorts of communication and collaborative tools to facilitate interaction between students, but in most cases it is not possible to know exactly the content discussed during communication interactions between students (unless, of course, sophisticated language understanding mechanisms are employed, which is beyond the scope of this thesis). Hence, the course designers usually create discussion forums dedicated to specific lesson, topics, or concepts. In TADV communication activities are based on concepts, i.e. each discussion forum or chatting room should be dedicated to discuss a certain concept. Usually the name assigned to a discussion forum or a chatting room will be the same name of the concept supposed to be discussed within. TADV will use the number of communicative interactions (post question, post an answer or comment, etc.) a student has made within the communication activity dedicated to discuss a certain concept in order to judge the student's communication level with regard to that concept. To clarify, assume that $CI(c)_S$ is the number of the Communication Interactions made by a student S to the communication activities related to the concept c. Then, depending on this number, a student may be assigned to one of three fuzzy sets that describe student's Communication Level with respect to concept c denoted $CL(c)_S$. For example, it is possible to select the following criteria to determine $CL(c)_S$:

The students is *uncommunicative (UC)* if $0 \le CI(c)_S \le 2$

The student is *normally communicative (NC)* if $2 < CI(c)_S \leq 5$

The student is *highly communicative (HC)* if $CI(c)_S > 5$

The boundaries (0, 2, and 5) mentioned above are just examples. The availability of research-based or experience-based values for these boundaries is important to correctly judge students' communication levels. Since we do not have a standard way, or research results, by which it is possible to determine the optimum boundaries for this criterion, TADV offers two alternatives to define these boundaries. The first alternative gives the teacher the possibility to define the boundaries he believes reasonable to judge the students' communication level in any of the course concepts. Of course this depends on the teacher's previous experience and on the nature of the domain. The second alternative determines the boundaries of a concept *c* as a function of the number of the communication interactions made by the students within the communication activities of *c*. To clarify, TADV first calculates the average communication level of *c* – the average number of communication interactions, made by the whole class, to the communication activities of *c*. Then, depending on the value of this average and on the number of communication interactions made by each student to the communication activities of *c*, it is possible to determine the communication status of each individual student as follow:

If $CI(c)_S <$ the average communication level then student is UC regarding *c*;

If $CI(c)_S =$ the average communication level then student is NC regarding *c*;

If $CI(c)_S >$ the average communication level then student is HC regarding *c*.

To illustrate, assume that a class of five students (S_1, S_2, S_3, S_4, S_5) who made (3, 0, 6, 1, 0) interactions respectively to a discussion forum dedicated to discuss *c*. Now, as the average communication level is 2, the communication status of the students is (HC, UC, HC, UC, UC) respectively.

It is worth noting here that average may not always be a reliable measure, however, it may reflect some cultural aspects of the students regarding such communication activities.

To evaluate a student's general communication status regarding a specified set of concepts, the average number of the communication interactions made by the students to the communication activities related to the set of concepts is calculated. Then, using the same criteria defined for a single concept, compared with the average number of all communication interactions made by the whole class to the same set of communication activities.

In the same manner, TADV evaluates the communication status of a group or a class with respect to a concept *c* by calculating the average number of communication interactions made by all students in the group to the communication activities dedicated to discuss *c*. Then, compares the calculated average with the concept's average communication level to determine the group's communication status as HC, NC, or UC regarding *c*. Using fairly similar criteria, TADV can evaluate communication status of a group or a class of students regarding a specified set of concepts.

4.7. Summary

This chapter presented the architecture of TADV and described the functions of its components. The following four aspects of the TADV framework for generating advice to the facilitators in distance leaning environments have been discussed in detail:

- The proposed courseware structure and metadata attributes used to describe domain knowledge.
- The structure of the student, group, and class models.
- The student model builder based on student tracking data generated by WCMS.
- The fuzzy approach used to diagnose the knowledge and communication levels of individual students, groups, and classes.

In the next chapter, the remaining aspects of the TADV framework – the advice generator and the advice generating criteria used – are presented in order to provide a more comprehensive description of the proposed framework.

Chapter 5

Advice Generation

5.1. Introduction

We have discussed the need for a computational framework for advising teachers to help them manage distance classes. Such a framework, called TADV, was outlined in Chapter 4 where the TADV architecture was presented. Core components of TADV, such as the domain meta-knowledge and the student, group, and class modelling mechanisms were discussed in detail. A critical component in TADV is the Advice Generator (AG), which is the kernel of the proposed framework. This chapter presents the advice generator in significant detail.

The AG is required to reason about the students' knowledge status, including both individual and group bases, and to decide appropriate advice. Actions, recorded by WCMS and transformed by the student model builder (see Chapter 4) into student models, serve as the source from which diagnostic information about the student might be extracted. As discussed in Chapter 4, this information indicates which concepts were presented to the student, the duration of time the student spent working with learning objects related to a specific concept, which concepts probably mastered by the student and which concepts not yet mastered. AG uses student, group, and class models to identify, respectively, the status of individual students, groups of students, and the overall class. This is used as a source for the generation of appropriate advice to the course facilitator. The course facilitator can then pass the advice to the students or consequently take some pedagogical actions that should be educationally appropriate.

Next in this chapter, a taxonomy of advice types is presented. Then, the advice generating mechanism based on a set of criteria for selecting appropriate advice according to the current student situation is explained in detail.

5.2. Proposed Advice Types

In TADV, a set of predefined conditions is used to define advising situations based on the information from the SMs, GM, and CM. For each situation, a predefined advice template(s) is described. When AG recognises a situation, the corresponding template is activated to generate advice to the facilitator. For example, if a student is struggling with a specific domain concept and the SM indicates that this student has visited little course material about the concept, the facilitator will be informed about the problem and will be advised to encourage the student to read the material related to this concept.

TADV is designed so that it is possible to deliver several types of advice. Advice will be delivered when the reasoning of the system indicates a necessity to highlight important information to the course teachers (most cases highlight a possible problem of a student and how this problem may be rectified). This information may be related to an individual student, a group of students, or to the whole class. Advice will be delivered to the course facilitator, in most cases, together with some recommendation of what can be sent to the student. TADV adopts some heuristics based on which it is believed that this recommended advice or help will be appropriate in certain situations. The course facilitator should have the option to send the recommended advice as it is to the student, change it before sending, or completely skip it. In some cases, TADV may just produce a statement that describes a case or a problem without suggesting what the teacher should do to remedy the problem. This happens when TADV is either unable to identify reasons for the problem (for example, when a student's model indicated that a student did not learn concept *c* and TADV found that the student read the necessary learning objects, participated in communication activities related to *c*, and mastered all prerequisite concepts but poorly solved the assessment quizzes related to *c*) or considers appropriate to merely highlight the problem to the facilitator and let him decide what pedagogical action is needed based on his subjective view.

As discussed in Chapter 4, for each of the domain concepts three levels for student's knowledge status are defined: *Completely Learned*, *Learned*, and *Unlearned*. This means that at any instance during the course period, TADV is able to evaluate the student's knowledge by determining which concepts are completely learned, which are learned and which are not learned. This enables the identification of possible reasons for the existence of some incompletely learned or unlearned concepts.

Furthermore, following the mechanism suggested in Chapter 4, a general evaluation level for a student (*Excellent*, *Good*, and *Weak*) with respect to a set of concepts already studied can be defined. This general evaluation level is useful to categorise the students according to their knowledge status. Thus, knowing the students who often experience problems, TADV both informs the facilitators about and suggests appropriate activities to stimulate these students. In addition, the teacher may be advised to encourage excellent and good students to help their weaker peers.

In TADV, advice is generated to the facilitator in three levels, as in Figure 5.1:

- Advice concerning individual students performance (Type-1 advice);
- Advice concerning each group performance (Type-2 advice);
- Advice concerning the whole class performance (Type-3 advice).

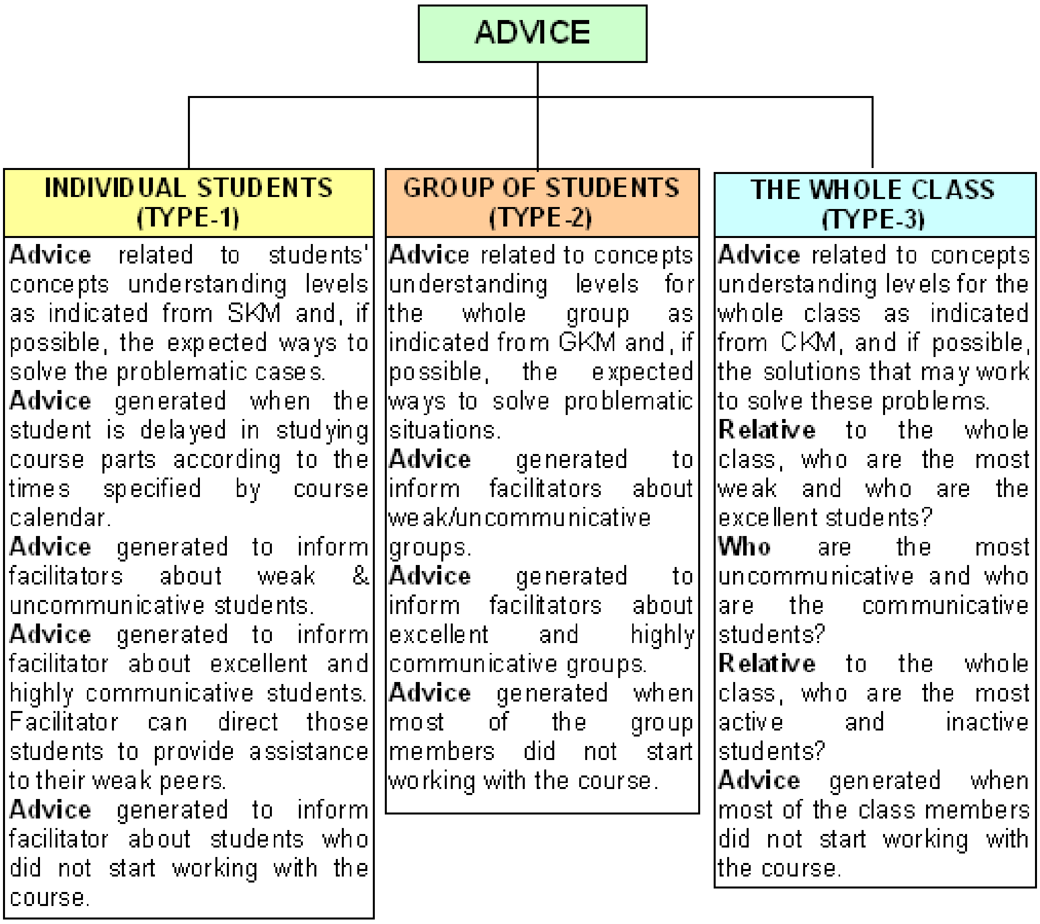

Figure 5.1 Advice types proposed in TADV.

The advice in TADV is based on our analysis of problems with distance courses as discussed in the literature (see Chapter 2) and has been confirmed in interviews with several Web-based course instructors. These interviews were conducted on a one-to-one basis with teachers from the University of Leeds in UK and from the Arab Academy of Science and Technology in Egypt, who have experiences with WBDE environment especially those created with WCMS platforms. Deciding about the type of advice and the information that should be provided to the teachers were the main objective behind these interviews. Figure 5.1 shows the general description of the proposed advice defined in each of these main types of advice categories. More details about the main types of advice and the corresponding subtypes are presented in the next subsections.

5.2.1. Generating Type-1 Advice

Type-1 advice is used to inform a course facilitator about problems that individual students face. Type-1 advice also includes some suggestions to the facilitator of how to remedy a problem, depending on the reasons that have led to the problem, as indicated from a student's interactions. This type of advice is divided into several subtypes, as described below.

Type 1-1 Advice is used to inform a facilitator about the problems related to the student's knowledge status. As mentioned earlier (see Section 4.6.3), TADV measures the student's knowledge status regarding each domain concept as "Completely Learned", "Learned", or "Unlearned". Type 1-1 advice will be generated when the student knowledge model shows concepts with "Unlearned" or "Learned" understanding levels. In this case, AG should investigate the reason(s) that led to this problem, which may include:

- The student has not completely read and worked on the learning objects and assessment quizzes related to the concept.
- The student has not completely mastered the related prerequisite concepts.
- The student has not participated in the communication activities related to the concept.

To specifically investigate the possible reason(s), it is necessary for AG to perform more detailed analysis using the information available in the student behaviour model and the student knowledge model (see Chapter 4).

Type 1-2 Advice is used to inform a facilitator about the student's progress with course material related to a certain concept. The AG will use the course calendar (which is part of DMK) and the student behaviour model (which is part of the student model) to determine if the student is delayed with (lagging behind) the course-studying plan. The AG will deliver advice to the facilitator with information such as the student name, the concepts with which student is delayed, and the delay time (time-lag) of each concept. The facilitator may send this information to the student or take the necessary actions depending on the delay times and student case. Besides assisting facilitators to be more knowledgeable about their distant students, this type of advice is useful in making students feel that they are being supervised from their distant teachers.

Type 1-3 Advice offers more attention to the students who are at unsatisfactory learning levels. Type 1-3 advice is used to focus on the students evaluated as “Weak” (see Section 4.6.3). TADV will classify those “Weak” students according to their communication levels (Weak and uncommunicative, Weak and normally communicative, Weak and highly communicative). The facilitator could take some action, e.g. talking directly to the students, creating special online chatting sessions to discuss the reasons for their lagging behind their peers and encouraging the students, or directing the students to contact their more knowledgeable peers.

Type 1-4 Advice is used, in contrast to Type 1-3 advice, to inform the facilitator about the students with advanced learning levels. In this case, the AG looks for students evaluated as “Excellent” (see section 4.6.3). As in Type 1-3 advice, TADV will classify the “Excellent” students according to their communication levels. The facilitator may use this information to encourage those students to maintain their general learning levels and/or to direct them to help other “Weak” peers by talking to them through mail or discussion forums.

Type 1-5 Advice is generated to inform facilitator about the students who had not started working with the course till the time of advice generation session. If this type of advice is generated for one of the students, then other Type-1 advice will be suppressed.

5.2.2. Generating Type-2 Advice

Type-2 advice is concerned with a group of students. The learning level of each concept and the general learning level of a set of concepts will be monitored to identify problematic situations concerning the group’s learning. This type of advice enables the facilitators to know about common problems that face a group and correlate these problems to the group characteristics. In addition, the facilitator could try to solve the highlighted problems by providing the students with appropriate feedback and guiding information. The following subtypes are considered:

Type 2-1 Advice is used to inform a facilitator about problems related to the group’s knowledge status. This advice subtype will be generated when the group knowledge model shows concepts with “Unlearned” or “Learned” levels (see Section 4.6.3). Similar to the actions performed in Type 1-1 advice, AG searches for reason(s) that may lead to this situation and presents this information to the facilitator together with a recommendation of some actions that may be taken.

Type 2-2 Advice is used to inform the facilitators about the problematic situations related to the groups' learning levels. The facilitator's attention is directed to groups, which have unsatisfactory learning levels. Type 2-2 advice that concerns groups is similar to Type 1-3 advice that concerns individual students. Advice Type 2-2 is used to highlight to the facilitator the "Weak" groups (see Section 4.6.3). TADV will classify those "Weak" groups according to their communication levels (weak and uncommunicative, weak and normally communicative, and weak and highly communicative). The facilitator can take some actions, such as talking directly to the group members, creating a special discussion forum or chat sessions for the group, or guiding group members to "Excellent" peer students especially from the same group.

Type 2-3 Advice is used to inform the facilitator about groups with satisfactory learning levels. In this type of advice, AG should look for the "Excellent" groups (see Section 4.6.3). As in Type 2-2 advice, TADV will classify "Excellent" groups according to their communication levels. This information will be highlighted to the facilitator who may decide to encourage students in these groups to maintain their general learning levels and/or to give help to their "Weak" peers via e-mail, chat, or by posting on the discussion forums.

Type 2-4 Advice is generated to inform facilitator that most (more than 50%) students in the group have not started working with the course up to the time of advice generation session. In this case, other Type-2 advice will not be generated because it is expected that most of the group concepts' learning level are unlearned.

5.2.3. Generating Type-3 Advice

Type-3 advice is concerned with the status and behaviour of the whole class. Advice of this type does not automatically result in subsequent recommended advice or feedback to individual students instead it is primarily used to advise and guide course facilitators while they are managing their distance classes. The overall class learning level will be monitored according to each concept learning level. This type of advice is important to the facilitator because it gives an overview of the class, and highlights the common problems. The facilitator may try to solve these problems during the course period by taking appropriate educational actions. Furthermore, analysing the generated information and the reasons behind common class problems, the facilitator may consider how to avoid the occurrence of these problems in the following courses.

Type 3-1 Advice is used to inform the facilitator about problems related to the knowledge status of the whole class. This advice will be generated when the AG detects concepts with Unlearned or Learned levels in the class knowledge model. The AG will search for possible reason(s) that might have led to this situation and will notify the facilitator about it. The course facilitator may then make, according to the situation, appropriate decisions and pass them to all students in the class. For example, if the class knowledge model indicates that a concept *c* is "Unlearned" by the class because most students have not studied the learning objects related to *c*, TADV will highlight this situation to the facilitator. In this case the facilitator may encourage the students to start studying learning objects related to *c*.

Type 3-2 Advice is generated to inform the facilitator about excellent students (for example, the top three) and weak students (for example, the bottom three) relative to the whole class during each of the advice generating sessions.

Type 3-3 Advice is generated to the facilitator to inform him about the most and least communicative students relative to the whole class during each of the advice generating sessions.

Type 3-4 Advice is generated to the facilitator to inform about the most and least active students relative to the whole class during each of the advice generating sessions. Students' activity is measured by the aggregate number of interactions (hits) made by the student in different sessions. Information from this advice can be compared to information from advice Type 3-2 to correlate between the students' activity and their general learning levels.

Type 3-5 Advice is generated to inform the facilitator that most (more than 50%) students in the class have not started working with the course up to the time of advice generation session. In this case, other Type-3 advice concerned with class learning and communication levels will not be generated.

It should be noted here that it is possible to add new advice to the subtypes considered above. In this case, reasons that determine the need for the advice have to be defined based on the conditions in the student, group, or class models.

5.3. Advice Generating Criteria

As discussed earlier, there are two main processes in TADV. The first, performed by the student model builder discussed in Chapter 4, is the process of building student, group, and class models using the information delivered from WCMS. The second main process is advice generation. This process depends on the resultant models from the first process. In other words, it is necessary to execute the student model builder prior to generating advice to ensure that AG provides up to date advice. The executing of SMB just before running the AG will drive all recent students' interactions to update the different parts of student models.

AG is designed so that it is possible for the teacher to select the types and subtypes of advice he desires to generate. In a specific execution of AG the facilitator may select, for example, to generate only advice related to Type-1. In addition, it is also possible to suppress generation of one or more subtypes of advice related to the selected main type. This means that TADV gives some flexibility to course facilitators to control the types of the generated advice according to needs and according to the aspects to be monitored. Accordingly, the facilitator will control the amount of advice he wants to observe, which may prevent advising overload.

Advice generation criteria are based on the predefinitions of the advising situations. For each situation the following items should be specified:

- ***Stimulating Evidence (E):*** the situation that motivates AG to generate the advice. E is generally formalised as $E(e_1, e_2, e_3)$ where e_1 is the name of the student, group, or class that causes the stimulating evidence, e_2 is the name of a domain concept, and e_3 is the status of the domain concept (CL, L, UL, or delayed) carried by e_2. For example, $E(S_1, c_b, UL)$ means that for student S_1, concept c_b is "Unlearned". The stimulating evidence $E(G_1, c_b, UL)$ and $E(C_1, c_b, UL)$ will be interpreted with the same meaning but for group G_1 and class C_1, respectively. If e_2 is not specified, then e_3 is considered as the status of the student. For example $E(S_1, Weak)$ means that student S_1 is evaluated by TADV as a weak student.
- ***Investigated Reason (R):*** according to the stimulating evidence discovered, the AG will investigate the reason behind this evidence using the student, group, or class models. The investigated reason is generally formalised as $R(r_1, r_2, r_3)$ where r_1 is the name of the domain concept related to e_2 with r_2 concept type of relation (Strong/Moderate/Weak) and r_3 is the status of r_1. For example, if $R(c_a, Strong, UL)$ is the investigated reason of $E(S_1, c_b, UL)$, then AG might reason that the unlearned status of c_a that is strongly related to c_b is the reason for this E. If r_2 is not specified, then r_1 should be equal to e_2 of the current stimulating evidence and r_3 will carry the status of the student in relation to the learning objects, assessment quizzes, and or communication activities related to the domain concept specified in r_1. For example, if $R(c_b, Learning\ objects\ not\ started\ yet)$ is the investigated reason of $E(S_1, c_b, UL)$, then the AG will highlight that student S_1 has not read the available learning objects related to c_b. More examples are given in Table 5.1 and Appendix-C contains the comprehensive collection of advice types and sub-types.

- ***Advice from TADV to facilitator:*** depending on the investigated reason, the AG will deliver the appropriate Advice ***(A)*** to the facilitator. Advice to the facilitator is generally formalised as $A(P_1,\ldots, P_n)$ where $P_1,\ldots, P_n$ are the parameters carried with the template. The number of parameters considered is varied in different types of advice. There are four basic parameter types used in advice templates: concept name, student name, group name, and class name. Example templates are provided in Table 5.1.

Table 5.1 Examples of defining situations for generating advice to individual students (Type-1), groups of students (Type-2) and the whole class (Type-3).

Investigated Reason (R)	Advice from TADV to facilitator (A)	Recommended advice from facilitator to the student (T)	Next AG Action
Type-1 Student advice [Stimulating Evidence is *E(S, c_b, UL)*]			
(c_b, learning objects and/or assessment quizzes are not activated by S)	Student *S* should be advised to work on the available learning objects and assessment quizzes related to c_b	In order for you to understand c_b we suggest you refer to its available learning objects and solve related assessment quizzes.	Look for new evidence
(c_a, Strong, UL)	Student *S* should be advised to study c_a	In order for you to master c_b, it is highly recommended that you study c_a first.	Look for new evidence
(c_a, Moderate, UL)	It may be useful to advise student *S* to study c_a	In order for you to master c_b, it may be useful to study c_a first.	Look for other reasons
Type-2 Group advice [Stimulating Evidence is *E(G, c_b, UL)*]			
(c_a, Strong, L)	*G* members should be advised to work more with concept c_a	c_b appears to be a common problem for students in *G*. It is preferred to work more on c_a.	Look for other reasons
(c_a, Weak, UL)	It might be useful to advise G members to study c_a	c_b appears to be a common problem for students in *G*. It might be useful to study c_a	Look for other reasons
Type-3 Class advice [Stimulating Evidence is *E(C, c_b, UL)*]			
(c_a, Strong, L)	c_b appears to be a common problem for students in *C*. The prerequisite c_a is not completely mastered by the class members. It might be useful to advise class members to study c_a	Facilitator should take the necessary actions.	Look for other reasons
(c_b, Uncommunicative)	c_b appears to be a common problem for students in *C*. TADV notes that class members are not participated in the c_b discussion forum. *C* members should be encouraged to participate in communication activities related to c_b.	Facilitator should take the necessary actions.	Look for new stimulati ng evidence

- ***Recommended advice from facilitator to student/group/class:*** If possible, depending on the investigated reason, the AG will automatically produce a predefined advice template ***(T)*** that recommends advice that the facilitator may send to student, group, or class. This item does not exist when the AG is unable to find reasons that have led to the current stimulating evidence or when the advice is concerned merely with highlighting important information to the facilitator. The advice template is generally formalised as $T(P_1,\ldots., P_n)$ where $P_1,\ldots., P_n$ are parameters carried with the template. The number of these parameters differs. Table 5.1 shows some templates with recommendations and more are depicted in Appendix-C. It is important to point out here that TADV does not consider the use of natural language generation mechanisms, which are outside the scope of this project. Ideally, appropriate generation techniques may enable coherent and expressive recommendations to be generated. The template-based approach is rather restricted but the facilitator can be given the opportunity to edit these recommendations (as shown in the exemplification of TADV; Chapter 6).

- ***Next AG Action:*** For some SE there is a possibility of having many reasons. When a reason is investigated, AG will proceed with the reason and generate the appropriate advice. At this point and depending on the investigated reason, AG will either end processing of the current evidence or keep searching for other reasons. In the proposed taxonomy, the likelihood of a reason being the cause of the evidence is represented as its "Next AG Action". When reason is considered to be sufficient, then its "Next AG action" is specified as "Look for new stimulating evidence" to notify AG to END processing of the current evidence. On the other hand, when a reason is considered to be insufficient, then its "Next AG action" is specified as "Look for other reasons" to notify AG to continue processing of the current evidence by searching for other candidate reasons. For example, assume that $E(S, c_b, UL)$ is the current AG stimulating evidence. If AG found that a reason behind this evidence is $R(c_a, Strong, UL)$, then AG will generate the appropriate advice templates (see Table 5.1), stop processing the current evidence, and start searching for new stimulating evidence. In this case, AG will not search for other reasons because c_a is a strong prerequisite for c_b which implies high probability of $R(c_a, Strong, UL)$ being the reason. On the other hand, if AG found that the reason is $R(c_a, Strong, L)$, then AG will generate the appropriate advice templates and continue to search for other possible reasons because c_a (even if it is a strong prerequisite for c_b) is learned which implies low probability of $R(c_a, Strong, L)$ being the only reason behind the current evidence.

Table 5.1 shows a section of the advice situations proposed for individual students, groups of students, and whole class. The presented advice situations are of Type1-1, Type2-1, and Type3-1 and situations are related respectively to stimulating evidences $E(S, c_b, UL)$, $E(G, c_b, UL)$, $E(C, c_b, UL)$. The table also shows all items associated with each advice situation. All advice situations proposed for individual students, groups and classes are given in Appendix-C. For each advice type, advice situations are ordered in the way that should be followed by AG. It should be noted here that the proposed set of advice described in Appendix-C is based on our analysis of problems that took place with distance courses as discussed in the literature. The problems have been confirmed in interviews with several Web-based course instructors who suggested most of the proposed TADV advice. This taxonomy of advice may not be comprehensive and other advice types may be needed, however, giving a general model for advice generating is necessary to enable us to capture more advice types. The suitability of this proposed taxonomy is one of the issues addressed during TADV evaluation phase and discussed in Chapter 7.

Figure 5.2 depicts the advice generation data model. It shows the entities required in the process of advice generation and how these entities are related to domain meta-knowledge and student, group or class models. A brief description of these entities is shown below and more detailed specifications are presented in Appendix-D:

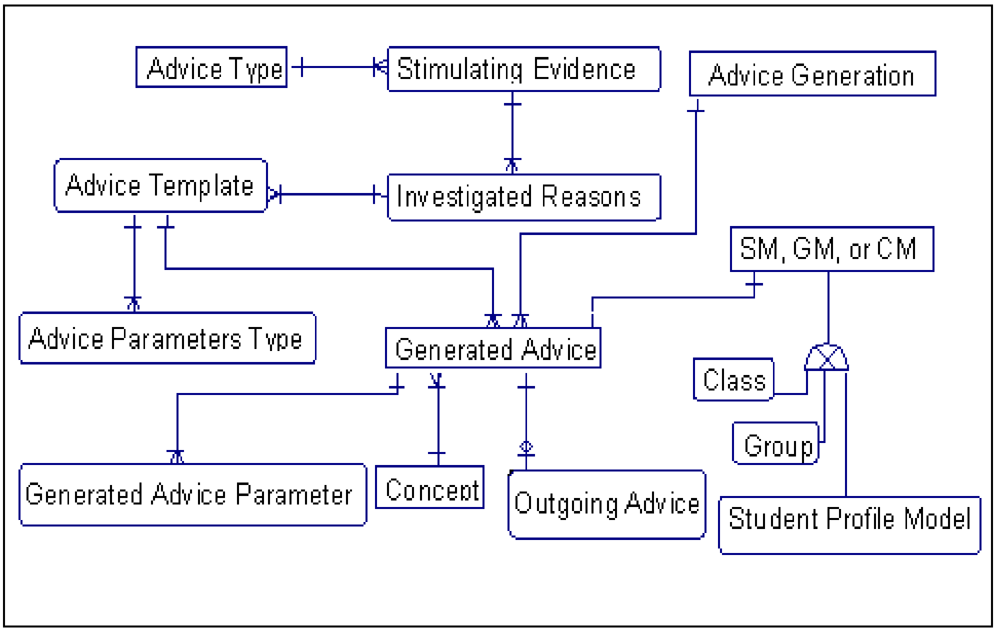

Figure 5.2 Advice Generation Data Model. The entity relationship diagram shown is represented using Crow's foot convention (Hoffer et al., 2001). More detail about the conventions used is shown in Appendix-A.

- ***Advice Type Entity:*** Table that contains the description of main advice types and the status of each type i.e., suppressed or not.

- ***Stimulating Evidence Entity:*** Table that contains the description of the different stimulating evidences related to each advice type.
- ***Investigated Reason Entity:*** Table that contains the possible reasons that may cause stimulating evidence.
- ***Advice Template Entity:*** Table that contains the advice template designed for each investigated reason. Some of the advice templates carry variable information e.g., a name of domain concept, a name of a student, a name of a group, or a name of a class. These variables will be referred to as "advice parameters" and the type of the information they carry determines the type of each parameter. Different types of parameters are described in ***Advice Parameters Type Table*** (see Appendix-D).
- ***Generated Advice Entity:*** Table that contains information (for example, date, to whom advice is generated, the concept concerned, the send status, etc.) about the advice generated in different advice generation sessions. If appropriate, each advice generated will be related to ***Generated Advice Parameter Table***, which contains information about the values of the parameters related to the generated advice (see Appendix-D).
- ***Outgoing Advice Entity:*** Table that contains the final advice messages delivered to the student, group or class either as generated from the system or as modified by facilitators.

Figure 5.3 shows the advice generation criteria in terms of the main processes performed during generation (see Appendix-E for detailed algorithm for generating Type-1 Advice). There are three main processes:

- ***Look for stimulating evidence process:*** uses inputs mainly from SM, GM, or CM (see Chapter 4) to locate the concepts with problematic certainty factor values (i.e. unlearned and learned concepts). It also uses the course calendar to find delay status. The major output of this process is the stimulating evidence *E*.
- ***Find reason process:*** it uses *E* (from the last process), domain knowledge model (concept maps) and SM, GM, or CM to investigate the reason behind the given *E*. The major output of this process is the investigated reason *R*.
- ***Find template, parameters, and generate advice process:*** According to the reason *R* from the previous process, this process locates the appropriate advice templates and their parameter values.

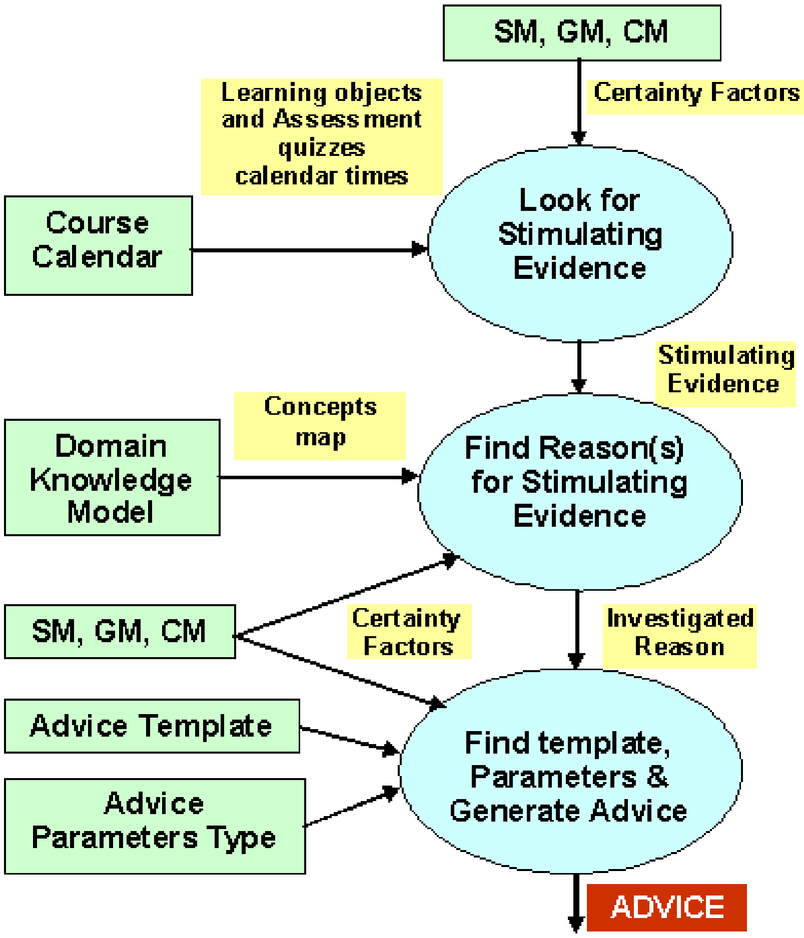

Figure 5.3 Advice Generation Criteria.

5.4. Summary

In this chapter, the main issues related to advice and their generation are depicted and discussed, namely, advice types, advice selection, advice formulation, and advice generation criteria. The advice types and advice generation criteria presented in this chapter are quite general. They are not by any means dependent on a specific domain or on a specific WCMS. The description of the TADV framework is completed, and the demonstration of the proposed ideas in a practical environment is now possible. The TADV framework is demonstrated in a Discrete Mathematics course in Chapter 6. The evaluation of the prototype takes into consideration the validity of the framework, the suitability of the advice types, and the benefits gained by facilitators and students.

Chapter 6

The TADV Prototype

6.1. Introduction

The applicability of the framework elaborated in chapters 4 and 5 will be demonstrated with a prototype developed within an existing Web course management system. In the previous chapters, the architecture of an intelligent teacher advisor has been proposed and five issues have been addressed:

- Structuring the course (domain knowledge base) so that it would be appropriate for the proposed ideas of advice generating.
- Defining domain metadata according to existing standards and the special requirements of the project.
- Designing student, group, and class models.
- Defining a mechanism for student modelling to be performed by the Student Model Builder (SMB) and setting criteria for diagnosing student knowledge.
- Formulating a taxonomy of advice types and defining an appropriate advice generation mechanism.

The TADV prototype was developed as an implementation of the proposed framework following the architecture discussed in Section 4.2. The prototype was developed as an extension of CENTRA – a Web-based course management system.

In this chapter, we will describe the TADV prototype that is exemplified in a Discrete Mathematics course. First, we will introduce the CENTRA WCMS selected for this prototype and other implementation tools used in developing the prototype. Definitions of the selected domain, the course structure, and the prepared metadata are presented. The chapter also includes the main tasks carried out to implement the proposed student models and the advice generation model and how they have been integrated within CENTRA WCMS. The TADV interface designed for facilitators and students is presented. Finally, some examples for advice situations are presented to illustrate how the teachers and students used the prototype.

6.2. WCMS and Implementation Tools

The TADV design is based on an extensive study of tracking information provided by WCMS, including practical experience with several platforms, such as WebCT and Centra Knowledge Server. The latter is employed in the demonstration of TADV presented here. In this section, a brief description of Centra Knowledge Server and the list of software tools used for the TADV implementation are provided.

6.2.1. Centra Knowledge Server

The Centra Knowledge Server[1] is a flexible repository that can be used by educational organisations to tag and index their learning objects. It facilitates the capture, storage, delivery, and centralised management of knowledge. The browser-based Centra Knowledge Centre allows users to view personalised, assigned learning topics and access and search a catalogue of available learning resources. Together, the Centra Server and the Centra Centre offer powerful features to the users, for example, personalised learning, easy learning object creation, support for industry standards e.g. SCORM, and IMS (see Chapter 2), easy to use interface, and others. The word "CENTRA" is used through out this thesis to denote both the Centra Knowledge Server and the Centra Knowledge Centre. CENTRA uses standard relational databases and can be easily integrated with other learning management systems[2]. Like most WCMS, CENTRA provides student tracking features which record detailed information about all types of interactions students make with the available learning objects, assessment items, and communication and collaboration tools.

CENTRA V6.0 was selected for this implementation of TADV prototype because:

- It provides the common functionality of WCMS (discussed in Chapter 2) and enables the implementation of TADV algorithms outlined in chapters 4 and 5.
- It is a simple WCMS, which allows the demonstration of TADV to include features common for most WCMS, we do not rely on special advanced functionality that is often specific for a particular WCMS. This enables the implementation of a general prototype to illustrate TADV.
- The software is available in AAST (the Arab Academy for Science and Technology, Alexandria, Egypt) – the organisation in which the TADV prototype

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[1] Product of Centra Company located at Lexington, MA, USA. http://www.centra.com

[2] Centra Knowledge Center User Guide, Centra Software Inc. (2002).

was used. The implementation of the TADV prototype on CENTRA was approved from the authorised dealer in Egypt.

- Finally, CENTRA was one of the WCMS used during the study conducted to examine tracking data generated by WCMS. We had substantial knowledge of the format and representation of the data in CENTRA, which enabled a relatively quick implementation within the time limits of this work.

CENTRA uses Microsoft SQL 2000 Server[3] as a backend database management system, therefore, it was necessary to know a great deal about its relational database model: where tracking information is stored, how tracking information can be interpreted against the used course materials and the students involved, etc. In summary, we can say that most of the tracking information required to build the proposed student models (discussed in Section 4.4) is generated by CENTRA and its availability was ensured before going forward with building the TADV prototype.

6.2.2. Implementation tools

The TADV prototype was implemented in Microsoft SQL Server 2000 and Active Server Pages (ASP)[4] technology with ODBC[5] (Open Data Base Connectivity) drivers. The Web server was Microsoft Internet Information Server (MS-IIS)[6] under a Microsoft Windows 2000[7] server. Microsoft Visual Interdev V6.0[8] was used as a development tool and Visual Basic[9] and Java scripts[10] were used as development languages. The Domain Meta-Knowledge base, student, group and class models, and advice generation model are stored as relational databases on the MS SQL Server. It contains tables to store metadata for all learning objects and assessment quizzes, relationships between domain concepts, course calendar, students' profiles, the models constructed to assess the knowledge of students, groups and classes, and all information related to the process of advice generation. The prototype was implemented as an extension of CENTRA and followed the architecture described in Chapter 4, Section 4.2.

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[3] http://www.microsoft.com/sql/default.asp
[4] http://www.webopedia.com/TERM/A/Active_Server_Pages.html
[5] http://msdn.microsoft.com/library/default.asp?url=/library/en-us/off2000/html/defODBC.asp
[6] http://iroi.seu.edu.cn/books/ee_dic/whatis/iis.htm
[7] http://www.microsoft.com/windows2000/default.asp
[8] http://msdn.microsoft.com/library/default.asp?url=/library/en-us/vidref98/html/dvrefglossary.asp
[9] http://www.webopedia.com/TERM/V/VBScript.html
[10] http://www.webopedia.com/TERM/J/JavaScript.html

6.3. Domain and Course Preparation

6.3.1. Discrete Mathematics domain

A Discrete Mathematics course was selected for demonstrating the TADV prototype. The availability of the domain expert who volunteered to help in the process of course preparation and its metadata was a key reason behind selecting this domain. Other reasons include the possibility to teach part of this course in a distance manner which was important for the evaluation (see Chapter 7), and the availability of this course in most of the schedules of the academic terms in AAST which insured that a good number of students usually enrol in this course.

Discrete Mathematics is the part of mathematics devoted to the study of discrete objects, i.e. objects consisting of distinct or unconnected elements (Rosen, 2003). It describes processes that consist of a sequence of individual steps (Epp, 1993). More generally, Discrete Mathematics is used whenever objects are counted, when relationships between finite sets are studied, and when processes involving a finite number of steps are analysed (Rosen, 2003). Discrete Mathematics includes several topics of mathematics, some of them go back to the early stages of mathematical development while others are recently added to the domain (Kenney & Bezuszka, 1993). A key reason for the growth in the importance of Discrete Mathematics is that information is stored and manipulated by computers in a discrete fashion (Rosen, 2003). Regardless of their choice of career path, it is necessary for most computing students to receive some instruction in discrete Mathematics. Through this course, student can develop his ability to understand and create mathematical arguments. Moreover, Discrete Mathematics provides the mathematical foundations for many Computer Science courses, including data structures, algorithms, database theory, etc. (Rosen, 2003).

6.3.2. Course preparation

Since our main objective behind prototyping TADV was to check the applicability of the proposed framework, it was necessary to deploy the prototype in realistic settings. According to an agreement with the administration of AAST, it was decided to run an experiment with the prototype during the last two lessons of the Discrete Mathematics course offered to computer engineering students at AAST (see Chapter 7). These lessons covered two topics: “Functions” and “Relations”.

Following the guidelines for structuring the course described in Chapter 4, the course was divided into two lessons: functions (Lesson-1) and relations (Lesson-2).

Each lesson was then divided into a set of concepts (17 concepts for each lesson). The concept maps (described in Chapter 4) were then prepared for each of the specified lessons. The difficulty levels and weights assigned to each of the course concepts were then determined (see Appendix-F for all information related to course structure and metadata).

Preparing learning objects related to each of the course concepts was one of the major tasks. The domain expert provided us with the text and examples necessary, from his point of view, for building the required knowledge of the selected lessons. The learning objects of each concept were then created using these materials. There are two main groups of learning objects related to each concept: a group which contains the text required to explain the concept and a group which contains examples necessary to demonstrate the concept. A naming convention is used such that the learning objects of the first group are named as follow:

Concept Identification_Concept Name_T

For example, the learning object named as "102_Arrow_diagram_T" contains the **T**ext material required to explain the second (02) concept (Arrow diagram) of the first lesson (1). The naming convention used for the second group is:

Concept Identification_Concept Name_En

where *n* is the serial number assigned to the learning object inside this group. For example, the learning object named as "102_Arrow_diagram_E1" contains the first **E**xample available to demonstrate the concept (Arrow diagram) while "102_Arrow_diagram_E2" is the second example. Figure 6.1 shows the learning object prepared for one of the examples used to demonstrate the concept of One-to-one function.

Each learning object was prepared using the following formats:

- HTML: Hyper Text Mark-up Language suitable for Internet browsers.
- DOC: Document suitable for Microsoft Word.
- PPT: Microsoft PowerPoint presentation.
- CPF: Microsoft PowerPoint presentation converted by CENTRA Knowledge Composer for PowerPoint. The resulted presentation takes the CPF extension. Converting PowerPoint presentations to CPF format makes them easy to display from CENTRA and facilitates tracking the interactions that students make with these presentations.

The number of the different learning objects prepared for the TADV prototype was 70 (34 for the Functions lesson and 36 for the Relations lesson).

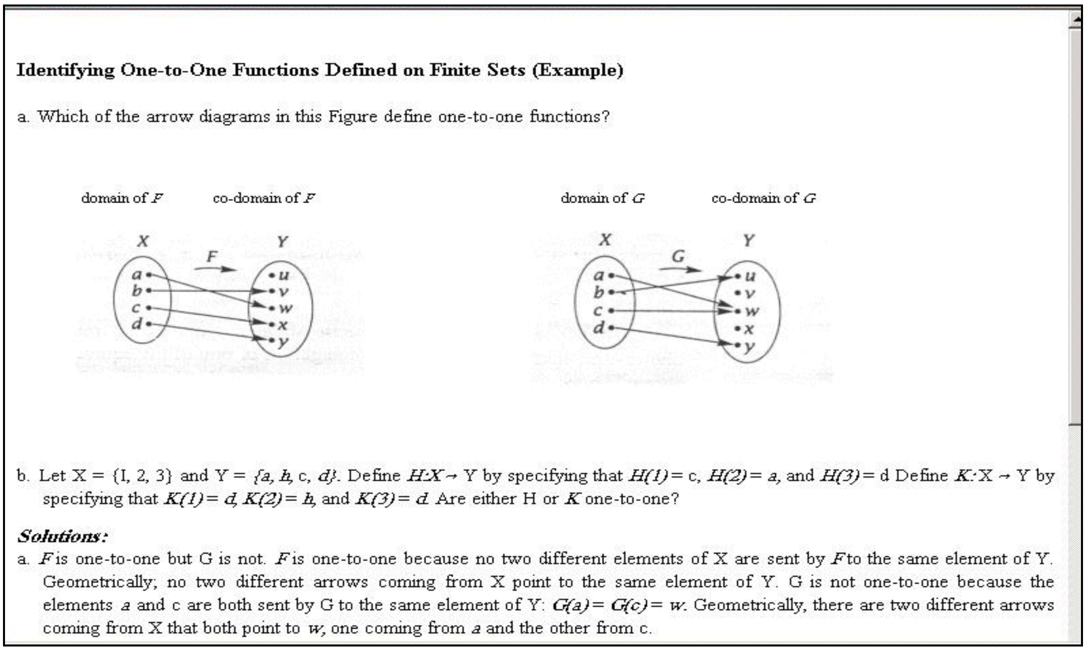


Figure 6.1 A screen shot showing the contents of the learning object 107_One_to_One_Function_E1 – an example used to illustrate the concept One-to-one function.

Another major task was the preparation of the assessment quizzes. All quizzes were prepared by the domain expert in a multiple-choice and true/false format. The domain expert (teacher) provided us with the all concepts related to each quiz along with its correct answer. The total number of quizzes prepared for the prototype was 49 (35 for the Functions lesson and 14 for the Relations lesson). Figure 6.2 shows one of the quizzes related to the functions lesson. In naming of these quizzes, it was difficult to relate them to the concept name because a quiz may be related to many concepts. So, their names were related to the lesson names by the following convention:

Lesson Name_ASSESSMENT_n

For example, "**FUNCTION_ASSESSMENT_09**" is the ninth quiz prepared for the Functions lesson.

6.3.3. Metadata acquisition

The acquisition of the metadata required for describing learning objects and assessment quizzes was the last step in the course preparation phase. All prepared learning objects and assessments were returned back to the domain expert to decide the values of the required attributes necessary for the proposed fuzzy approach. The TADV belief graph (discussed in Section 4.6.1) was explained to the expert so that it could be easily used during this task. For each learning object the expert was asked to provide the values of *T1* and *T2* (the optimal reading time interval), *MB* (measure of belief), and *MD* (measure of disbelief) while for each quiz he asked to provide the values of *MBC* (measure of belief of correct answer), *MDW* (measure of disbelief of wrong answer), and *MDN* (measure of disbelief if quiz is not solved). Samples of metadata acquired for the learning objects and assessment quizzes are presented in Appendix-F. For example, the expert supplied the following values for the learning object shown in Figure 6.1: *T1= 10* minutes, *T2= 15* minutes, *MB=0.4*, and *MD=0.1* and supplied the following values for the quiz shown in Figure 6.2: *MBC* = 0.8, *MDW=0.4*, and *MDN=0.2*.

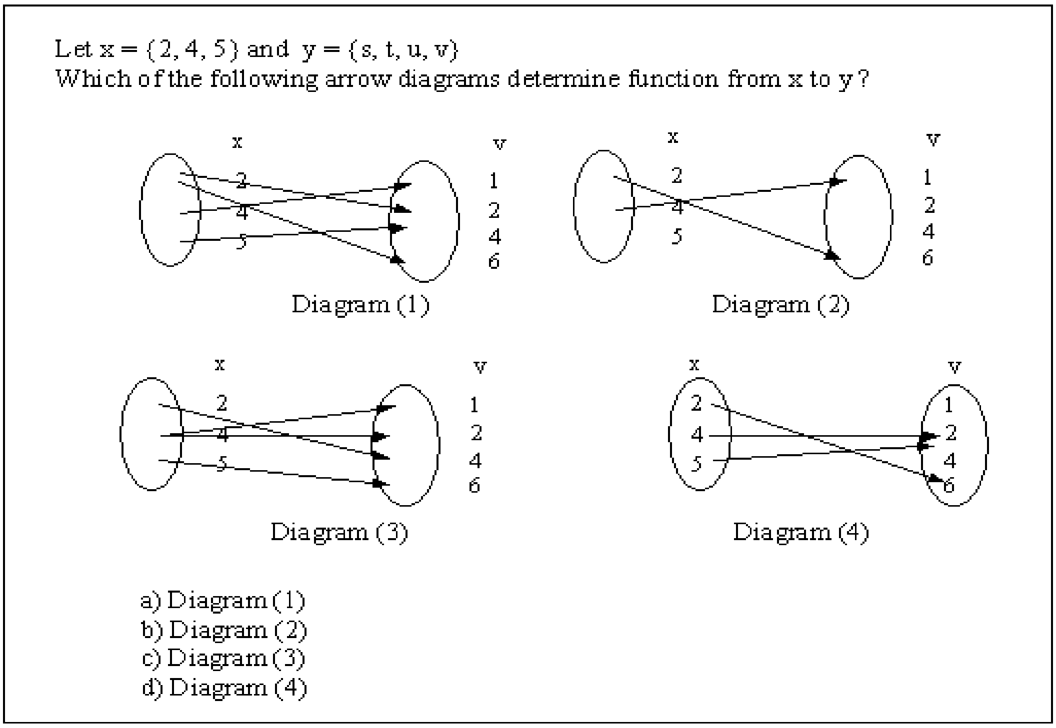


Figure 6.2 One of the assessment quizzes related to the "Functions" lesson.

6.4. Implementation of the TADV Models and their Integration in CENTRA

This section presents the tasks carried out in order to implement the required TADV models as an extension of a selected WCMS – CENTRA. We will show that it is possible to apply the TADV framework within conventional WCMS that keep logs of tracking data.

As explained in Chapter 4, the TADV architecture has three main data models that should be implemented – a model for Domain Meta Knowledge (DMK) base, a model for student modelling features (individual student, group, and class models), and a model for advice generation features. In addition to these models there is a model for the Domain Knowledge Base (DKB), which already exists through using WCMS (CENTRA).

The proposed course structure is easily applied to the CENTRA content manager. CENTRA uses different terminology for courseware structuring (e.g. learning goals, learning objectives, etc.). Understanding what this terminology means and how they are related was very important to know how to create the course in a way similar to the proposed course structure. The CENTRA content manager deals with many types of learning resources. Some of these resources (required in our project) and how they are defined by CENTRA[11] are listed below:

- *Learning goal*: is a statement about what the learners should be able to do after taking the whole instruction. It can be divided into many learning objectives.
- *Learning objective*: is a statement about what the learners should be able to do after taking a part of the whole instruction.
- *Learning objects*: ‘chunks’ of content that collectively support learning objective.
- *Assessments*: are the tests. An assessment may contain one or many questions.
- *Discussion*: is an online forum for learners to interact with one another by posting responses to topic threads.
- *Learning track*: is a grouping of related learning resources, for example objects, assessments, discussions, etc.

According to these definitions and with reference to our proposed course structure (discussed in Section 4.3) we used “learning goal” to represent “course”, “learning

[11] Centra Knowledge Center Author Role User Guide, Centra Software Inc. (2002).

objective" to represent "lesson", and "learning track" to represent "concept". Learning objects related to a concept are assigned to one track. This shows the applicability and generality of the proposed course structure.

CENTRA used SCORM standards to describe learning objects. As mentioned in Chapter 2, SCORM combines standards from IEEE and IMS. Therefore, some of the metadata attributes proposed for DMK (see Section 4.3) are already kept by CENTRA. The attributes required for fuzzy calculations (e.g. measures of belief and disbelief) are not represented by CENTRA and have been added for the purpose of TADV.

CENTRA keeps student tracking data in a database format, which facilitates the process of a direct access to this data. Knowing the relational database model of CENTRA and the meanings of different attributes, codes, and keys was not a straightforward task. However, the availability of sufficient tracking data in database format eliminated the need to develop the Interaction Interpreter. The data available in the CENTRA database is considered directly as the Student Behaviour Model (see Section 4.4.1).

CENTRA keeps profiles of the registered students. Part of the data proposed for the Student Profile Model (see Chapter 4 and Appendix-A) is already available in the profiles maintained by CENTRA.

In summary, the study of CENTRA's capabilities showed our need to access the data stored in the following tables from its database:

- ADM_USER table: includes information about CENTRA users (learners, teachers, authors, etc.).
- ITEMS table: defines different content items like learning goals (courses), learning objectives (lessons), learning tracks (concepts), learning objects, assessments and discussion forums.
- ITEM_REL table: defines relations between different learning items described in ITEMS table.
- ITEMS_TYPES table: defines the types of different learning items specified in ITEMS table.
- WORK_FLOW_HISTORY table: includes detailed information about students' interactions with all types of learning items.

This implies that we needed to implement and integrate the following parts of TADV models within CENTRA:

- The model proposed for Domain Meta-Knowledge to include the metadata attributes required by TADV and not represented by CENTRA. This model was described in Chapter 4.
- The model proposed for student, group, and class modelling except the Student Behaviour Model and some attributes from the Student Profile Model. This model was described in Chapter 4.
- The model proposed for advice generation. This model was described in Chapter 5.

The Entity Relationship Diagrams of the models implemented for the TADV prototype are shown in Appendix-G. Several ASP pages were created to handle reading and writing of data from and to these models.

Two other major tasks were required. The first was the development of the Student Model Builder (SMB). In this implementation of TADV, SMB was developed to read information about students' interactions directly from the CENTRA database and to calculate student, group and class models according to the mechanisms explained in Section 4.6. The module was developed such that it was possible to be automatically executed (in a batch mode) daily at a pre-scheduled time. This means that each run of SMB considered all students' interactions that occurred in the last 24 hours before the execution. In this way, TADV keeps daily models for students, groups, and classes. On the other hand, it is possible to execute SMB at any time or just before the process of advice generation.

The second task was the development of the core module – the Advice Generator (AG). This module was developed to generate the proposed advice according to the criteria explained in Chapter 5. The module was designed to use the most recent models constructed by SMB to generate the advice. AG could be executed from the facilitator interface at the facilitator's request at the time he needed to generate the advice.

Figure 6.3 illustrates how the proposed architecture (discussed in Section 4.2) was implemented as an extension of CENTRA WCMS. The main system's components and information flow between the components are shown as well as the tools used for implementing the prototype.

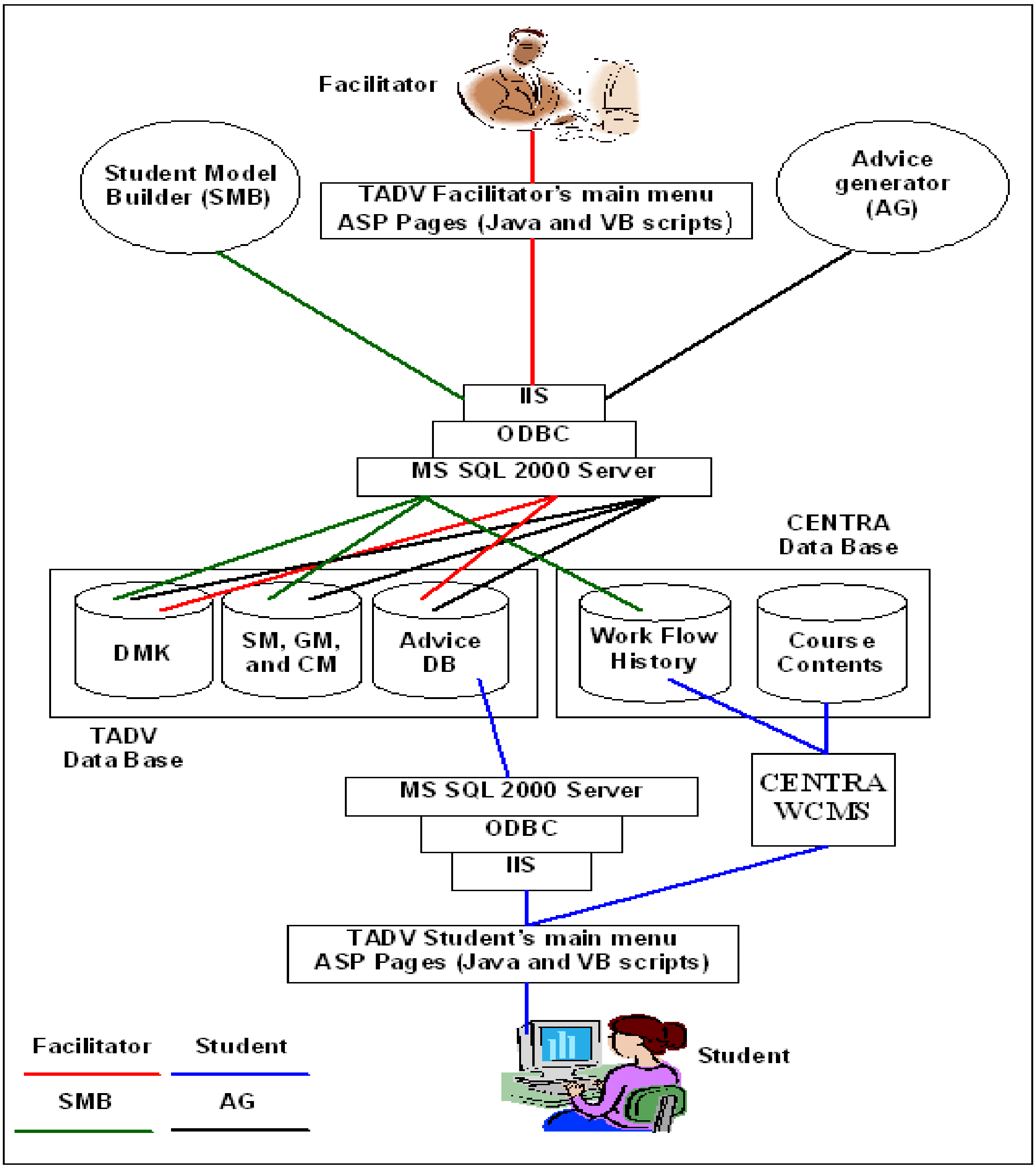


Figure 6.3 The Architecture of the TADV prototype: main components and implementation tools.

The description in this section shows that the implementation of TADV components as an extension of CENTRA required substantial time and effort invested to understand the architecture of CENTRA at a deep level. This is common for all software engineering projects that require new components to be built on the top of the existing, well-established ones. Despite the computational effort in extending WCMS, we believe that it is more feasible to apply TADV in this way, rather than to tie the implementation of the framework to the development (from scratch) of WCMS with integrated TADV. Moreover, we have demonstrated that within a couple of months

TADV can be implemented as an extension of an existing WCMS. This period of time includes the familiarisation with the low-level architecture of WCMS. This process can be much simpler and quicker, if the developers already know the design and the functionality of WCMS.

6.5. Designing Facilitator and Student Interfaces

One of the design issues we considered during the implementation of TADV was to fully integrate features of TADV and CENTRA so that users (facilitators or students) would not feel that there were two different systems. Therefore, it was important to determine the functions that should be included in the facilitator and student main menus. This section presents the interfaces designed for the facilitators and the students. The system was designed such that any user should log-in to the system through the TADV main login screen, which in turn directs the user to the appropriate menu according to his profile. Below we describe *Facilitator's main menu* and *Student's main menu*.

6.5.1. Facilitator's main menu

As shown in Figure 6.4, there are six options in the facilitator's main menu: system parameters, select advice types, course and assessments metadata, management of students, groups, and classes, generate advice, and view advice. One more option called "Statistics" was added to this menu to facilitate data retrieval for the sake of TADV evaluation discussed in the next chapter. Through the description of these options, we will also show how were used to prepare the TADV prototype for the experimental study presented in the next chapter.

TADV system parameters

The "System parameters" option allows the facilitator to set the parameters required for the student modelling mechanisms explained in Chapter 4. Some of these parameters are included to simplify the process of metadata acquisition (see Section 6.3.3) and entry. These values should be entered before entering the values of metadata attributes specified for learning objects and before starting the course. The parameters, shown in Figure 6.5, include the following attributes:

- *TMIN* parameter: if a value is entered to this parameter, then *TMIN* (the minimum time required for familiarising with a learning object, see Chapter 4) for all learning objects will take the same value. Otherwise, a *TMIN* value should be acquired from the domain expert and entered for each learning object.

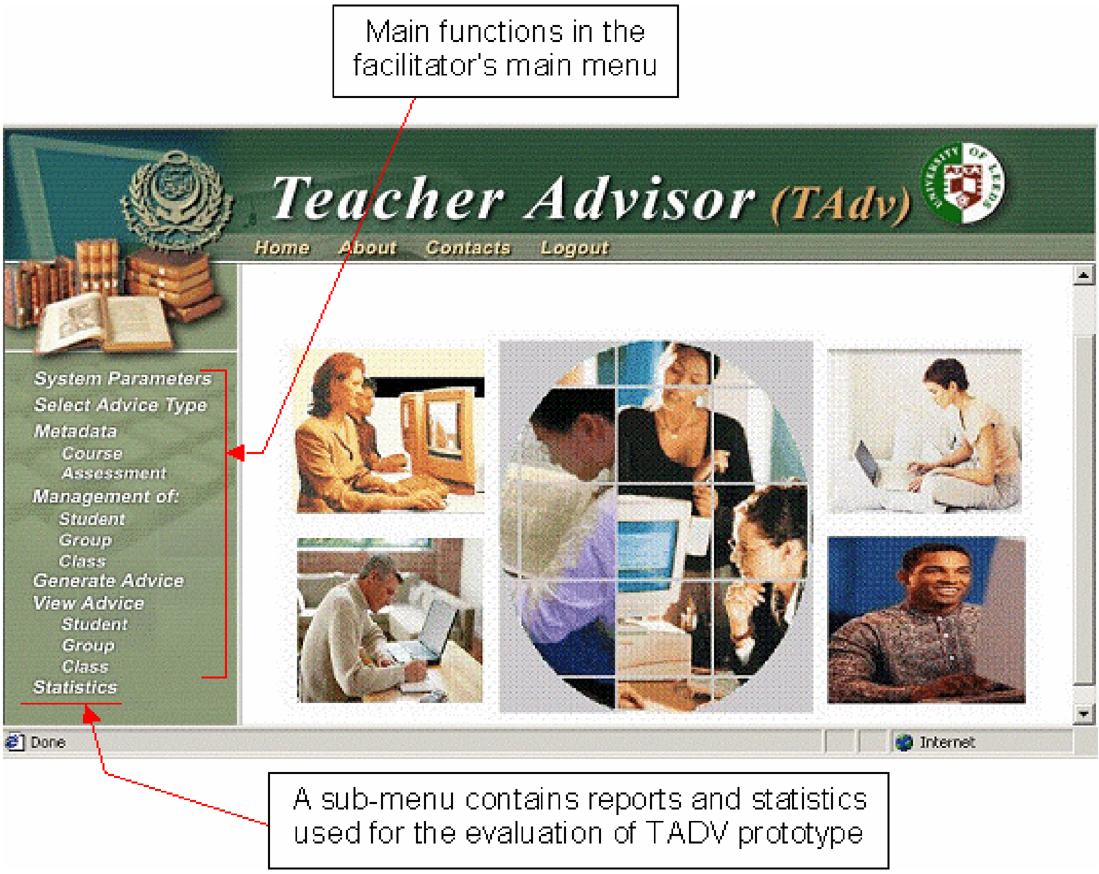


Figure 6.4 Facilitator's main screen.

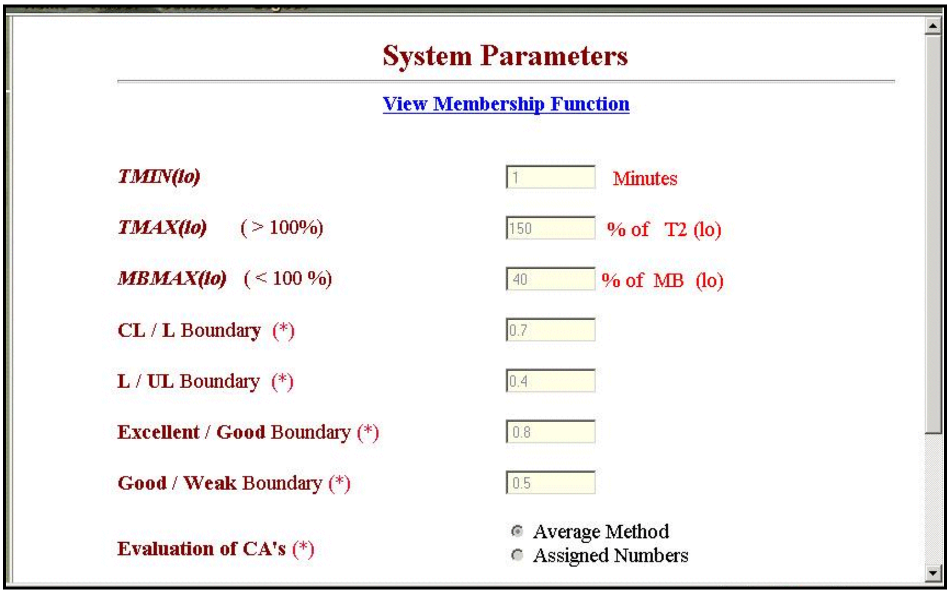


Figure 6.5 System parameters screen.

- *TMAX* parameter: Like *TMIN*, this parameter, if used, automatically calculates the values of *TMAX* (maximum familiarising time, see Chapter 4) for all the learning objects as a percentage of *T2* (the upper limit of the optimal time interval). The value of this parameter should be greater than 100. For example, if *TMAX* is set to be 150% of *T2*, then for a learning object with *T2* = 10 minutes, *TMAX* will be 15 minutes.
- *MBMAX* parameter: This parameter, if used, automatically calculates the values of *MBMAX* (understanding measure of belief at the maximum familiarising time) for all learning objects as a percentage of the *MB* (learning object measure of belief). The value of this parameter should be less than 100 because *MBMAX* is always less than *MB* (see Chapter 4)
- CL/L and L/UL boundaries: These mandatory parameters are used to determine the certainty factor boundaries used to evaluate concepts' learning status - Completely Learned (CL), Learned (L), and Unlearned (UL).
- Excellent/Good and Good/Weak boundaries: These mandatory parameters are used to determine the average certainty factor boundaries used to generally evaluate students regarding a group of concepts.
- Method to evaluate communication status: This parameter allows a facilitator to select one of the two approaches explained in Chapter 4 to diagnose the students' communication status.

For this implementation of TADV the following parameter values were selected upon discussion with the domain expert and facilitators who participated in the experimental study discussed in the next chapter:

TMIN (o) = 1 minute (for all concepts)

TMAX (o) = 150% of the *T2 (o)* (for all concepts)

MBMAX(o) = 40% of *MB(o)* (for all concepts)

CL/L boundary = 0.7

L/UL Boundary = 0.4

Excellent/Good boundary = 0.8

Good/Weak boundary = 0.5

The average method (discussed in Section 4.6.4) was selected for judging communication status.

We have to acknowledge here that the values selected for the above parameters, which certainly affect the judgements of the TADV, were selected by a particular group of teachers. Other teachers might have selected different values for these parameters according to their own view. The subjectivity of these parameters and the values of metadata attributes will be discussed in Chapter 8.

Selection of advice types

The option "Select advice types" allows the facilitator, as shown in Figure 6.6, to select the types and the subtypes of the advice he likes to be generated by TADV. To be able to evaluate our proposed advice taxonomy (see Chapter 5), all advice types were selected for generation in this TADV implementation.

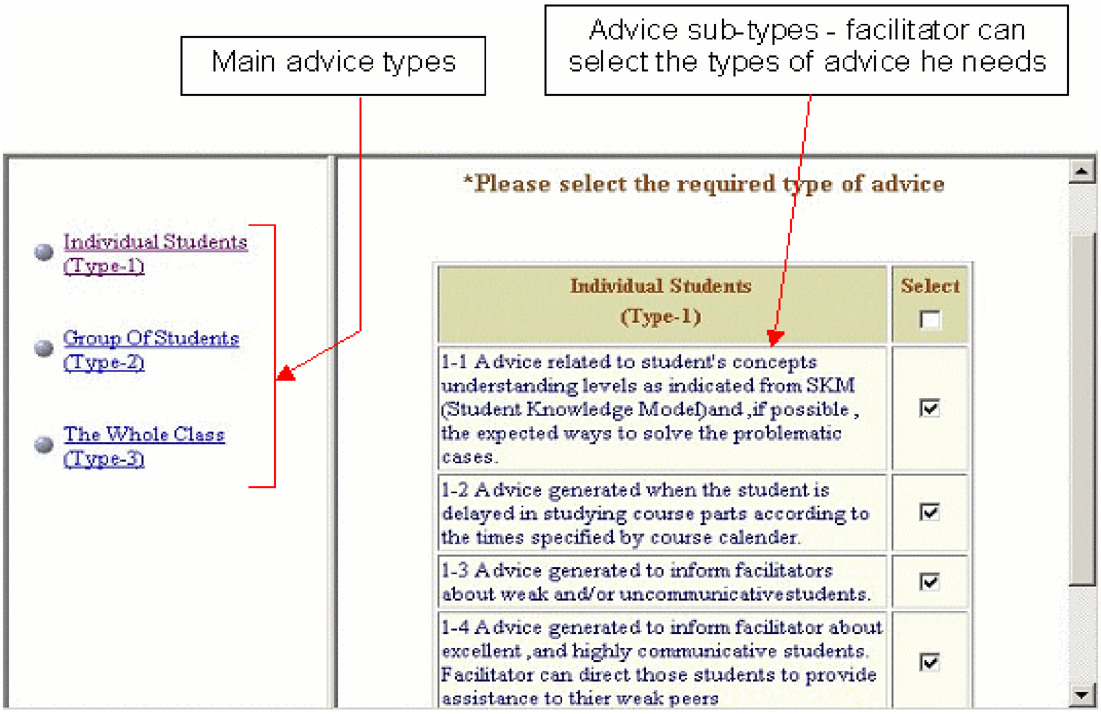


Figure 6.6 Screen for selecting advice types.

Creating course and entering values of metadata attributes

The option named "Metadata" allows the facilitator (or any one on behalf) to enter the values of required metadata attributes to the DMK. Due to the integration we have made with CENTRA, it was necessary first to create the course using CENTRA authoring tools then use the "metadata" option to enter the values of metadata attributes according to the parts of the created course. The option is designed such that it reads and displays the metadata of course parts already defined in the CENTRA database and allows the facilitator to complete entry of the metadata required for TADV. Figures 6.7, 6.8, and 6.9 show some of the screens designed for this purpose.

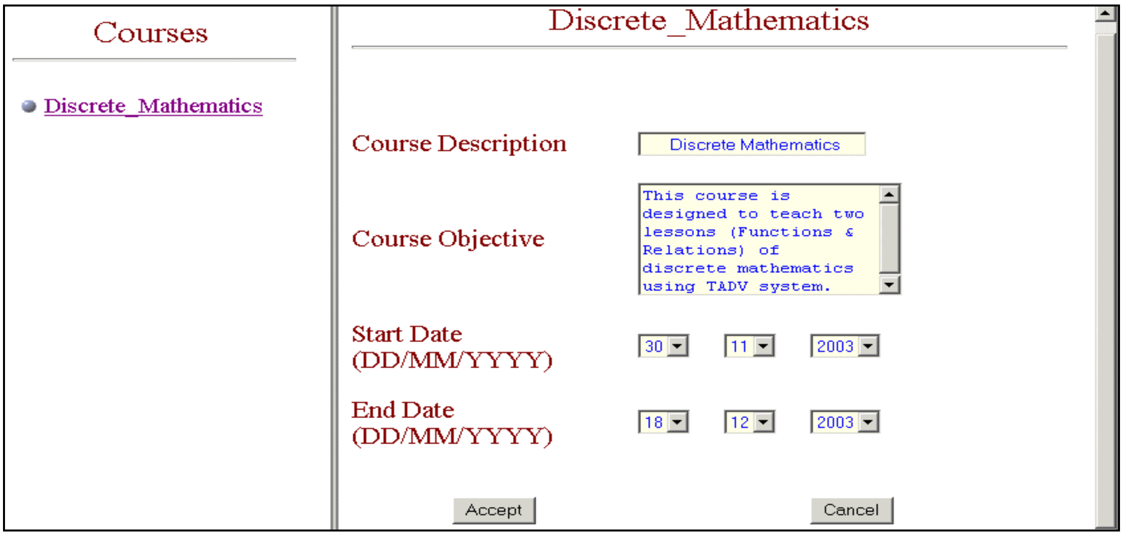


Figure 6.7 Screen used to define a course.

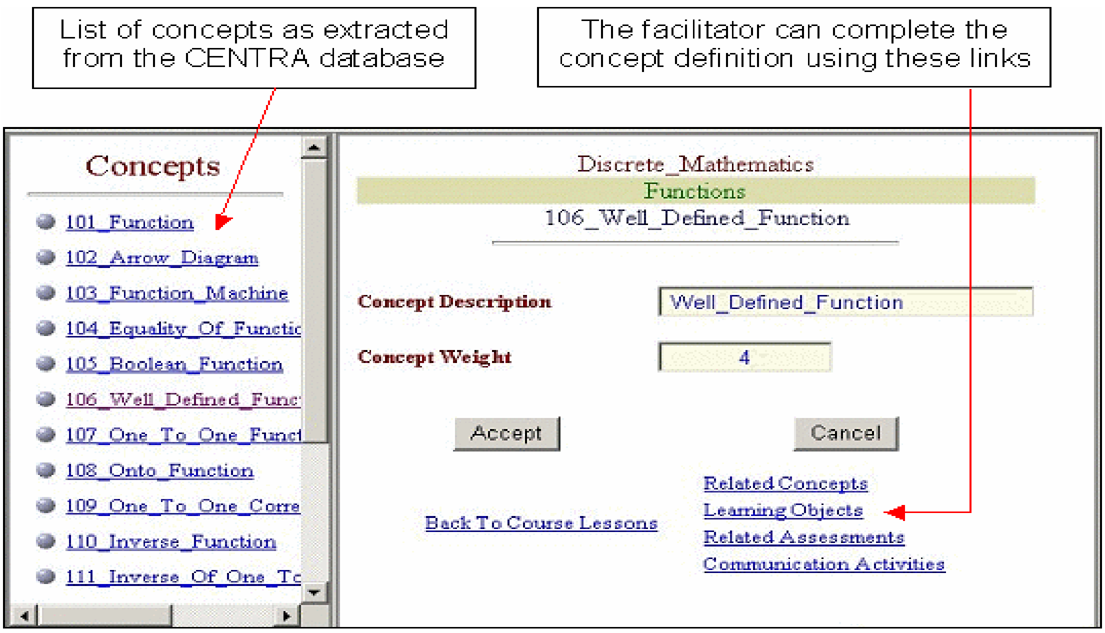


Figure 6.8 Screen used to define the metadata for domain concepts.

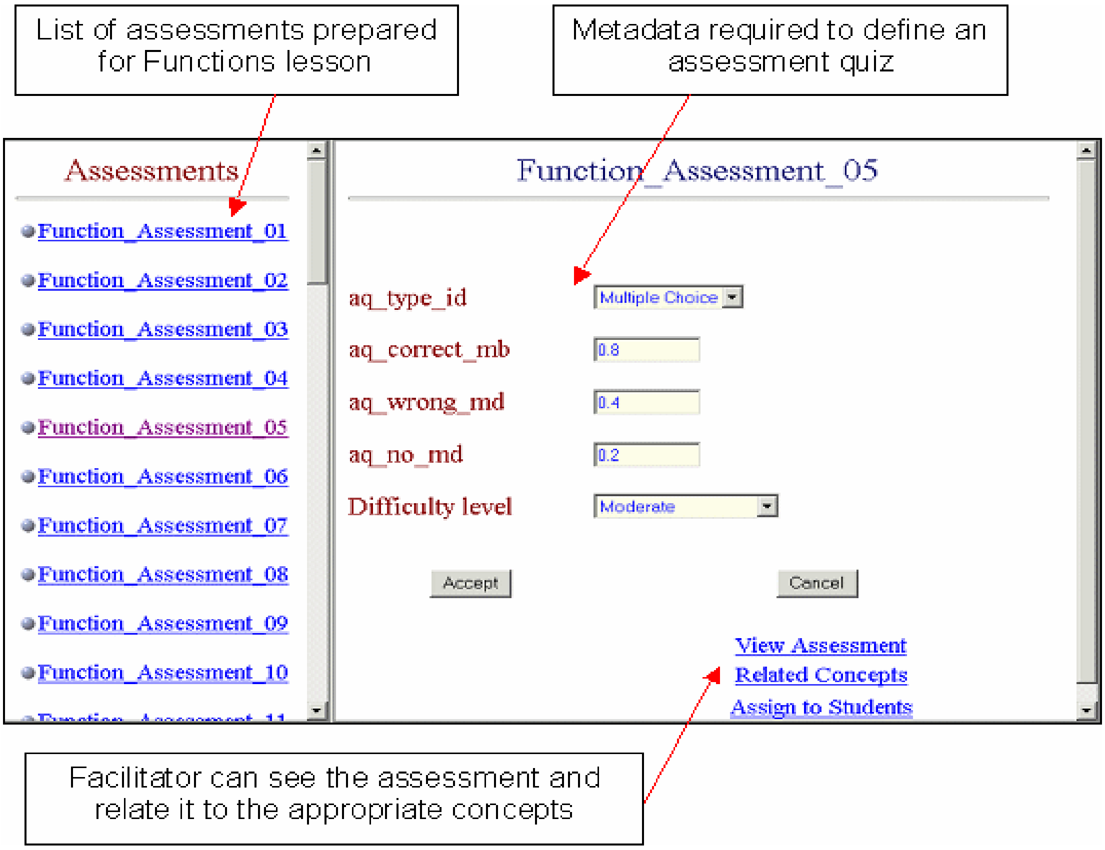


Figure 6.9 Screen used to define metadata for assessment quizzes.

Managing students, groups, and classes

The option tagged "Management of Students, Groups, Class", allows entry of information related to Student Profile Models. It is also used to define groups and classes of students and facilitates assigning students to the defined groups and classes. Similarly to entering course metadata, the CENTRA user management capabilities are used to enter students and part of their profile. For the purpose of the experimental study explained in the next chapter, two classes are created (Class1 and Class2) with 20 students per class and two groups (Group1 and Group2) are defined within Class2. Figure 6.10 shows the screen used to complete a student's profile information.

Generating advice

The option "Generate Advice" is used to start the process of advice generation. AG will generate only the types of advice selected by the facilitator using "Select Advice Type" option discussed earlier in this section. The generated advice will be stored in the database prepared for this purpose along with the date of generation. TADV keeps all advice generated on different dates.

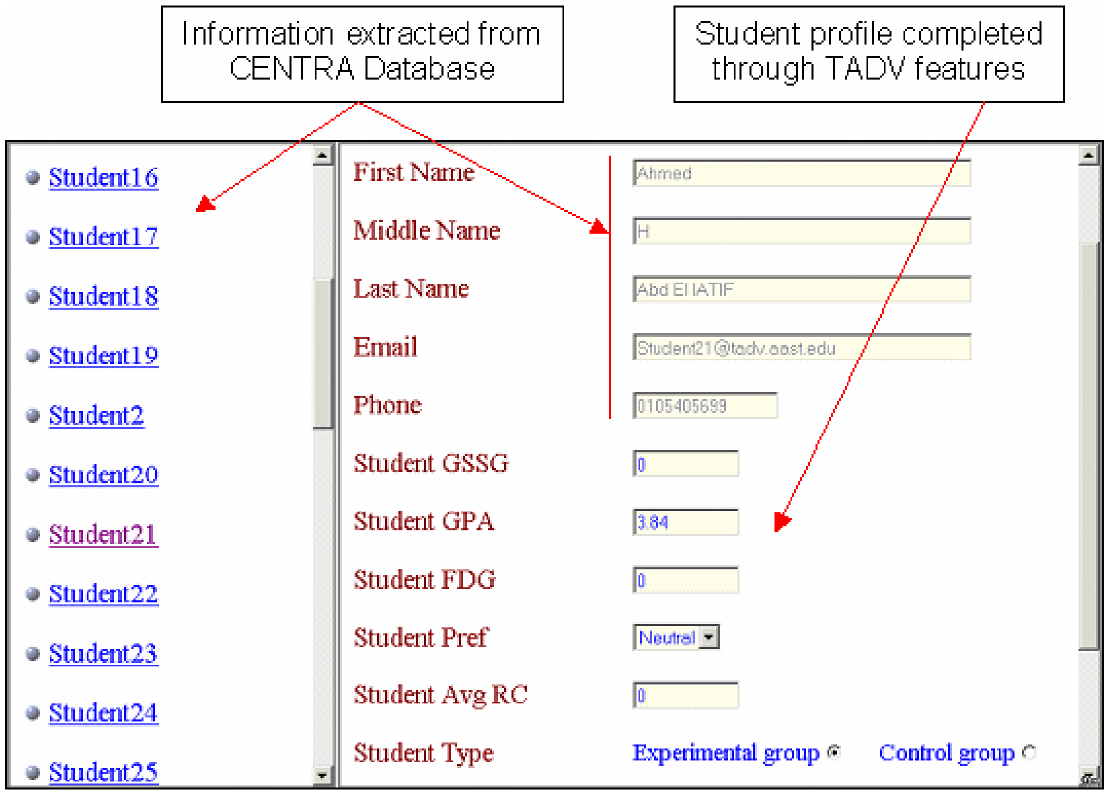


Figure 6.10 Screen used to enter student's profile.

Viewing and sending advice

The "View Advice" option allows the facilitator to see the advice generated by the TADV. The facilitator can display the generated advice according to its main type (individual students, groups, or classes) and according to the selected student, group, or class. The facilitator can also review the recommended feedback proposed by TADV for students and, if needed, modify it or freely compose the appropriate feedback according to the knowledge he grasped from TADV generated advice. In addition, the facilitator can select to send this feedback to the student or discard it. One of the important features offered by TADV is the possibility to open (display) the Student Knowledge Model to the facilitator. This feature gives the facilitator an overview (in one screen) of the status of student knowledge. It can be used also to examine the link between the generated advice and what is currently in the student knowledge model.

Figure 6.11 shows the screen which contains the list of students assigned to Class2. The facilitator can easily click to view advice generated regarding students' progress. The red bullets flag students who have not started the course. Figure 6.12 shows the screen which displays the generated advice, presented in four columns:

- The first column is used to present advice directed to the facilitator. Each advice is flagged by a coloured asterisk (*) according to its importance. A red asterisk is used to denote very important advice, while green and blue asterisks are used to denote the important and less important advice, respectively. Advice is ordered according to the importance level.
- The second column is used to display the advice or feedback TADV recommends to the student. The facilitator can, if he wishes, modify the text in this column (three Asterisks (***) are used to signify the feedback modified or composed by facilitators. In this way, the facilitator may use what TADV suggests to be sent to the students directly, or modify it by adding or deleting text. The facilitator may decide not to send TADV recommendations at all but even so, he has seen what TADV has reported about the situation (first column) and may use this in the pedagogical activities.

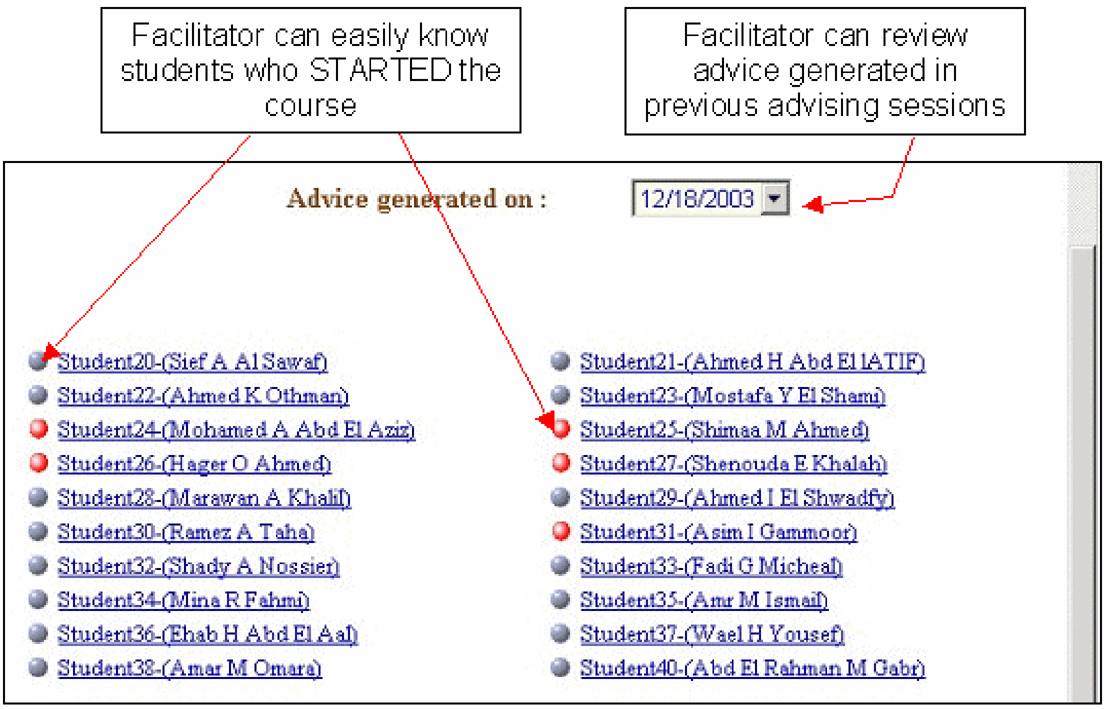


Figure 6.11 Screen shows the list of students assigned to Class2.

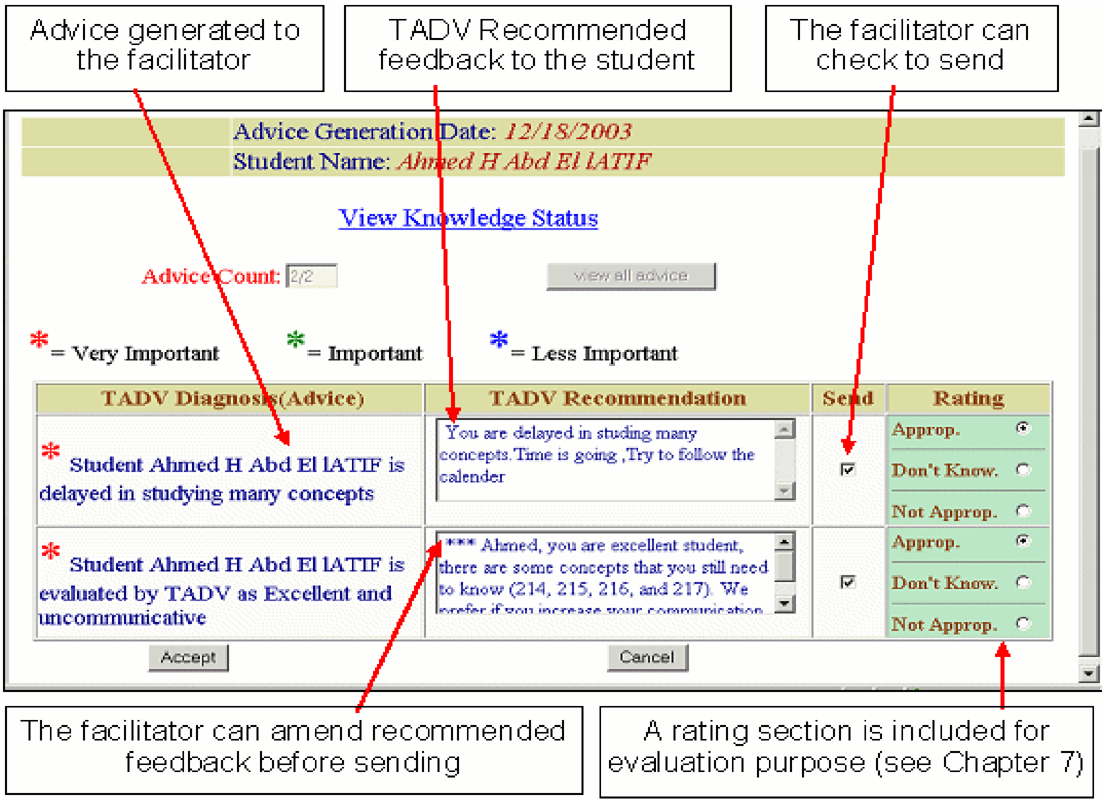


Figure 6.12 The screen used to display advice.

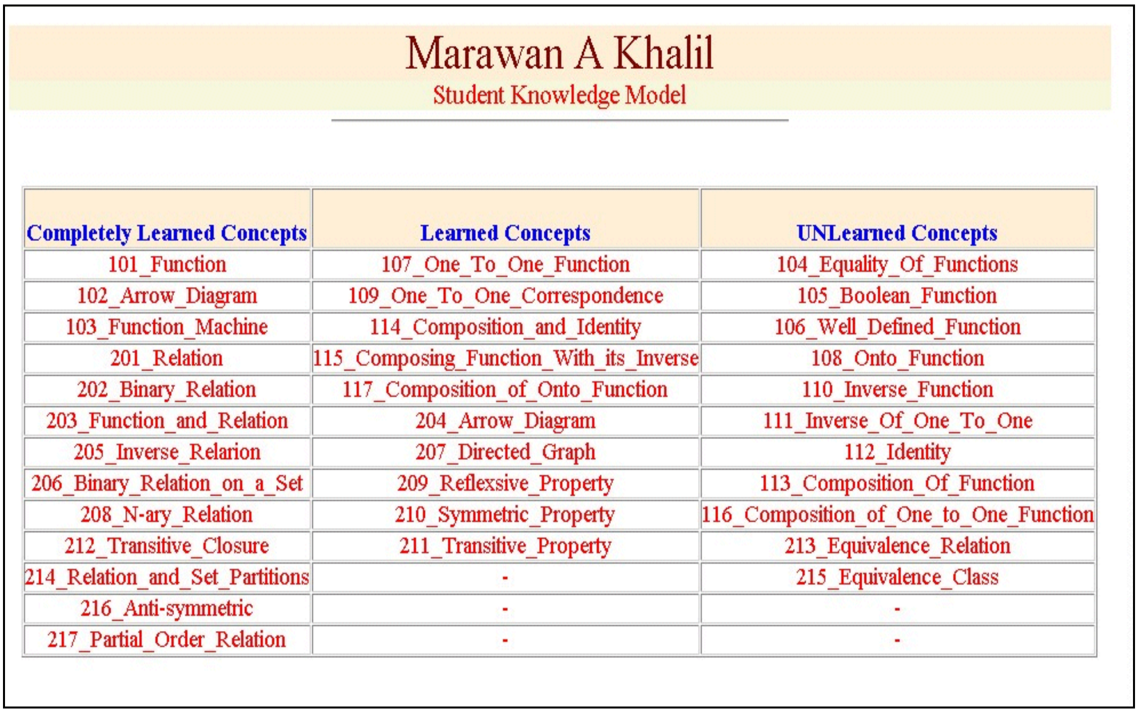
- The third column contains send check boxes. If the facilitator checks a box, then TADV will send the text from the second column to the student, group or class.
- The fourth column allows the facilitator to rate advice according to its appropriateness. This column is added for the sake of the TADV evaluation discussed in the next chapter.

Similarly, the facilitator can display, modify, and send advice generated about groups and classes.

Figure 6.13 presents an opened knowledge model of a student. The facilitator can reach this screen by clicking the link "View Knowledge Status" located on the top of the screen that displays the advice related to the student. Using similar method, the facilitator can review group and class knowledge models.

6.5.2. Student's main menu

As shown in Figure 6.14, there are six options in the student's main menu: my learning, course calendar, assessment score, my peers, review feedback from facilitator, and my profile.



Marawan A Khalil

Student Knowledge Model

Completely Learned Concepts	Learned Concepts	UNLearned Concepts
101_Function	107_One_To_One_Function	104_Equality_Of_Functions
102_Arrow_Diagram	109_One_To_One_Correspondence	105_Boolean_Function
103_Function_Machine	114_Composition_and_Identity	106_Well_Defined_Function
201_Relation	115_Composing_Function_With_its_Inverse	108_Onto_Function
202_Binary_Relation	117_Composition_of_Onto_Function	110_Inverse_Function
203_Function_and_Relation	204_Arrow_Diagram	111_Inverse_Of_One_To_One
205_Inverse_Relarion	207_Directed_Graph	112_Identity
206_Binary_Relation_on_a_Set	209_Reflexsive_Property	113_Composition_Of_Function
208_N-ary_Relation	210_Symmetric_Property	116_Composition_of_One_to_One_Function
212_Transitive_Closure	211_Transitive_Property	213_Equivalence_Relation
214_Relation_and_Set_Partitions	-	215_Equivalence_Class
216_Anti-symmetric	-	-
217_Partial_Order_Relation	-	-

Figure 6.13 A screen showing a student knowledge model.

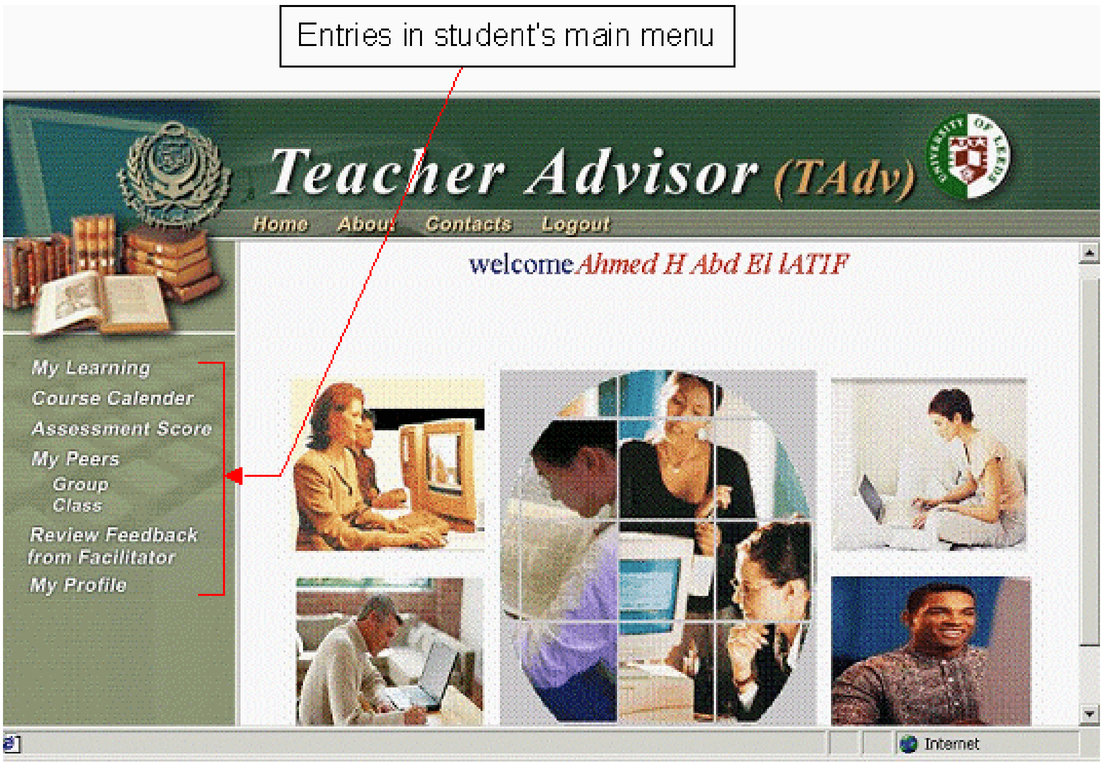


Figure 6.14 Student's main screen.

Interacting with the course

The “My Learning” option is the place from which the student can interact with the course and assessment quizzes. This option allows the student to select either “My Course” or “My Assessment”. Using “My Course” the student can go to CENTRA, start working with the assigned concepts, open the available learning objects, and communicate with student and teacher through the discussion forums. Figure 6.15 shows how CENTRA displays the tracks (concepts) defined in the Discrete Mathematics course. Figure 6.16 shows, for example, a screen which displays learning objects related to the concept 107_One_to_One_Function. The student can select the required learning object to display its contents as shown in Figure 6.16. Using “My Assessment” the student can display the list of assessments available for each course lesson then simply select assessments.

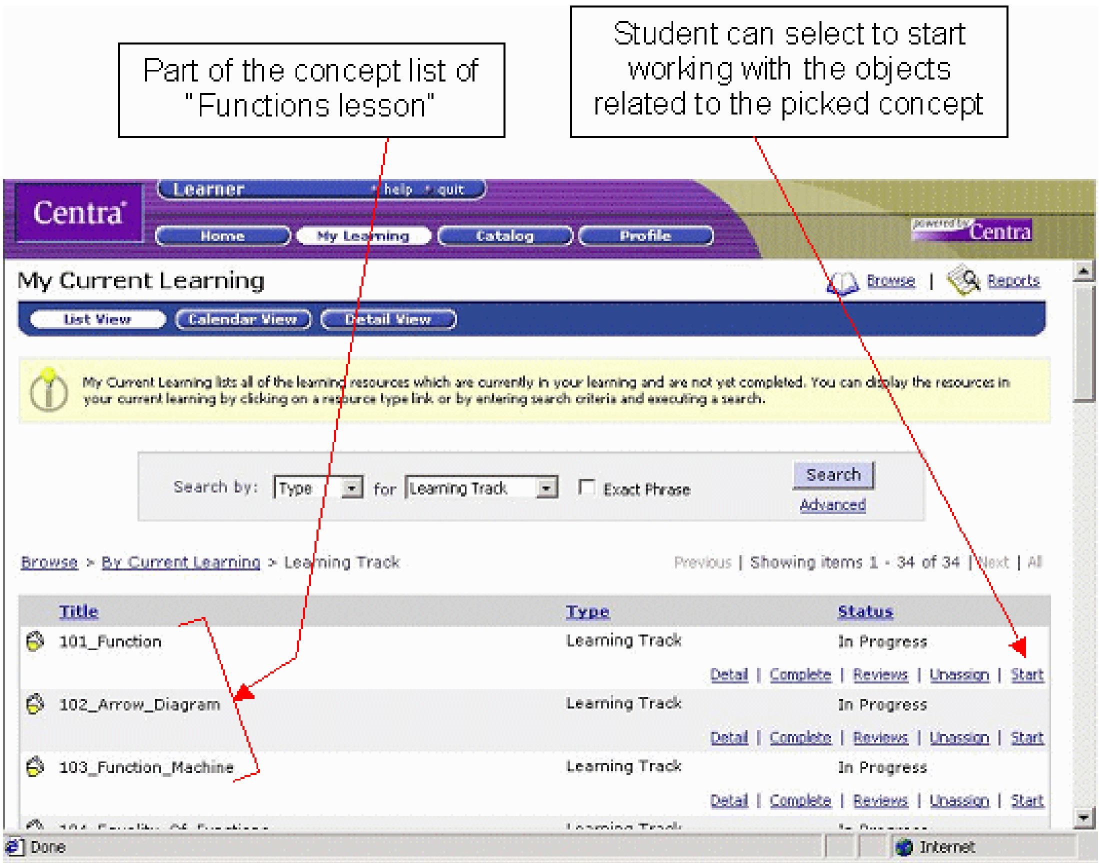


Figure 6.15 List of tracks (concepts) displayed by CENTRA.

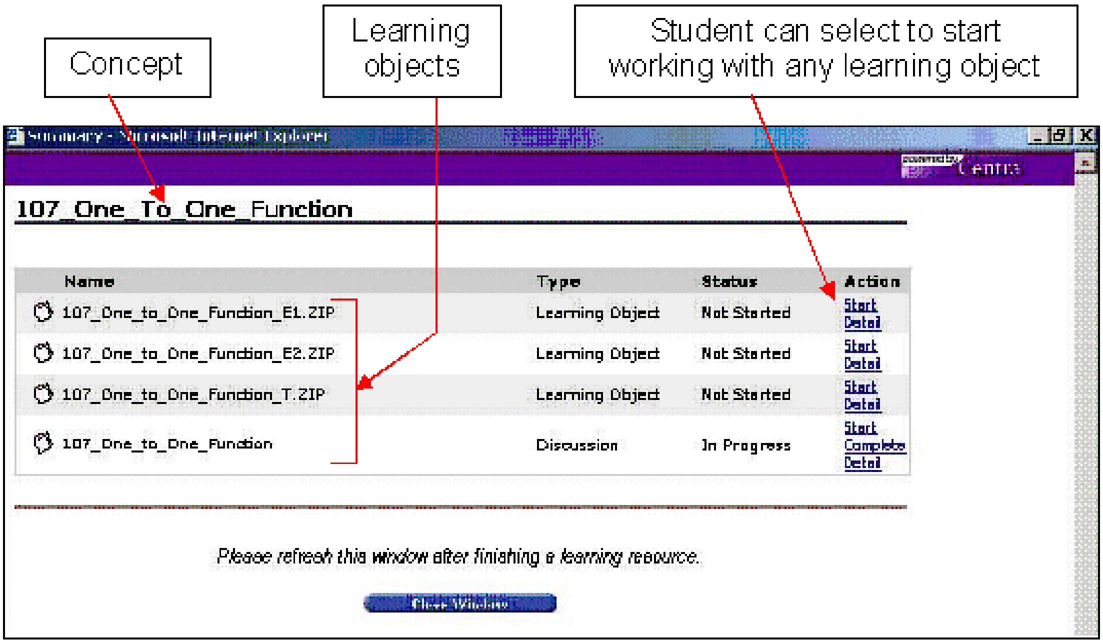


Figure 6.16 List of learning objects displayed by CENTRA.

Viewing the course calendar

The student can view the course calendar using the "Course Calendar". This shows the tasks that he should carry out in a certain period of time. In the TADV prototype, the tasks are scheduled by the course facilitator for each day of the course period. Figure 6.17 shows part of the course calendar prepared for the Discrete Mathematics course.

Viewing assessment scores

The student can click on the "Assessment Score" option to view the assessments he solved and the scores obtained.

Contacting other students

The student can use the option "My Peers" to view a list with the names, phones and e-mails of the student peers in his group or class. The student can easily send e-mails to his peers.

Viewing feedback from the facilitator

The student can use this entry to review the feedback/advice sent from the facilitator through the TADV system. The student can display advice sent especially for him and also the advice sent to the group and class to which he belongs. To facilitate evaluation of the TADV prototype (see Chapter 7) students are asked to rate the feedback they receive. Figure 6.18 shows part of the advice sent to one of the students participating in the study described in the next chapter.

Start Date	End Date	Concepts	Assessments
11/30/2003	11/30/2003	101_Function 102_Arrow_Diagram 103_Function_Machine 105_Boolean_Function 104_Equality_Of_Functions	Function_Assessment_01 Function_Assessment_02 Function_Assessment_03 Function_Assessment_04 Function_Assessment_05 Function_Assessment_06 Function_Assessment_07 Function_Assessment_08 Function_Assessment_09 Function_Assessment_10
12/1/2003	12/1/2003	106_Well_Defined_Function 107_One_To_One_Function	Function_Assessment_11 Function_Assessment_12 Function_Assessment_13 Function_Assessment_14 Function_Assessment_15 Function_Assessment_16

Figure 6.17 Part of the Discrete Mathematics course calendar.

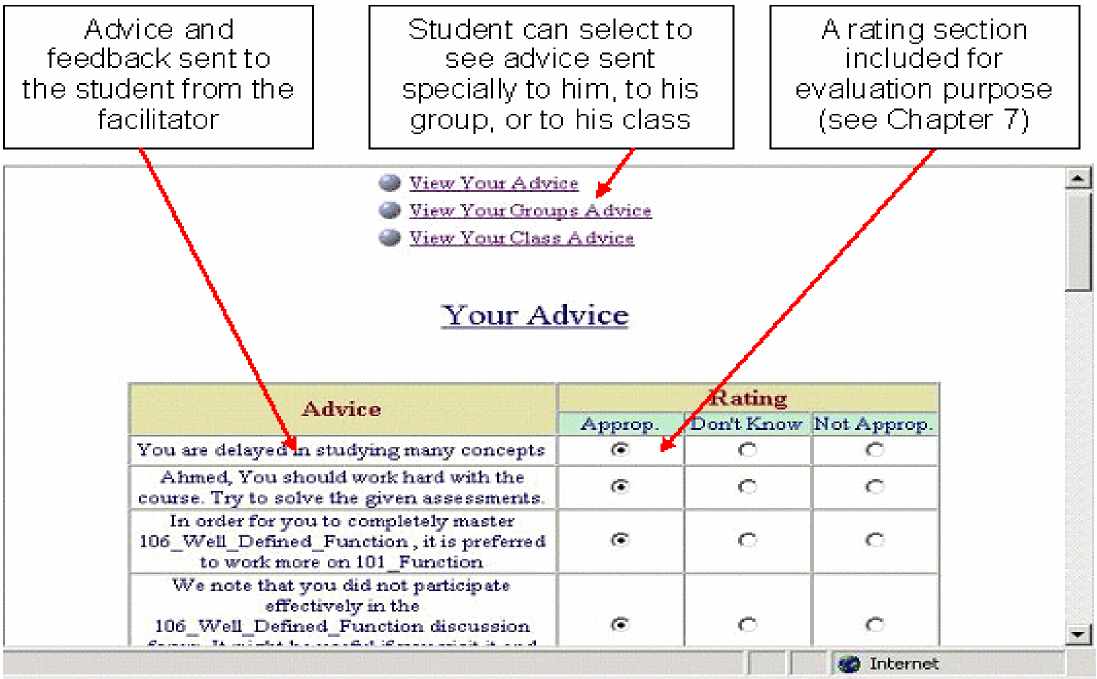


Figure 6.18 Student's feedback screen.

Updating student profile

Through the “My Profile” option the student can view his profile information and change it, if required.

6.6. Examples of TADV Advice

To illustrate different situations of advice generation, several examples are presented in this section. The examples presented are extracted from the advice generated during the experimental study conducted to evaluate the prototype (see Chapter 7). We aimed to show the importance of the information provided by the generated advice and how it helped the facilitators to be acquainted with the cognitive, behavioural, and social aspects of the students in different levels (individuals, groups, and whole class). Moreover, the examples shown demonstrate the role of the advice in helping facilitators to guide students appropriately. Each example is shown and discussed in a separate table. The table contains the advice generated to the facilitator and the recommended advice/feedback to the student, if any. Following these two items, an explanation of the situation is presented followed by the results occurred due to the generated advice, i.e. the facilitator’s reactions and expected effect on the students.

6.6.1. Examples of advice about individual students

The following examples show some situations of Type-1 advice generated to highlight important information about individual students to the facilitators.

Example (1): A student delayed with starting the course.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Sief A Al Sawaf has not started the course yet.</td><td>You have not started the course yet. You should start the course as soon as possible.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the student did not start the course. TADV sent this information to the facilitator and suggested the shown feedback to the student.
Results: The facilitator realised that the student was late with starting the course, and sent the recommended feedback to the student. When the student see the feedback and recognises that his facilitator knows that he is late this may encourage him to start the course and let him feel that although he is a distant student, he is still being supervised by his teacher.</td></tr>
</table>

Example (2): A student delayed with studying some concepts.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Amr M Ismail is delayed in studying concepts {212_Transitive_Closure, 114_Composition_and_Identity, 115_Composing_Function_With_its_Invers }, he should be advised to start studying these concepts.</td><td>You are delayed in studying the topics of {212_Transitive_Closure, 114_Composition_and_Identity, 115_Composing_Function_With_its_Invers}, you should start work on these topics as soon as possible. Take care time is going.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the student is delayed with studying the three mentioned concepts. TADV sent this information to the facilitator and recommended the text on the right to be sent as feedback to the student.
Results: The facilitator realised that the student is slightly delayed, sent the feedback to the student. The student was informed to study the mentioned concepts, which may encourage him to do so. Feeling of being under supervision may build a link with the facilitator.</td></tr>
</table>

Example (3): Excellent but uncommunicative student.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Ahmed H Abd El Latif is evaluated by TADV as Excellent and uncommunicative.</td><td>*** Well done Ahmed, try to help your peers.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the student is excellent but he is uncommunicative. TADV sent this information to the facilitator. The right part was written by the facilitator after seeing the information from TADV.
Results: The facilitator became more knowledgeable about this particular student. He composed the shown feedback and sent it. The facilitator used the knowledge he got to encourage the student and motivate him to be more communicative with his peers. The student saw that the facilitator recognised his good work on the course.</td></tr>
</table>

Example (4): Excellent but uncommunicative student, the facilitator uses information gained from student knowledge model to guide the student.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Ahmed H Abd El Latif is evaluated by TADV as Excellent and uncommunicative.</td><td>*** Ahmed, you are excellent student, there are some concepts that you still need to know (214, 215, 216, and 217). We prefer if you increase your communication with other students in the class.</td></tr>
<tr><td colspan="2">Explanation: Same as above, however, the facilitator’s reaction is changed.
Results: The facilitator opened the student knowledge model and picked the concepts which were not completely learned by the student. The facilitator composed the shown feedback and sent it to the student. The facilitator appreciated the student work and asked him to be more communicative. The student knew that the facilitator recognised his good work on the course and also the weak parts. In addition, the student felt that he was guided and supervised by the facilitator (using TADV).</td></tr>
</table>

Example (5): Weak and uncommunicative student.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Mostafa Y El Shami is evaluated by TADV as Weak and uncommunicative.</td><td>*** You should work hard with the course. Try to solve the given assessments. You should also communicate with your peers through the discussion forums prepared for each concept.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the student was weak and uncommunicative. TADV sent this information to the facilitator who used it to compose the feedback to the student.
Results: The facilitator got the knowledge and used it to motivate the student. The facilitator composed the shown feedback and sent it. The student realised that facilitator was aware of his bad performance. This may motivate the student to work harder on the course.</td></tr>
</table>

Example (6): Encourage a student to communicate with his peers.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Mostafa Y El Shami should be encouraged to participate effectively in the communication activities related to 113_Composition_Of_Function. Student {Ahmed H Abd El Latif} is communicative and have already mastered concept 113_Composition_Of_Function.</td><td>We note that you did not participate effectively in the 113_Composition_Of_Function discussion forum. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact Ahmed H Abd El Latif to discuss 113_Composition_Of_Function.</td></tr>
<tr><td colspan="2">Explanation: TADV found that the concept 113_Composition_Of_Function was learned (but not completely learned) by the student (Mostafa) and Mostafa did not participate in the discussion forum related to this concept. TADV located a student (Ahmed) who had mastered the concept and recommended that Mostafa should be encouraged to contact Ahmed. TADV summarised the situation to the facilitator and recommend feedback to be sent to the student.
Results: The facilitator was informed about the problem and was recommended the solution. The facilitator sent the suggested feedback. The student was directed to communicate with his peer. Most importantly, he felt that he got help from the facilitator and he was not isolated in the distance course.</td></tr>
</table>

Example (7): Concept is not learned because the student has not studied learning objects.

<table>
<tr><th>Advice to the facilitator</th><th>Recommended feedback to the student</th></tr>
<tr><td>Student Amr M Ismail should be advised to work with the available learning objects and assessment quizzes related to 111_Inverse_Of_One_To_One.</td><td>In order for you to understand 111_Inverse_Of_One_To_One we suggest you refer to its available learning objects and solve related assessment quizzes.</td></tr>
<tr><td colspan="2">Explanation: TADV found that concept 111_Inverse_Of_One_To_One is unlearned by the student because he did not work on learning objects and assessment quizzes related to the concept. TADV highlighted this information to the facilitator and recommended the shown feedback.
Results: The facilitator recognised that the student was struggling with 111_Inverse_Of_One_To_One, and sent the TADV recommendation to the student. The student was directed to study the concept.</td></tr>
</table>

Example (8): A student struggles with a concept because its prerequisites are not mastered.

Advice to the facilitator	Recommended feedback to the student
Student Mostafa Y El Shami should be advised to study 112_Identity.	In order for you to master 114_Composition_and_Identity, it is highly recommended to study 112_Identity first.
Explanation: TADV found that the student was struggling with the concept 114_Composition_and_Identity because this concept is strongly related to 112_Identity which was unlearned by the student. TADV informed the facilitator about this and recommended feedback to be sent to the student. **Results:** The facilitator realised that the student was struggling with both concepts and decided to send the feedback to the student. The student was guided to study the appropriate concept.	

6.6.2. Examples of advice about groups of students

The following examples show some situations of Type-2 advice generated to highlight important information about groups of students to the facilitators.

Example (9): Group members are delayed with the course.

Advice to the facilitator	Recommended feedback to the group members
TADV can not evaluate group Group1 because most of its members have not started course yet.	*** For the group members who did not start the course, time is going, please start the course as soon as possible.
Explanation: TADV found that most of the Group1 members did not start the course and informed the facilitator who composed the appropriate feedback. **Results:** The facilitator became knowledgeable about the problem and composed the shown feedback to the group members. This may motivate the students to start the course. In addition, the facilitator can contact group members through e-mail or phone.	

Example (10): Weak and uncommunicative group.

Advice to facilitator	Recommended feedback to the group members
Group2 is evaluated by TADV as Weak and uncommunicative group.	*** To all members of the Group2: You should work more effectively with the course. Try to solve the given assessments. You should also communicate with your peers in the group through the discussion forums prepared for each concept and through mail.
Explanation: TADV found that Group2 was weak and uncommunicative. TADV informed the facilitator who composed the shown feedback. **Results:** The facilitator became more knowledgeable about this group and decided to send the feedback to motivate the group members.	

Example (11): A group needs to discuss more about a concept.

Advice to the facilitator	Recommended feedback the group members
Group2 members should be encouraged to participate effectively in the communication activities related to 116_Composition_of_One_to_One_Function.	We note that some students of Group2 members did not participate effectively in the 116_Composition_of_One_to_One_Function discussion forum. It is recommended to participate together in 116_Composition_of_One_to_One_Function discussion forum. You can post your questions there.
Explanation: TADV found that Group2 was uncommunicative about concept 116_Composition_of_One_to_One_Function. TADV informed the facilitator and recommended the shown feedback. **Results:** The facilitator become more knowledgeable about this group and decided to send the generated feedback to the group members. The students were guided to contact each other and participate in the discussion group of the specified concept.	

Example (12): Group struggles with a concept and most students have not mastered the prerequisite for this concept.

Advice to the facilitator	Recommended feedback the group members
Group2 members should be advised to study 202_Binary_Relation.	203_Function_and_Relation appears to be a common problem for students in Group2. For those students who do not master 202_Binary_Relation, it is highly recommended to study the perquisite 202_Binary_Relation first.
Explanation: TADV found that Group2 was struggling with the concept 203_Function_and_Relation because concept 202_Binary_Relation was unlearned by the group. TADV generated the shown advice and recommendation. **Results:** The facilitator got the knowledge and decided to send the generated feedback to the group members to study concept 202_Binary_Relation.	

6.6.3. Examples of advice about the whole class

The following examples show some situations of Type-3 advice generated to highlight important information about the whole class to the facilitators.

Example (13): Majority of the class members delayed with starting the course.

Advice to the facilitator	Recommended feedback to the students
TADV can not evaluate class Class2 because most of its students have not started course yet.	*** For the class2 members who did not start the course, time is going, please start the course as soon as possible.
Explanation: TADV found that most of the Class2 students did not start the course and informed the facilitator who composed the shown feedback. **Results:** The facilitator got the knowledge and decided to send the shown feedback to the class. This may motivate the students to start the course. In addition the facilitator can contact students via e-mail.	

Example (14): Excellent and weak students.

Advice to the facilitator	Recommended feedback to the students
Students Shady A Nossier, Ahmed H Abd El Latif are the most Excellent students relative to the whole class, while Students Amr M Ismail, Abd El Rahman M Gabr, and Mohamed A Abd El Aziz are the weakest students.	*** To all class members: There many students who did not start working with the course; this makes class evaluated by the system as Weak. Please, those students should start the course as soon as possible. Most students should work hard with the course, solve the given assessments, and communicate with other students through the discussion forums prepared for each concept. Students who face problems can communicate with Shady A Nossier and Ahmed H Abd El Latif; they are excellent.
Explanation: TADV informed the facilitator about the most excellent and most weak students in the class. The facilitator composed the feedback. **Results:** The facilitator read all advice generated about the class not just the shown one. He got knowledge about the class and composed the shown feedback to the class. This may motivate students to actively work on the course. It is noted here that the facilitator preferred to encourage excellent students but did not name the weak ones. However, he might be more encouraging with the struggling students.	

Example (15): Active and inactive students.

Advice to the facilitator	Recommended feedback to the students
Students Ahmed H Abd El Latif, Shady A Nossier, and Mostafa Y El Shami are the most Active students relative to the whole class, while Students Asim I Gammoor, Shimaa M Ahmed, and Hager O Ahmed are the most inactive students	
Explanation: TADV informed the facilitator about the most active and inactive students in the class without recommending any feedback to students. **Results:** The facilitator got the knowledge and decided not to send feedback to the students.	

Example (16): Common problem for the whole class.

Advice to the facilitator	Recommended feedback to the students
206_Binary_Relation_on_a_Set appears to be a common problem for students in Class2. The perquisite 203_Function_and_Relation is not mastered by the class members. It may be useful to advise class members to study 203_Function_and_Relation	*** Many students still need to work more effectively with the course, solve the given assessments and communicate with other students, especially Shady A Nossier, Ahmed H Abd El Latif, and Fadi G Micheal. Those students are excellent and they are willing to help everybody. Please try to contact them through e-mail or discussion forums.
Explanation: TADV found that concept 206_Binary_Relation_on_a_Set was generally not learned by the class because its prerequisite 203_Function_and_Relation was also not learned. TADV informed the facilitator who was composed the shown feedback. **Results:** The facilitator read this advice and other advice generated during the session. He opened the class knowledge model and found that the majority of concepts were not learned. Accordingly, he composed the shown feedback and sent it to the whole class.	

6.7. Summary

This chapter has described in detail how the TADV prototype was implemented to demonstrate our proposed computer based advice-generating framework presented in chapters 4 and 5. We have shown how TADV provides a means for advising distance learning facilitators and equips them with important knowledge about their distant students and classes. The tasks carried out to build the main components of the system as an extension of one of the WCMS (CENTRA) were described in detail.

In this chapter, we have presented how the selected course (Discrete Mathematics) was prepared according to the proposed structure to build Domain Knowledge Base (course contents), how the required metadata was acquired and prepared to build the Domain Meta Knowledge Base, and how the course and its metadata were integrated within the CENTRA WCMS.

The process of building the required physical models for Domain Meta Knowledge, student models (SM, GM, and CM), and advice generation is also discussed along with the process of integrating them within the selected WCMS. The detailed system architecture is also presented to describe how the Student Model Builder module and Advice Generator module are used to extend the CENTRA WCMS. The implementation of these modules follows the computational framework presented in previous chapters.

The chapter has demonstrated also the design of the facilitator and student interfaces, the options included in each of them, and the way they are integrated within CENTRA WCMS.

Several examples taken from the experimental study with TADV presented in the next chapter have been presented and discussed to illustrate typical advice generation situations and how they are carried out by the facilitators. More situations and a detailed discussion will be presented in the next chapter where we evaluate the TADV prototype to examine potentials and limitations of our approach.

Chapter 7

TADV Evaluation

7.1. Introduction

In the previous chapters, we presented the general architecture of TADV and explained in detail ideas concerning both modelling students and generating advice. We also presented a prototype that implemented TADV in a Discrete Mathematics course and validated the framework. Like all educational software, it is necessary to evaluate TADV in experimental settings before applying the framework in real distance learning environments. Estimating strengths and weaknesses of the proposed framework is necessary to facilitate the development of similar advising and help systems. This chapter presents the empirical evaluation conducted to evaluate the prototype described in Chapter 6. The evaluation focused on revealing benefits and possible pitfalls of the TADV so that it can be improved and practically applied in learning environments.

A short review of relevant evaluation approaches is given to justify the methods used for the TADV evaluation. Then, the aims of evaluation are outlined and the two main phases of evaluation - formative and summative - are reported. The results collected, together with a summary of the experimental study, are also presented. Finally, the main evaluation issues - suitability of advice, benefits for facilitators, and benefits for students – are discussed.

7.2. Review of Relevant Evaluation Approaches

The evaluation phase is one of the most important phases in the development of intelligent educational systems. We will review here how the evaluation process is tackled in related projects in order to decide the design of the TADV evaluation.

The benefit of carrying out evaluation of ITS is to distance the focus of attention away from the short-term delivery and open up dialogues on issues of *appropriateness*, *usability* and *quality* of the system design (Iqbal et al., 1999). Kinshuk et al. (2000) stress the importance of developing benchmarks for assessing computer-aided learning systems in real life learning environments and point out the challenge to decide *what* to evaluate, *who* should carry out the process and *how* it should be carried out. In the same line of argument, Willis (1995) stresses the need for developing some *evaluation strategy*, i.e. to plan how and when to evaluate the effectiveness of instruction. Willis also states that following the implementation of any educational system it is necessary to carefully analyse the evaluation data to identify *gaps or weaknesses* in the instructional process, which is equally important to identifying *strengths and successes*. In the context of distance learning, the evaluation has a significant value as a "check-up" tool, which can provide timely feedback and constructive criticism used by designers and developers to improve systems in following courses (Hawkes, 1996).

The evaluation of intelligent educational systems, like all computer-based educational systems, is usually a difficult task. Comprehensive empirical evaluations of adaptive educational systems and user modelling approaches are hard to find (Chin, 2001; Weibelzahl, 2002). Furthermore, it is still difficult to find solid research measures of learner achievement (Strother, 2002). The evaluation of adaptive systems in distance learning is even more challenging. Some major obstacles that hinder systematic evaluation of distance learning technologies are reported in Hawkes (1996), e.g. the absence of standards, high cost, and scarcity of expertise. On the other hand, the absence of significant empirical evaluations of adaptive learning systems is attributable to some structural problems, e.g. short development cycle, and some methodological issues, e.g. what has to be done to measure the outcomes of the approach under evaluation (Weibelzahl, 2002).

This research relates to intelligent educational systems and to distance education. A review of the available literature related to these fields points out the lack of standard methodologies that can be followed to develop the evaluation process (Ainsworth, 2003). Instead, and in most cases, researchers select different evaluation criteria depending on the goals of the evaluative studies they conduct. There are no reports of evaluative studies geared towards measuring the benefits of advising instructors in distance education. In search for criteria for evaluating the impact of TADV, we will review some studies and projects related to the evaluation of distance education courses and intelligent tutoring systems.

Many researchers, for example Murray (1993), Legree et al. (1993), and Kinshuk et al. (2000), suggest that the evaluation of a tutoring system has to be carried out in two stages. In the first stage, usually called *formative evaluation* (Mark & Greer, 1993; Willis, 1995), the system should be evaluated for its usability and effectiveness. This stage highlights what amendments of procedures and interface design are needed. In the second stage, called *summative evaluation* (Mark & Greer, 1993; Willis, 1995), the effectiveness of the system is determined in real environments. Within the context of formative and summative evaluation, data can be collected through *quantitative* and *qualitative* methods (Willis, 1995). Accordingly, in the TADV evaluation, we will consider both formative and summative evaluation and will combine quantitative and qualitative approaches. The summative evaluation will require clearly defined criteria tailored to the main objectives of the framework.

Mark and Greer (1993) report that an experimental study is one of the most common methodologies used to evaluate educational systems, including intelligent ones because it enables researchers to examine relationships between teaching interventions and student-related teaching outcomes, and to obtain quantitative measures of the significance of such relationships. Many experimental studies have been conducted to determine the effects of specific features or aspects of intelligent and Web-based educational systems (e.g. Ainsworth & Grimshaw, 2002; Ainsworth & Loizou, 2003; Dimitrova, 2003; Hartley & Mitrovic, 2002, Mitrovic, 2003; Heffernan, 2003). In the TADV evaluation, an experimental research methodology with *control group design* was adopted to study the effects of the generated advice on the facilitators and the students (see Section 7.5).

Within the context of the TADV experimental study, it is possible to collect data which may be used in quantitative and qualitative analysis. The quantitative data can be used for *objective* analysis while qualitative data can be used for *subjective* analysis. Willis (1995) points out that in quantitative evaluations data collected through surveys, scales, check lists, closed questions, etc., can be statistically tabulated and analysed to draw conclusions. Quantitative data provides simple and efficient way of identifying problems but is insufficient for in-depth analysis, for which qualitative data is normally used. Qualitative evaluations involve the analysis of data collected through interviews, observations, content analysis, etc. to examine social phenomena in a more subjective way (Willis, 1995). However, the analysis can be time consuming and costly. In the evaluation of TADV, both kinds of data were combined in the analysis.

Hara and Kling (1999) present a qualitative case study of a Web-based distance education course. They point out the lack of qualitative research based on observations and interviewing in Web-based courses, and stress the fact that research on the effect of Web-based distance education has been mainly focused on measuring student outcomes but not on the affective aspects related to issues, such as the students' frustration and the effective advising from instructors. The latter is the main focus of TADV and was addressed in the evaluation (as discussed in Section 7.8). We also expected that effective advising from tutors would have some impact on the students' satisfaction with the course, which might eliminate the conditions leading to students' frustration. Hara and Kling (1999) used observation methodology to determine how the instructor facilitated the dialogue among students during online discussion and used interviews to collect qualitative data from the students. Similarly, monitoring interactions, observations, and interviews were employed in the TADV evaluation to examine the benefits of the proposed framework.

7.3. Aims of the TADV Evaluation

To facilitate the development of practical educational computer-based advising systems that follow the TADV framework, an empirical evaluation of the prototype was conducted. This evaluation focused on estimating pitfalls and outlining benefits of the framework, so that it can be improved and employed in distance courses based on WCMS. The TADV evaluation was primarily concerned with details of the system and aimed at verifying the usability and functionality of its components. In addition, the impact of the approach on facilitators and students was examined. Following the discussion in the previous section, TADV was evaluated in two phases, i.e. both formative and summative evaluation.

7.3.1. Questions addressed in the TADV formative evaluation

Formative evaluation obtains detailed information about the system performance to inform further modifications and improvements. In our case, it was important to identify potential users' (facilitators and students) problems and concerns. The formative evaluation of TADV was concerned with identifying the following issues:

- <u>Does the TADV system work as it is intended to work</u>. More specifically, do the TADV modules (mainly SMB and AG) work properly? This issue basically represents the testing phase which should be performed to ensure that programs work accurately.

- <u>TADV usability</u> – Does the system satisfy the expectations of both facilitators and students? Are there any problems with the user interface? Is there any unclear information?

7.3.2. Questions addressed in the TADV summative evaluation

Summative evaluation of educational systems focuses on the impact provided by the system. This means that the summative evaluation of TADV should assess the usefulness and benefits of the overall approach. Such evaluation is appropriate once the main development is completed and a stable prototype exists. In order to fully judge the usefulness of the approach applied in TADV, system integration within a learning environment was needed. To investigate the benefits of the TADV framework, the following issues were addressed:

- Suitability of advice – How do the facilitators evaluate the generated advice? How do the students evaluate the advice sent from their facilitators via TADV?
- The benefits for the facilitators – Is the generated advice useful and helpful for facilitators to appropriately manage their distance classes? Does it make them more knowledgeable about their students? Finally, does it lessen the facilitator's workload and communication load?
- The benefits for the students – Is the advice sent by the facilitators (either automatically generated by TADV or composed by the facilitators based on problems highlighted by TADV) useful to the students? In other words, does it address the students' needs? Does it help them during the course? Does it affect their learning gains? Finally, does it affect their overall satisfaction?

It is important to mention here that the above issues are specifically tailored to the purpose of the TADV evaluation. They are not directly derived from previous studies, as there is a lack of studies that examine the effect of advising teachers in the way proposed in this thesis. Similarity with some distance learning studies has been discussed in Section 7.2. It is also important to mention that our evaluative study focused on the first two issues, which were directly related to the TADV objectives stated in Chapter 1. Nevertheless, some benefits for the students were examined, too. However, a proper examination of the third issue requires long-term studies, which could not be conducted within the scope of this project.

7.4. TADV Formative Evaluation

The formative evaluation phase obtained detailed information about the performance of the system and pointed out further modifications and improvements. In this phase, the TADV prototype discussed in Chapter 6 was used in two main stages. The first stage was the *system-testing stage*; the following activities were considered:

- Module testing with test data – each program module was tested with valid and invalid data. Errors were discovered and modules were modified accordingly.

- Link testing with test data – all modules were tested to see if they would work together within an integrated system. Flawed features were detected and removed.

At the end of the first stage, a working system (prototype) that could be evaluated by some intended users was produced. In the second stage – the *prototype-testing stage* – several participants (three facilitators and three students) worked with the system, commented on its features, and suggested possible enhancements. The facilitators were selected from the staff members of the AAST colleges who have experience with WBDE environments. The students were selected from the students of computer engineering department who studying Discrete Mathematics course during the time of the evaluation. A one-to-one testing approach was used to make detailed observations. Special attention was paid to the effectiveness of the user interface. The facilitators were asked to explore potential situations predicting the behaviour of distant students. All comments and observations were collected from the participants and, when appropriate, used to modify the prototype.

The following modifications and suggestions were collected from the facilitators during the TADV formative evaluation:

- If a student *S* is delayed in studying domain concept *c*, then there is no need to generate advice like "*S* should study learning objects related to *c*" or "*S* should solve assessment quizzes related to *c*". The facilitators stressed that knowing that a student was delayed in studying a specific concept meant that he did not work on the learning objects and assessment quizzes related to that concept. This led to the issue of generating lengthy advice and pointed to the need for compact advice.
- If *S* is delayed in studying up to three concepts, then advice should state these concepts by name, but if *S* is delayed in studying more than three concepts, then advice should say that "*S* is delayed in studying *many* concepts" without listing the names of all concepts. This showed that the facilitators preferred *concise* advice.
- Add new advice that tells the facilitator that a specific student has not started working on the course combined with a feedback to the student to encourage him to start the course as soon as possible. This point showed the need for a new advice type.
- For a group or class, if the number of students who did not start the course is more than half of the group or the class, then there is no need to generate advice which evaluates concept understanding levels (Types 2-1 & 3-1) because in this case the system generates a lot of advice to motivate students in the group or the class to

study learning objects and solve assessment quizzes. The facilitators suggested that in this case it would be sufficient to generate advice saying that *most* of the students in the group or class had not started the course yet, therefore, TADV was unable to effectively evaluate the group or the class. This point showed the need for advice aggregation in some situations.

The following suggestions were collected from the students:

- Students suggested adding a page that shows e-mail addresses and phones of their peers either in the group or in the whole class. This showed the students' interests in knowing information related possibly to social and communicative activities.
- Add the possibility to go directly to the "my assessment" part without going first to "my learning", i.e. the course part. This showed a usability problem and the students' need to access the quizzes part separately from the course material part.
- Add the possibility to view the student's assessment scores from the student's interface. This indicated the students' need to know the results of their previous work on the assessment part.

The above suggestions collected from the facilitators and the students were used to update the TADV prototype. The improved version was used in the summative evaluation of TADV.

7.5. TADV Summative Evaluation: The Experimental Study

The summative evaluation phase focused on the assessment of the impact and benefits gained by the overall approach. In order to fully judge the usefulness of the approach applied in TADV, it was necessary to integrate the system within a distance education environment. TADV was used by *three facilitators* and *forty students* enrolled in the Discrete Mathematics course in the department of Computer Engineering at the Arab Academy for Science and Technology (AAST). The Students were in their third year. They had attended nine face-to-face Discrete Mathematics lectures before participating in the TADV experimental study to work on two chapters of the course. This section outlines all issues related to this experimental study.

7.5.1. General information about the experimental study

The following points give some general information about the experiment:

- ***Location:*** AAST – one of the Arab League organisations, Alexandria, Egypt.

- ***Colleges:*** Two colleges were involved, the Engineering College to which participating students belonged and the Computing & Information Technology College responsible for offering and teaching the Discrete Mathematics course.
- ***Duration:*** The experimental study was conducted during the 10^{th}, 11^{th}, and 12^{th} weeks of the fall term 2003/2004 (December 2003).
- ***Participants:*** Students enrolled in the Discrete Mathematics course in the traditional face-to-face classrooms during the specified term. Most of these students did not have experience in Web-based courses before this experiment.
- ***Distance course:*** students were required to use the TADV prototype to study, from a distance, the Functions and Relations lessons of the Discrete Mathematics course. They did not attend lectures on the module during the experimental period, the whole teaching was done via the Internet to simulate a realistic distance learning situation.
- ***Methods used:*** TADV aims at improving the facilitators' knowledge about their distant students and classes, which in turn may lead to a positive effect on students. Therefore, it was necessary to assess the effects of having the advising features of TADV on the facilitators and students and to compare the assessment results to the case in which these advising features were absent. The TADV evaluation was carried out by combining an experimental study with the observation of the course facilitators during the advising sessions, and a semi-structured interview with the participating facilitators at the end of the study. The experimental study involved two groups of students – a control and an experimental group (more about these group is presented in Section 7.5.3). A questionnaire was administered to investigate the students' impression. By using the questionnaire it was possible to collect massive data from the students in a short time. Moreover, high return was granted through administering the questionnaire during the class time. It was difficult to arrange interviews, which usually require considerable time, with the students during the end of the semester when the students were very busy preparing for their final exams. Therefore, interviews were used only with the facilitators. Finally, the generated advice and its rating by the facilitators and the students, and the students' score in the pre- and post-tests were analysed.

7.5.2. The agreement with the administration

One of the difficulties that face the evaluation of educational systems is to get approval from the stakeholders in the educational organisations to conduct the evaluation. Another problem is the difficulty to find real support from the stakeholders during the different phases of the study. Normal work overload, the required administration efforts, and fear of any negative effect on the students' learning levels are the main reasons behind these difficulties.

Inevitably, the TADV evaluation faced these difficulties, which required a clear agreement with all stakeholders. A top management meeting was conducted one month before the experiment to decide the important issues concerning the TADV experimental study. The ideas of TADV were presented and an evaluation plan was outlined. After some lengthy discussion, the stakeholders approved a protocol that guided all parties during the experiment. The protocol included the following points:

- All students enrolled in the Discrete Mathematics course (40 students) must be allowed to participate in the experiment, i.e. not to select a sample as was initially planned. The issue of giving equal opportunities to all students was stressed.
- The time of the experiment was restrained from 30/11/2003 to 18/12/2003 (19 days). During this period, the students did not attend normal lectures or tutorials; instead, they only studied via the TADV online course.
- The students' scores in the 7th week exam were considered to be their pre-test scores for the TADV evaluation (this exam was on topics different from the ones studied with TADV).
- At the end of the experiment, the course teacher was required to perform a post-test to assess the students in the experimented chapters (functions and relations). This test was considered as the 12th week exam of the course (20% of the total score). To encourage the students' participation, incentive bonus scores were offered to the students who actively worked on the system. This will not affect the experimental results because we had to ensure that many students work with the system in order to examine a sufficient number of different situations and to simulate high workload for the facilitators.
- The course teacher was asked to teach the experimented chapters in face-to-face sessions after the post-test and before the final exam (but the students were informed about this after the end of the study, during the study they only knew that the Web-based course was the only means for studying the selected topics).

- Three teachers were allowed to participate in the experiment as distance course facilitators – the course teacher, the domain expert, and a teacher assistant. All of them have previous experience with managing WBDE courses.

7.5.3. Actions carried out before starting the experimental study

Several tasks were carried out before conducting the study. These included:

Collecting information about the students: Two sources were used to collect information about the student participants. Academic records and some personal information were collected from the AAST information centre. The other information required for profile models (see Chapter 4) was collected through a meeting with the students. In this meeting, the students were briefed on TADV, the experiment, the agreement with the administration, and their participation during the experiment.

Training the students and the facilitators: Several introductory sessions were conducted to train the students to use the TADV. Other orientation sessions were also conducted to train the facilitators to work with the TADV facilitator's menu.

Forming control and experimental groups: The 40 students enrolled in the Discrete Mathematics course were divided into two groups (20 students per group). None of the students had previous experience with WBDE courses. The *Control group* (or alternatively *Class-1)* worked with the TADV prototype via distance. TADV built models for the students in this group but these models were not used to generate advice and, consequently, the facilitators were not recommended with appropriate help information about the students. This means that the students in the control group used the Discrete Mathematics course in the normal way provided by WCMS. They were able to communicate with the facilitators via e-mail and discussion forums. However, facilitators are not forced to communicate with students of the control group via e-mail or discussion forums. This issue was left optional to the facilitators as in most real WBDE environments. The *Experimental group* (or alternatively *Class-2*) also worked with the TADV prototype via distance. TADV built models for them, generated advice to the facilitators, and recommended feedback to be sent to the students. Hence, the students in this group received feedback and help information from the facilitators as a result of the advice generated. The students were also able to contact the facilitators via e-mail and discussion forums. To form two relatively similar groups the following dimensions were considered: the General Point Average (GPA) (to ensure relatively similar academic levels), the age (to guarantee similar levels of maturity), and nationality and gender (for similarity of cultural and demographic aspects). Appendix-H gives details about the students in both groups. The composition of the control and experimental groups is shown in Table 7.2 under sections 7.5.7.

Creating and distributing the student accounts: A TADV account was created for each student (student ID and Password) and the available data was used to create the student profiles.

Other tasks: Several other tasks were also carried out, e.g. initialisation of student, group, and class models, and determination (according to the facilitators' views) and entry of the values of the TADV parameters (discussed in Chapter 6). A computer lab with 15 PCs was prepared to ensure that the participants had unrestricted access to the system throughout the experimental study.

7.5.4. Actions carried out during the experiment

There were many tasks carried out by the experimenters during the period of the course (e.g. technical support and monitoring the server). However, managing and observing the advising sessions (where facilitators read TADV advice and sent feedback to the students) was the most important task during this phase. Seven advising sessions were conducted during the study. The times of the advising sessions were pre-arranged, so that the experimenter could observe the facilitators when using TADV and record their impression and possible problems. Although these times were scheduled according to the facilitators' request, this did not influence their behaviour with TADV. They knew that their use of TADV was monitored and their feedback was needed for evaluating TADV. During the sessions, all facilitators' inquiries were answered and their reactions and suggestions were observed and collected.

7.5.5. Actions carried out after the experiment

At the end of the period agreed for experimenting with TADV, we started the phase of collecting results, through the following methods and sources:

Administering of students questionnaire: The student questionnaire was administered one week after the end of the study and just before the post-test exam. The questionnaire was designed to reveal the students' opinions and impressions about TADV and to compare between responses collected from students to examine the effect of the advising feature. The questionnaire, shown in Appendix-I, was adapted from surveys prepared for previous online educational research studies e.g. (Creed, 1996) and (Collins & Harris, 2002). The student evaluation for distance learning classes designed by Online Express[1] (a collaborative faculty training initiative) of Prince George's Community College) was also selected as one of the main sources used for the preparation of the questionnaire. Some questions were selected from the surveys mentioned and others were designed especially to help in the evaluation of the TADV. The questionnaire contained a total of 43 questions (35 closed and 8 open) in six parts: Student's general information, Student's interaction information, Course information (how a student evaluated the course), Advising and feedback information (only to Class-2 students), Social information, and Student's overall satisfaction.

Post-test: During the same lecture in which the questionnaire was administrated and just after collecting the responses, the course teacher conducted the post-test exam related to the topics of functions and relations covered in the study.

Interview with the facilitators: Knowing the facilitators' opinions, impression, and comments was very important in the evaluation of TADV. A group interview with the facilitators was conducted three weeks after the end of the experiment. The interview lasted about two hours. The following dimensions were addressed:

- What the facilitators wanted their students to gain from the course.
- Up to what level they felt that the students gained what was required.
- How the facilitators evaluated the process of preparing the course using the TADV proposed structure.
- How the facilitators evaluated the TADV advising features.
- How the advising features may be improved.
- What difficulties the facilitators had faced while teaching this course.
- What the facilitators wanted to tell us about this course.
- What the facilitators thought that we should know about the TADV prototype.

7.5.6. Summary of the data collected

In summary, the data from the experimental study was collected from the following four sources: *TADV databases* (containing information about the generated advice and their ratings by the facilitators, as well as records of the feedback sent by the facilitators to the students and how the students evaluated these feedback messages), *Pre- and post-tests scores* (students' scores in the 7th week exam and in the 12th week exam), *Interview conducted with the facilitators*, and *students' responses to the questionnaire*. The quantitative data collected from these sources was used for objective analysis while qualitative data was used for subjective analysis. Most of the data collected and

[1] Prince George's Community College, Online Express (OLE), Student Evaluation for Distance Learning Classes (November, 2001) http//:academic.pg.cc.md.us/ole/student_evaluation_for_distance_.htm

prepared for the analysis is presented in appendices H, J, K, and L. It was not possible during this experimental study to collect information on the students' response to the advice given. Studying such behavioural aspects would require further work to accumulate data over a longer period of time.

7.5.7. Overview of the system usage during the study

In this section, we present a very brief overview of the participants in the experimental study and how the system was used during the study. The summary shows some important information, which reflects the behaviour of the participants during the experiment and shows the similarity of the control and experimental groups considering the dimensions mentioned in Section 7.5.3.

Table 7.1 presents some numeric information about the involvement of participants (either students or facilitators) in the experiment. It can be seen that 27.5% of the students didn't attend any kind of training before the experiment. Ten students (25%) didn't work on the system at all - 5 from Class-1 (3 of them withdrew the course) and 5 from Class-2 (1 of them withdrew the course).

Table 7.1 Involvement of participants in the experimental study.

Description	Number
Students allowed to participate	40
Students who filled in the student profile form	32
Students who attended TADV orientation (training) sessions	24
Students who individually attend quick TADV orientation sessions	5
Students who didn't come to receive their TADV account information	4
Students who received their accounts but didn't work on the course	6
Total number of students who didn't work on the course	10
Students who worked on the course	30
Students who responded to the questionnaire	27
Facilitators who participated in the experiment	3

Table 7.2 shows a comparison between the demographic and academic aspects of the participating students in the control (Class-1) and the experimental (Class-2) groups. When we consider all students, the comparison shows similarity between the two groups with regard to female ratio, age average, and GPA average, while there was a slight difference with regard to non-Egyptians ratio (20% for Class-1 and 15% for Class-2). However, considering only the students who worked on the course, a small difference between the two groups with regard to age and GPA averages and a difference in the dimensions of female ratio (13% for Class-1 and 6% for Class-2) and non-Egyptian ratio (27% for Class-1 and 13% for Class-2) can be noted. This difference

was outside our control during the study. However, we believe that the difference is small and does not undermine the results of the comparison between the two groups.

Table 7.2 Control group vs. experimental group.

Description	Control Group	Experimental Group
All Students		
Original No. of students	20	20
Female ratio	3/20	3/20
Non-Egyptians ratio	4/20	3/20
Age Average	21.37	21.13
Age STDEV	1.959	1.720
GPA Average	2.504	2.499
GPA STDEV	0.737	0.671
Students worked on the system		
No. of students worked on the course	15	15
Female ratio	2/15	1/15
Non-Egyptians ratio	4/15	2/15
Age Average	20.9	21.23
Age STDEV	1.599	1.884
GPA average	2.583	2.433
GPA STDEV	0.832	0.761

7.6. About the Suitability of TADV Advice

Generating advice to course facilitators is one of our main objectives. In this project, we have introduced a taxonomy of advice types (see Chapter 5). Three main types of advice have been introduced in Section 5.2 – Type-1 for individual students, Type-2 for groups of students, and Type-3 for the whole class (see also Appendix-C for full details of advice types). The advice types were validated by examining which advice was considered as appropriate and which was discarded by the participants in the study. The examination includes the suitability of the advice generated to facilitators and the feedback/help sent to the students based on the TADV advice. Examining the suitability of advice validated the algorithms for student modelling and advice generation, i.e. it validated the whole framework. Suitability of advice can be measured by considering aspects like what facilitators think about the advice features, how they evaluated the generated advice, what advice they sent to their students and how the students evaluated the feedback they received. As mentioned in Section 7.5.6, we only analysed the students' rating of advice in this study. Nevertheless, we have observed some differences between the group of students who received advice and the students in the other group.

7.6.1. General feedback about suitability of advice

In this section, we present the general impression of the facilitators and the students regarding advice suitability. The group interview with the facilitators and the students' questionnaires were used to draw the results presented in this section.

From the interview with the facilitators

Investigation about the advice suitability was one of the important dimensions addressed during the interview conducted with the facilitators. Appendix-J presents a complete report of the interview conducted with the three facilitators who participated in the experimental study. The interview showed that the facilitators were *satisfied* with the advice generated by TADV regarding advice types, contents, and addressed situations:

> "*In general, the feedback from the TADV system is excellent. Delivering of such information to the facilitator is very useful in distance learning environments.*"

The facilitators found generated advice *necessary and useful* and *appreciated* the help from TADV:

> "*The types and contents of the advice generated for all levels were generally good. Advice revealed most of the problems that usually happen in the distance learning courses.*"

The overall impression was *positive*, some advice types (e.g. for groups and the whole class, cognitive and social information for individual students) were regarded as very helpful:

> "*Overall evaluation of the advising feature is good. I really appreciate the advice generated for groups and class. For me, advice that provided information like who are the most excellent or weak students, communicative or uncommunicative students, etc. is really very useful.*"

The facilitators did not mention any negative feedback regarding advice. However, they commented on the increased amount of advice in the last two sessions when most students started work on the system just before the course end. The facilitators stressed the issue of *reducing the amount of advice generated* in some situations by removing redundant advice:

"*My major concern is that in some cases the amount of advice is somewhat high. The reason behind this problem, from my point of view, is the repetition of a certain type of advice for many concepts.*"

"*I think that if the students follow the course calendar in their study, then the amount of advice should be less. But this is difficult to happen and some actions should be taken to reduce the amount of advice.*"

These comments reveal two important issues. Firstly, the facilitators may be concerned about the increase in the amount of advice; although advice is automatically generated and highlights important information about students, it may require some time to read and this might increase the cognitive overload. Secondly, a filter mechanism is needed to reduce the generation of redundant or similar advice. Examples for these situations will be discussed in Section 7.6.2. It is worth noting here that the issue of lessening the amount of generated advice was considered during the formative evaluation of TADV (see Section 7.4.), e.g. not to generate advice for students who have not started the course, generating one piece of advice for all concepts; a student is delayed with, etc.

The facilitators recommended that their comments, mentioned during the advising sessions, should be implemented to improve the TADV advising features. The facilitators' comments reflected their behaviour towards the overall advising features of TADV (not just the suitability of advice). These comments and suggestions were discussed in detail with the facilitators during the interview. Some of them were used to improve TADV during the course period, while others were left for future work. The suggestions include:

- Adding a sign beside each student's name (in the screen displaying student names) to indicate whether the student has started the course. This modification was implemented during the course period by adding red bullets beside the names of students who had not started the course (see Chapter 6, Figure 6.10).
- The facilitators suggested ordering and colouring of the displayed advice according to their importance levels. The reason for this suggestion was to ease locating important advice in order to take the necessary actions. This suggestion was implemented by defining an importance level (as suggested by the facilitators) for each advice type in TADV. Each displayed advice is preceded by a red, green, or blue asterisk (*) according to its importance level – very important, important, or less important, respectively.

- The facilitators suggested displaying the number of generated pieces of advice at the top of the screen just to know the amount of advice generated about a student, a group, or a class. The suggestion was implemented while the experiment was running (see Chapter 6, Figure 6.12).
- If advice generated to a student *S* says that he should, for some reason, study concept *c*, then there is no need to generate other advice saying that *S* should study *c* for another reason in the same session. The facilitators aimed to reduce the amount of advice through avoiding such cases. This comment was considered and a filter program was developed to examine the generated advice and address the occurrence of such case. Whenever found, the program keeps the first piece of advice and suppresses the displaying of the other similar pieces. Moreover, the program gives the facilitator the choice, through an action button, to either *view all advice* (i.e. without filtering) or to *filter* the advice and suppress the repeated pieces of advice. Figure 7.1 shows the "Filter/View all advice" action button in the screen used to display advice.

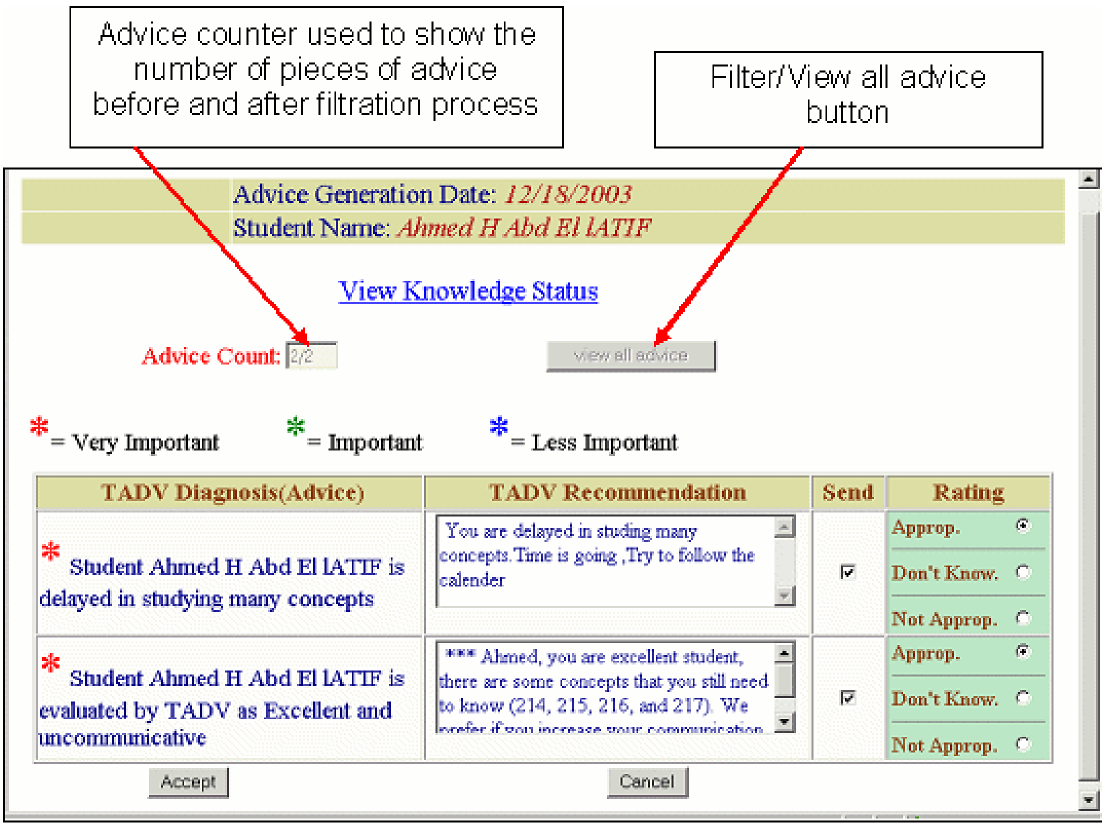


Figure 7.1 Filtration button in the screen used to display advice.

- In the case when a student is uncommunicative, much advice is generated saying that the student should participate more in the discussion forums related to different concepts. Facilitators suggested aggregating all this advice saying, for example, that the student should be more communicative without listing all concepts. This suggestion would lessen the amount of generated advice and could be also extended to advice related to groups and classes.
- For some of the advice that did not have predefined recommended feedback to the students (i.e. formulating feedback is left to the facilitator), the facilitators mentioned the possibility to standardise templates of the appropriate feedback that should be sent to the students. This would require extensive studies with many distance learning experts to agree on the appropriate feedback preferred by most of them. However, it may decrease the facilitators' effort in authoring and typing of the feedback messages especially when the number of students enrolled in the distance course is high. An alternative solution is to give the facilitators the possibility to enter their preferred feedback messages corresponding to each piece of advice through the "System parameters" option (see Chapter 6) before starting the courses, which may slightly increase the workload of course preparation, but should reduce the communication load later on.

From the students' questionnaire

The suitability of the advice/feedback sent to the students was addressed in questions Q21, Q26, Q27, and Q28 of the questionnaire presented in Appendix-I. The complete questionnaire results are presented in Appendix-K. The feedback found in the students' responses regarding advice/feedback suitability was very limited.

One student said about the advice "*It told me about the parts of the course that I am not good at*", another student preferred Type1-2 advice and said: "*I liked the advice coming when I am delayed*", while another student said: "*All are good*". A student saw that the TADV advising feature was normal, while another one was surprised by the existence of messages coming from the facilitator. Another student was concerned about the lack of new daily feedback, he stated: "*There is no new feedback for two or three days.*" Some advice confused one of the students; he said: "*Messages are sometimes difficult to understand. Why don't you use Arabic language?*".

Although these comments came from a handful of students, they emphasise the importance of providing feedback to the students and the appropriateness of the feedback they got through the TADV advising features. These students' comments emphasised some important points:

- The students were interested to know the course parts in which they were good and the parts in which they were not.
- The students needed reminding when they were delayed in studying course parts.
- The students were keen to understand the feedback coming from their facilitator; they recommended generating the advice in their native language (Arabic).
- The students were keen to get regular advice and feedback from their facilitator.

7.6.2. Suitability of advice types

The analysis presented here depends on information derived from the generated advice, advice types, and teacher and students' rating. Appendix-L depicts a sample of different advice types generated during the experimental study. The suitability of each advice type is discussed separately.

Suitability of Type-1 advice

A total of 570 pieces of advice of Type-1 (Individual student level) were generated; from those 35 were filtered out by TADV because they were considered as redundant. Accordingly, a total of 535 pieces of advice of Type-1 were displayed to the facilitators. Figure 7.2 shows the facilitators' rating for each subtype of Type-1 advice and the overall facilitators' rating for Type-1 Advice.

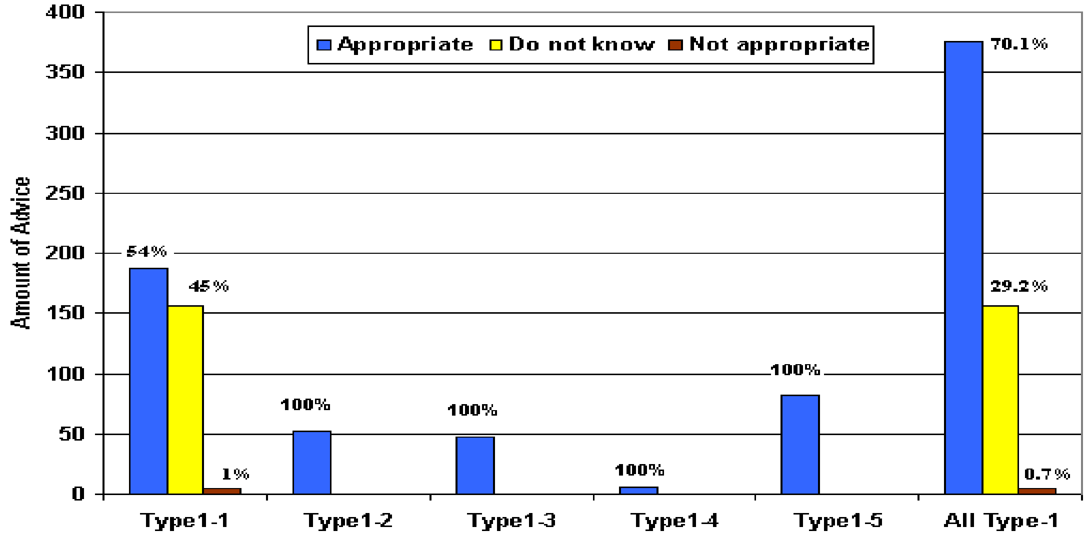


Figure 7.2 Type-1 advice (individual student level) – the facilitators' rating.

348 pieces of advice of Type1-1 (student's knowledge status) were displayed and rated by the facilitator as shown in Figure 7.2. The facilitators usually used "Do not know" (45%) when they believed that the TADV advice contained correct information

about the student but it was not necessary to send the recommended feedback. For example, consider the extract shown in Table 7.3, which presents some examples of advice rated as “Do not know” (marked as D). The examples are part of the advice generated to facilitators about a student during one of the advising sessions. The first piece of advice concluded that the student was weak and uncommunicative, upon which the facilitators composed the feedback shown (preceded by ***) to the student to encourage him to study the course topics and to communicate with his peers. When the facilitators reached the advice which highlighted that the student should be encouraged to participate in discussion of 102_Arrow_Diagram, 111_Inverse_Of_One_To_One and 105_Boolean_Function, they saw no need to do that because they had already encouraged the student to be communicative in a more general and short way. Accordingly, the facilitators decided not to send these pieces of advice (N in the S column) and rated them as “Do not know” (D in the FR column). As shown in Figure 7.3, rating 45% of Type1-1 as “Do not know” is linked to the percentage of advice sent to the students. This illustrates one of the important situations to be addressed in the filter process to reduce the amount of advice. On the other hand, although advice ranked as “Do not know” was not sent directly to students, informing the facilitators that students are not discussing certain concepts may be a good indication for the facilitator to initiate new discussion forum or to become more proactive in existing forums.

Table 7.3 Example situations of Type1-1 advice (student’s knowledge status) ranked as “Do not know”. The pieces of advice shown were generated during the same advising sessions. Column S - Send status (Y: Yes, N: No) shows whether the facilitators sent the advice, or not. Column FR – Facilitators’ Rating (A: Appropriate, D: Do not know, N: Not Appropriate) shows how the facilitators ranked the TADV advice.

Advice to the facilitator	S	FR	Feedback to the student
Student Mina R Fahmi is evaluated by TADV as Weak and uncommunicative	Y	A	*** You need to work hard with this course; we are about to stop the course. There are many concepts still need you work with. Communication with your peers may help you.
-----		---	-----
Student Mina R Fahmi should be encouraged to participate effectively in the communication activities related to 102_Arrow_Diagram	N	D	We note that you did not participate effectively in the 102_Arrow_Diagram discussion forum. It may be useful if you visit it and read what is there or ask your peers
Student Mina R Fahmi should be encouraged to participate effectively in the communication activities related to 111_Inverse_Of_One_To_One	N	D	We note that you did not participate effectively in the 111_Inverse_Of_One_To_One discussion forum. It might be useful if you visit it and read what is there or ask your peers
Student Mina R Fahmi should be encouraged to participate effectively in the communication activities related to 105_Boolean_Function	N	D	We note that you did not participate effectively in the 105_Boolean_Function discussion forum. It may be useful if you visit it and read what is there or ask your peers

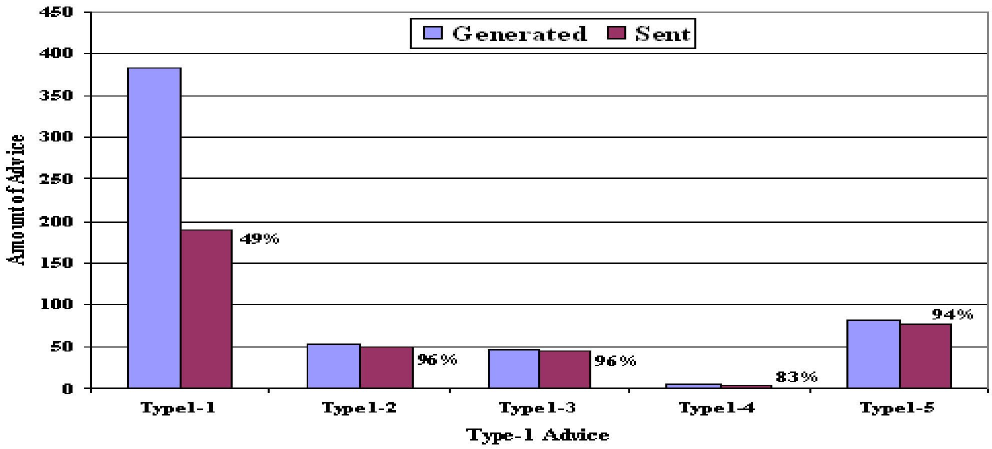


Figure 7.3 Percentages of Type-1 advice (student level) sent by the facilitators.

There are only four pieces of advice of Type1-1 rated by the facilitators as "Not Appropriate" (for details see Appendix-L). These related to situations when there were several prerequisite concepts for a concept *c* and a student was struggling with *c*, as well as its prerequisites. Consequently, TADV generated several pieces of advice saying that to master *c* the student should study its prerequisite concepts (see the case presented in Table 7.4). The three pieces of advice were generated to inform the facilitator that the student should study concepts 209_Reflexive_Property, 211_Transitive_Property, and 210_Symmetric_Property to master the concept 213_Equivalence_Relation. Such situations were predictable during the phase of advice generation design, however, it was important to have empirical data of how the facilitators would perceive and react to such cases in order to decide how to tune the advice generation mechanism. The facilitators saw that it was sufficient to display the first advice and suppress the rest or to just combine the three pieces of advice into one. This suggests another situation where filtration and aggregation can be used to reduce the amount of advice generated.

Table 7.4 Example situations of Type1-1 advice (student's knowledge status) ranked as "Not Appropriate". Column S - Send status (Y: Yes, N: No) shows whether the facilitators sent the advice or not. Column FR – Facilitators' Rating (A: Appropriate, D: Do not know, N: Not Appropriate) shows how the facilitators ranked the TADV advice.

Advice to the facilitator	S	FR	Feedback to the student
Student Mostafa Y El Shami should be advised to study 209_Reflexive_Property	Y	A	In order for you to master 213_Equivalence_Relation, it is highly recommended to study 209_Reflexive_Property first
Student Mostafa Y El Shami should be advised to study 211_Transitive_Property	N	N	In order for you to master 213_Equivalence_Relation, it is highly recommended to study 211_Transitive_Property first
Student Mostafa Y El Shami should be advised to study 210_Symmetric_Property	N	N	In order for you to master 213_Equivalence_Relation, it is highly recommended to study 210_Symmetric_Property first

Facilitators sent 189 pieces of advice of Type1-1 to the students. This number approximately represents the amount of Type1-1 advice rated as "Appropriate" by the facilitators (188). This shows a solid relation for Type1-1 between what the facilitators considered appropriate and what they sent to students. The students rated only 52% of what was sent[2]. Figure 7.4 shows the students' rating for each subtype of Type-1 advice and the overall students' rating for Type-1 Advice. Since the students were not observed while they worked with TADV and rated advice to ensure realistic conditions, it is generally difficult to explain exactly the reasons of each individual for the rating they have given. However, we noticed that 66% of the Type1-1 advice, which were rated by the students as "Do not know" and 100% of those rated as "Not Appropriate" were related to encouraging the students to participate in communication activities. This in turn, means that the students either did not wish to participate in communication activities, did not know how to do that, or did not realise that communication activities were beneficial for learning. This may be attributed to some cultural aspects that reflect the tendency to work mostly in an individual manner instead of working in teams. It is also worth noting that these students did not have any experience in Web-based courses and were exposed prior the experimental study predominantly to classical lecture-like teaching, which rarely involved group activities. Further research is required to examine how teacher advisors like TADV can recommend activities that can overcome cultural barriers or address communication difficulties among some individuals.

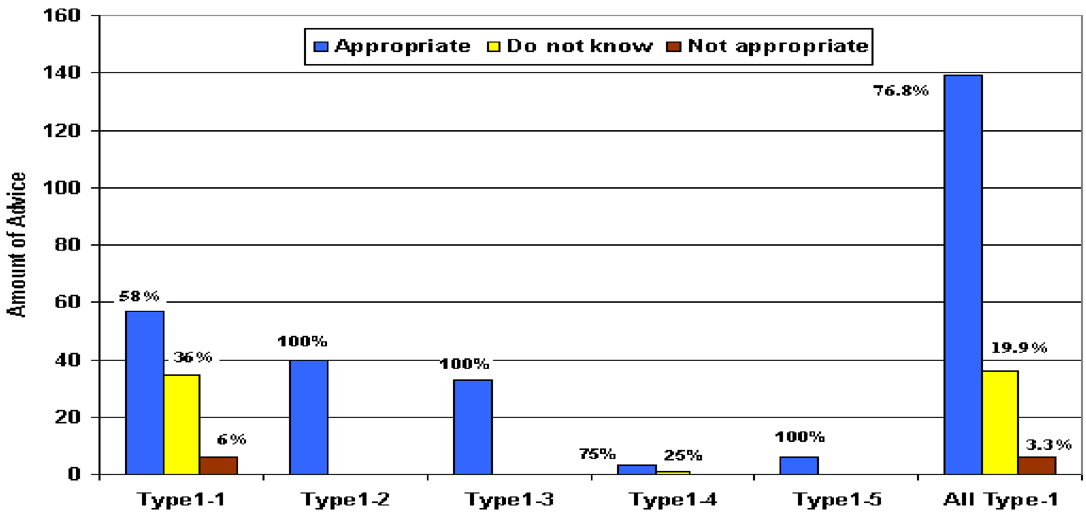


Figure 7.4 Type-1 advice (individual student level) – the students' rating.

[2] Since the students used the system through the Web, TADV gave them the possibility to read and rate the advice in an optional manner. It was inappropriate to force students to read and rate the advice, thus, it was difficult to identify why the students did not rate some advice. As a result, we cannot comment on the students' opinion about the advice they have not opened or rated.

The facilitators and the students rated Type1-2 (student's delays), Type1-3 (weak student), and Type1-5 (student has not started the course) as "Appropriate" with a percentage of 100%. The high percentages of advice sent to students from these types, as shown in Figure 7.3, *demonstrate their suitability*. Type1-2 and Type1-5 advice are important because they keep the facilitators knowledgeable about the behaviour of the students and give them the chance to discover the problems earlier and send feedback to appropriately guide the students. Type1-3 advice is also important for the facilitators because it points to the students evaluated, by the system, as weak and, therefore, needing more help and guiding. On the other hand, the appropriateness of Type1-2, Type1-3, and Type1-5 with respect to the students may be attributed to their need to be supervised and guided by their teachers. This may be specific for the participants in the study but may not be generalised for all students; some students may prefer to work on their own and not to be continuously guided by teachers. Nevertheless, we believe it is important for a teacher to know who may require guidance and to decide how to provide this guidance depending on his understanding of each individual student (which may be improved, as discussed in Section 7.7).

The facilitators rated all Type1-4 (excellent student) advice as "Appropriate". 5 out of the 6 pieces of advice of this type generated were sent to the students. Since this advice type was related to excellent students, we wondered why the facilitators did not send one of them. This case is given in Table 7.5, which suggests that the facilitators forgot to send the advice after composing the shown feedback. Students rated 3 pieces of advice as "Appropriate", 1 as "Do not know", and 1 not rated. Focusing on the advice rated as "Do not know", we found it was composed by the facilitator as "*** well done Ahmed, try to help your peers". Probably the student did not like to communicate with his peers for the reasons mentioned earlier. It is worth pointing out that being engaged mainly into traditional lectures the students participating in the study did not appreciate the learning benefits of collaborating with peers.

Table 7.5 Facilitator forgot sending his composed feedback. Column S - Send status (Y: Yes, N: No) shows whether the facilitators sent the advice or not. Column FR – Facilitators' Rating (A: Appropriate, D: Do not know, N: Not Appropriate) shows how the facilitators ranked the TADV advice.

Advice to facilitator	S	FR	Feedback to student
Student Shady A Nossier is evaluated by TADV as Excellent and highly communicative	N	A	***Well done Shady, Thank you.

Suitability of Type-2 advice

A total of 158 pieces of advice of Type-2 (Group level) were generated from which 17 were filtered out. Accordingly, a total of 141 were displayed to the facilitators. Figure

7.5 shows the facilitators' rating for each subtype of Type-2 advice and the overall facilitators' rating for Type-2 Advice.

127 pieces of advice of Type2-1 (group knowledge status) were displayed and rated by the facilitators as shown in Figure 7.5. There was not any "Not appropriate" advice, however, 75% were rated as "Do not know". We analysed these situations further. In one of the advising sessions, TADV generated 55 pieces of advice about Group1 to the facilitators. The group was evaluated by the system as weak and the group knowledge model revealed that the group members did not master all course concepts. The facilitators rated 34 of these 55 pieces of advice as "Do not know" and reported that in this case there was no need to display and send this large amount of advice even if they were correct. Instead, they decided to compose one message to encourage all students from the group to work harder on the course. The facilitators mentioned that it would be useful if TADV could *aggregate* this situation in one piece of advice.

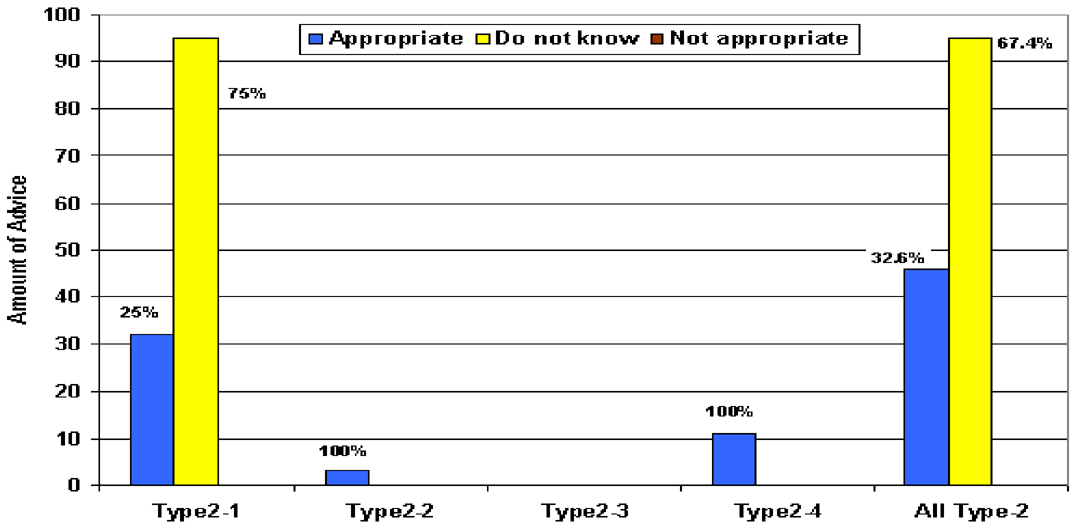


Figure 7.5 Type-2 advice (group level) – the facilitators' rating.

Accordingly, the amount of Type2-1 advice sent to the students was low as shown in Figure 7.6. Students rated 64% of what was sent from this type as appropriate, as shown in Figure 7.7. There are no clear common criteria between the advice rated by students as "Do not know" or "Not Appropriate" but we suppose that a student, as a group member, may rate advice as "Not Appropriate" or "Do not know" if it is not applicable to his case. For example, when most group members were struggling with a concept, TADV informed the facilitators and they sent a message to the whole group to encourage everybody to study the concept. For those students who had already studied the concept, this group message may not be applicable, hence, they may rate it as "Not Appropriate" or "Do not know". Nevertheless, the facilitators in the study used the group advice to create the feeling that the students belonged to a group. Other facilitators might find that a group message is not needed because the individual students have already been sent messages. As discussed in Chapter 6, the facilitator can use "Select advice type" option to suppress generation of certain advice or decide not to send the message.

The facilitators and the students rated advice Type2-2 (weak groups) as "Appropriate" with a percentage of 100%. The facilitators sent all generated Type2-2 advice. This shows the importance of the advice that highlights the evaluation of the groups. This also emphasises the need for including automatic student evaluation mechanisms in the WBDE environments.

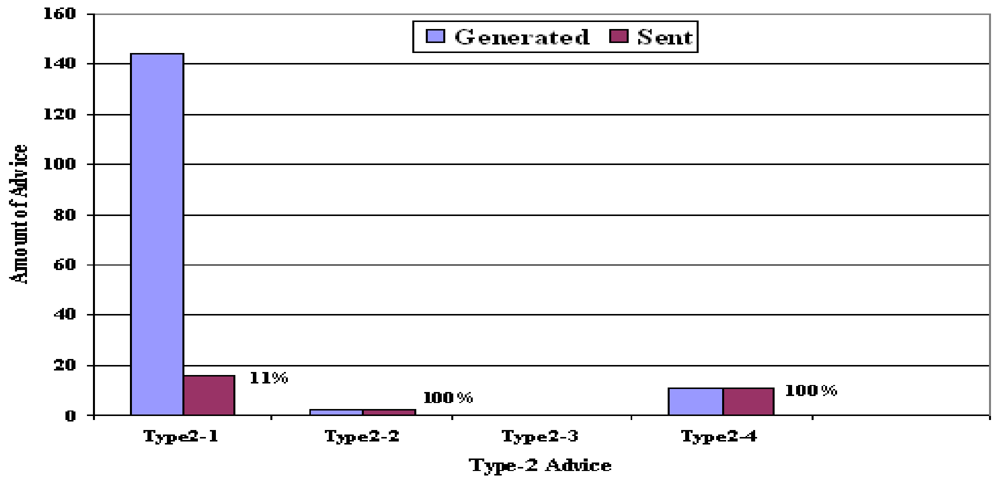


Figure 7.6 Percentages of Type-2 advice (group level) sent by the facilitators.

Advice Type2-3 is designated to highlight excellent groups of students. In this experimental study, Group1 and Group2 were evaluated by TADV as weak groups. Therefore, no advice was generated from Type2-3. There were four students in Group1 (two with high GPA and two with low GPA). The facilitators have formulated this group to see the effect of mixing good students with weak students. All Group1 members worked on the system but three of them were evaluated as weak while the fourth (with high GPA) was evaluated as excellent. It is worth noting here that this excellent student is the same student who has rated the facilitator's feedback as "Do not know" when asked to help his peers. This shows the need for further research to study the recommendations that can be generated to the teachers to deal with advanced students who do not wish to engage in group activities.

The facilitators formulated Group2 (three students) to monitor the behaviour of non-Egyptians. Only two students from Group2 worked on the system; one was evaluated as good and the other one as weak. We think that the time of the experiment was not enough for the facilitators to build a clear picture about the behaviour of these groups. However, studying group behaviour in depth was outside the scope of TADV evaluation; instead we aimed to examine that TADV was capable of monitoring groups and generating advice to the facilitators.

The facilitators rated all Type2-4 advice (most group members did not start the course) as "Appropriate" and sent it to group members. The students rated this type, as shown in Figure 7.7. Similarly to Type2-1 advice, when the facilitator sent advice to all group members saying that they should start working on the course, a student who had already started the course probably rated this advice as "Not Appropriate" or "Do not know".

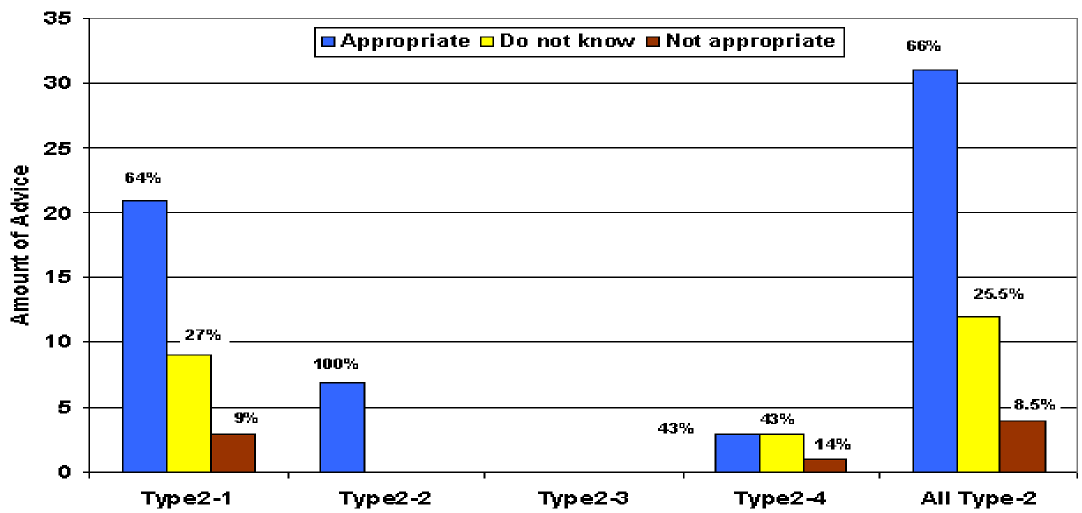


Figure 7.7 Type-2 advice (group level) - the students' rating

Suitability of Type-3 advice

It is important to recall that TADV did not recommend feedback to the students for all Type-3 advice (Class level). Instead, TADV provided information about the class and it was expected that this information would help the facilitators to formulate appropriate feedback. During the experimental study we noticed that in most cases for Type-3 advice, the facilitators read the delivered information and, accordingly, composed and sent one or two messages to all class students. Therefore, there was no direct relation between the amount of advice rated by the facilitator as appropriate and the amount of advice sent to the students (as this was discussed for Type-1). We have noticed that the facilitators were careful when sending feedback to the whole class. They attempted to formulate general feedback without highlighting the weak or inactive students. We think that the reactions to this type of advice vary from one facilitator to another depending on the facilitator's intervention strategy and his way of guiding the class. Therefore, it was considered inappropriate to generate recommended feedback to the students in the case of Type-3 advice, when TADV highlighted class problems.

A total of 130 pieces of advice of Type-3 were generated to the facilitators. Figure 7.8 shows the facilitators' rating for each subtype and the overall facilitators' rating for Type-3 advice.

104 pieces of advice of Type3-1 (class knowledge status) were rated by the facilitators, as shown in Figure 7.8. There was no advice ranked as "Not appropriate"; however, 32% were rated as "Do not know". As in the group case, the facilitators reported that when the class was evaluated by TADV as weak and the amount of generated advice increased, it was better to generate only one piece of advice to highlight the situation. This indicates again the need for advice filtering in some cases.

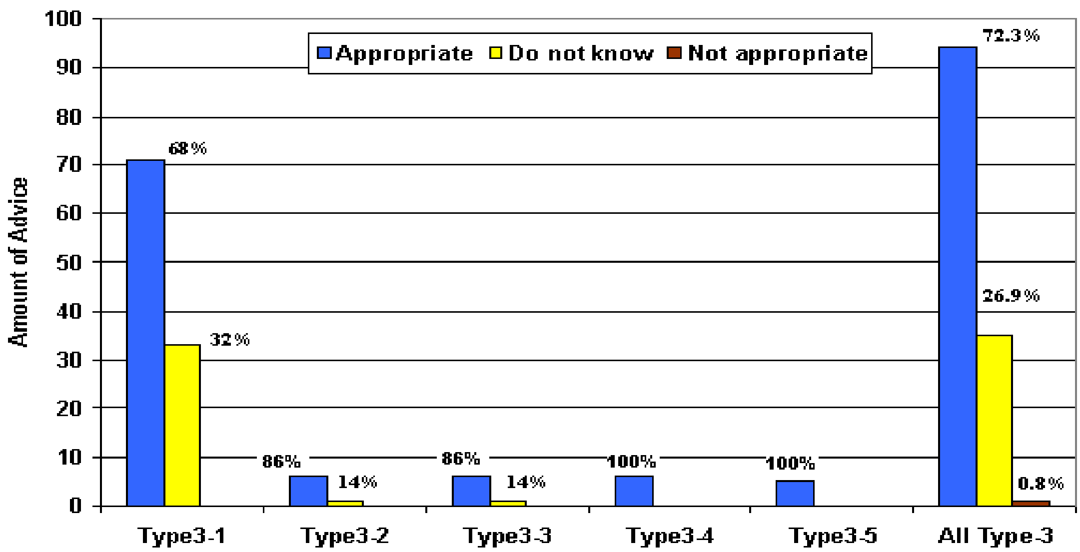


Figure 7.8 Type-3 advice (class level) – the facilitators' rating.

Although the facilitators rated 71 pieces of advice of Type3-1 (class knowledge status) as "Appropriate", they only sent one piece of advice of this type to the class, as shown in Figure 7.9. This shows that although the advice reported correct and important information about the class, the facilitators in this study preferred not to send it to the students. However, the facilitators used the knowledge gained from Type3-1 advice to compose a summarised feedback to the class, as we have mentioned earlier. As shown in Figure 7.10, a total of 10 students rated this advice – 5 as “Appropriate” and the other 5 as “Do not know”. The reason again is not certain and possibly due to the inapplicability of the advice to the students’ status.

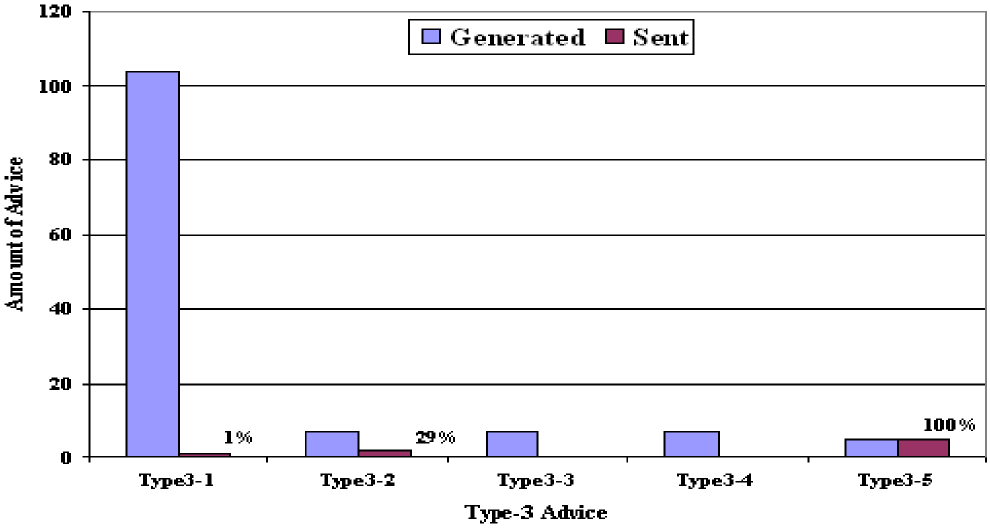


Figure 7.9 Percentages of Type-3 advice (class level) sent by the facilitators.

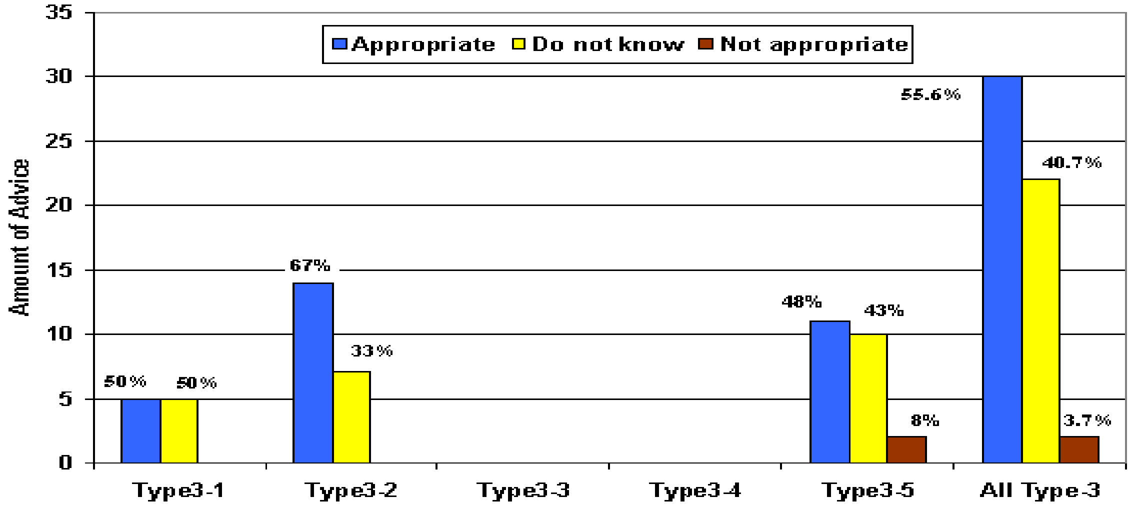


Figure 7.10 Type-3 advice (class level) – the students’ rating.

As shown in Figure 7.8, the facilitators rated 86% of Type3-2 advice (excellent and weak students relative to the class) and Type3-3 advice (Communicative and

Uncommunicative students relative to the class) as “Appropriate”. One piece of advice from each type was rated as “Do not know” due to a grammar mistake in the advice template which lead to misunderstanding the advice. The facilitators composed and sent feedback as a result to 2 pieces of advice from Type3-2. As shown in Figure 7.10, 21 students evaluated the facilitators’ feedback – 14 as “Appropriate” and 7 as “Do not know”. The facilitators did not send any feedback directly from Type3-3. This showed a situation where the facilitators decided not to send feedback to the students even though they got important information from the advice.

86% of Type3-4 advice (Active and Inactive students) was rated as “Appropriate” by the facilitators. Only one rated as “Not appropriate” because some students were considered as both active and inactive in the same advice due to a programming error, subsequently fixed. As in the case of Type3-3, the facilitators did not send any feedback directly from Type3-4, as shown in Figure 7.9.

5 pieces of advice of Type3-5 (most class members did not start the course) were generated, all of them rated by the facilitators as “Appropriate” and all were sent to the class. 23 students rated what the facilitator sent due to this type of advice – 11 as “Appropriate”, 10 as “Do not know” and 2 as “Not appropriate”. Table 7.6 shows the case of the advice rated by students as “Not appropriate”. The advice sent aimed to encourage the students to start working on the course upon information delivered from TADV, which reported that most of the students in Class-2 had not started the course. We think that these two “Not appropriate” ratings came from students who had already started the course. This can also be valid for advice rated by the students as “Do not know”.

Table 7.6 Example situations of Type-3 advice (most class members did not start the course) ranked as “Not Appropriate”. Column S - Send status (Y: Yes, N: No) shows whether the facilitators sent the advice or not. Column FR – Facilitators’ Rating (A: Appropriate, D: Do not know, N: Not Appropriate) shows how the facilitators ranked the TADV advice. Column SR – Students’ Rating shows how the students ranked the TADV advice.

Advice to the facilitator	S	FR	Feedback to the Student	SR		
				A	D	N
TADV can not evaluate Class-2 because most of its students have not started the course yet	Y	A	*** For the class members who did not start the course, time is going, please start the course as soon as possible.	0	2	2

7.6.3. Summary of findings about advice suitability

The following points summarise the findings collected from the facilitators and the students with respect to the issue of advice suitability:

- Facilitators were satisfied with the advice generated by TADV regarding advice types, contents, and the situations addressed. The facilitators appreciated the generated advice and reported its importance and usefulness.
- Students found that advice was good and guided them especially when they were delayed. Some students asked for advice to be generated on a daily basis and others suggested the advice to be in Arabic.
- The appropriateness of Type1-2 (student's delays), Type1-5 (student did not start the course), Type2-4 (most group members did not start the course), and Type3-5 (most class members did not start the course) show the importance of the advice types related to students' behaviour with the course.
- The appropriateness of Type1-3 (Weak student), Type1-4 (excellent student), Type2-2 (weak group), and Type3-2 (excellent and weak students relative to the class) show the importance of the automatic student evaluation mechanisms for the facilitators.
- The study shows the appropriateness and the importance of the advice types related to students' knowledge status [Type1-1 (student knowledge status), Type2-1 (group knowledge status), and Type3-1 (class knowledge status)]. However, for these types of advice the facilitators stressed the issue of reducing the amount of generated advice in some situations (discussed in Section 7.6.2) which showed the need to add some filtering and aggregation mechanisms. This will be discussed further in Chapter 8.

7.7. Benefits of TADV for Facilitators

TADV is directed towards helping facilitators to appropriately manage their distance classes through providing them with important information about the behaviour of their distant students. In this section, we aim to evaluate the extent to which this objective was achieved. The facilitators' feedback is considered as a crucial part in the assessment process of this study. The discussions took place with the facilitators during the advising sessions and during the interview conducted with them (Appendix-J). Although the study is constrained by many administrative arrangements (see Section

7.5.2), the feedback collected from the facilitators highlighted several benefits from TADV.

7.7.1. General benefits gained from TADV

During the TADV experimental study, the facilitators wanted their students to:

- Gain reasonable learning levels.
- Manage the course themselves and study on their own in a Web-based learning environment.

The facilitators acknowledged that although the course period was relatively short, their goals (as stated above) were achieved. Regarding the first goal, the course teacher and his assistant said, respectively:

> "*I can say that learning gain is relatively good for both classes. As it is clear from the post-test scores of both classes, learning gain for Class-2 is a little bit better than of Class-1.*"

> "*I think that students gained learning level relatively similar to what they normally gain during face-to-face approach.*"

It can, therefore, be argued that by using TADV as a framework for Web-based learning it was possible to achieve *similar learning gains* to what would have been achieved in a face-to-face learning environment. On the other hand, the facilitators did not attribute the achieved learning gains solely to interaction with TADV because they noticed that some students from Class-2 (the class which they monitored during the experimental study) did not use the available learning objects and others used TADV just to solve the available assessment quizzes. We believe that this point is true in all online distance education environments in which students can freely study using the online material, printed material, textbooks, or any supplementary materials. However, this led to the following outcomes:

- Using TADV, the facilitators were aware of the behaviour of their distant students, which is an objective we tried to achieve.
- If TADV is used in a real long-term distance education environment, then the facilitators may possibly be able to address unexpected student behaviour and use the information from TADV to improve the effectiveness of the courses they deliver.

The second goal is related to the ability of students to work on their own in a Web-based distance environment. It was pointed at during the interview that, using

TADV, the facilitators were positive about the students' abilities to manage courses on their own and the possibility to apply distance learning in their environment:

> "*The experiment showed that our students could be autonomous if they offered the chance to learn on their own.*"

> "*Most students appreciated the idea of having online distance courses with the condition of starting them from the beginning of the term to its end. This appreciation means that they like to be more autonomous and that they have the ability to mange courses themselves if they got the chance*."

> "*For this experiment, I believe that the students gained some experience in studying alone and independently managed this part of the course.*"

The facilitators also commented on the shortage of the experimental time and on the students' lack of experience with such distance education environments, which require serious commitment to the designated course plans and more communication between students. Studying the applicability of Web-based distance education in this community of students requires long-term experiments and is outside the scope of the TADV evaluation. In this line, the experimental time was sufficient to examine the TADV framework and to know the benefits and pitfalls of its advising features.

7.7.2. Benefits gained from TADV advising features

This section focuses on one of the key questions addressed in this study - the benefits facilitators gained through the advising features provided by TADV. Many issues are considered to address the expected benefits and pitfalls that might result, if any. These issues, presented below, are discussed by the means of questions and answers drawn from the analysis of data from the experimental study.

Did TADV make the facilitators more knowledgeable about their students?

This issue is addressed during the interview presented in Appendix-J. We present parts of what the facilitators said during the interview about this issue:

> "*I felt that most of the advice was generated to let us know about the problems that exist regarding individual students, groups or the whole class.*"

> "*No doubts that advice provided me with very important knowledge about the students in Class-2. I got to know about their study behaviours – who followed the course calendar, who is delayed, who has worked just before the end of the course, etc.*"

"*Class-2 seems clear to me - I can easily know who is delayed, who did not start the course, who is good and who is weak. I can also know what concepts students are struggling with.*"

"*We got useful knowledge from the system about students in Class-2, while on the other hand, we do not know anything about the other class.*"

This clearly shows that TADV has succeeded in making the facilitators in our study *more knowledgeable* about their distant students. TADV provided the facilitators with information which cannot be extracted using the traditional WCMS reporting features (see Section 2.4.1). Through the generated advice the facilitators became aware of the following issues:

- Problems with individual students, groups, and whole class, e.g. what concepts students were struggling with.
- Students' behaviour – who followed the course calendar, who was delayed, who was starting study just before the course ends, and who did not start the course.
- Students' knowledge status as judged by the system – how the students were progressing with the course material and what their communication status was.

Did the facilitators gain positive experience about the experiment?

The facilitators expressed a good impression of their participation in this experiment. They were happy and highly appreciated the idea of receiving computer-based advice from the system. They also acknowledged that they learnt many useful issues about the behaviour and attitude of their students toward Web-based learning.

How did the facilitators evaluate the process of course and metadata preparation?

The complexity of course preparation using the proposed structure was one of the issues raised during the interview with the facilitators. It was necessary to evaluate this task and see if it caused any difficulties. The domain expert was a key person in the accomplishment of this phase during the preparation of the TADV prototype. Appendix-J presents the comments pointed out by the domain expert regarding this issue from which the following points can be summarised:

- The task of dividing the course into concepts and determining the text and examples for each concept was very straightforward and posed no difficulties.
- Formulating Discrete Mathematics problems in a multiple-choice and true/false format was the only difficulty encountered during the task of preparing assessment quizzes. This concern is not a pitfall of our proposed course structure but may be

related to the nature of the Discrete Mathematics domain and to the difficulty of preparing electronic assessment materials that best check the understanding of its concepts.

- Drawing the concept maps and determining the type of relation between concepts was a fairly straightforward task.
- The task of acquiring metadata needed for fuzzy student-modelling required the domain expert to clearly understand what is meant by a measure of belief, a measure of disbelief, and other required metadata attributes (see Chapter 4). Nevertheless, the acquisition of metadata was fairly straightforward. However, the task of preparing metadata might not be easy for some teachers in different domains. It is important to stress that building knowledge bases and their meta-knowledge for intelligent educational systems is usually a tedious task and TADV required a fairly simplified process.

Did the facilitators face any difficulties during the experiment?

The facilitators pointed out some difficulties they faced during the experimental study:

- The facilitators considered the shortage of the time period assigned to the course as one of the difficulties they faced. This constraint was beyond our control, as the requirements of all stakeholders had to be met (see Section 7.5.2).
- The facilitators found that some students did not wish to participate in the empirical study and did not work hard on the system. They attributed this inattentiveness to the absence of strong incentives to participate in the study. They saw that offering a bonus score[3] was not enough but they did not recommend any alternatives. It is important to mention that the college administration refused the use of money or award incentives to encourage students to work on the system.
- The facilitators criticised the course contents because it depended only on HTML pages. This was a constraint of the CENTRA WCMS. As mentioned earlier in Chapter 6, learning objects were prepared in different formats, like for example Power Point format, but we used only HTML format due to the limited capabilities of the available version of CENTRA WCMS. Using Multimedia and graphical tools was not feasible with the resources dedicated to this project.

The above difficulties are not related directly to the ideas of TADV framework. For example, the facilitators did not mention any problems related to the use of the

[3] To encourage students working on the system, they were promised by their teacher to get bonus scores when they were evaluated by the system as excellent and active students.

TADV advising features or problems related to the system performance or the user interface. Also, the difficulties reported by the facilitators did not undermine the experimental study.

Did the use of TADV lessen the facilitators' load of replying students' e-mails?

It was difficult to compare the communication loads that resulted from both classes because the number of exchanged e-mails was very limited (the facilitator of Class-1 received 6 e-mails, while the facilitator of Class-2 received only 2). It is true that e-mails from Class-1 students were more than e-mails received from Class-2 students but it is not reasonable to conclude from these figures concrete results regarding this issue. The limited number of e-mails can be explained by the short experimental time and by the students' unfamiliarity with using e-mails to make contact with their teachers.

Did the use of TADV add more workload to the facilitators?

It is important to discuss the time the facilitators spent during the advising sessions in order to examine whether any additional load was added to the facilitators or not. Table 7.7 shows, for each of the seven advising sessions, the amount of advice generated, and the advising time (the time facilitators spent to read, compose, and send feedback to the students). Taking into account that the advising times shown include the times spent on other tasks (e.g. advice rating and side discussions) which will not be included in the normal implementations of TADV, the average time of an advising session did not exceed one hour (53 minutes). This demonstrates that *advising sessions did not consume much of the facilitators' time*, especially if compared to the online chatting sessions, which require much longer time to handle and are difficult to arrange, especially when students are from areas with different time zones (Smith-Gratto, 1999; Smith et al., 2000). Furthermore, it is difficult for the facilitators to gain understanding of their students – which they achieved with TADV – by using only the monitoring features provided by WCMS or by manual analysis of the poor tracking data generated by WCMS.

Table 7.7 Times spent in the advising sessions

Advising session	No. of generated pieces of advice	Advising session time (Minutes)
1	41	55
2	29	40
3	33	35
4	45	50
5	55	45
6	173	65
7	482	85

7.8. Benefits of TADV for Students

Although our main objective in this project was directed towards distance education facilitators, it was necessary to study the impact of the framework on the students who represent a major stakeholder in the educational process. We have to acknowledge that within the short period of the experimental study, it was not realistic to expect a significant enhancement in the students' learning gains and their affective aspects. Nevertheless, we were able to collect data that shows some potential benefits for students. Two major sources of data were used to address benefits for the participating students – students' questionnaire, and pre-test and post-test scores.

7.8.1. Analysis of students' questionnaire

In the following paragraphs the most important outcomes concluded from the answers of the questionnaire are summarised (the questionnaire is given in Appendix-I, while its results are illustrated in details in Appendix-K). To compare between answers of students in Class-1 (control Group) and Class-2 (experimental group) easily, it was decided to combine the "strongly agree" and "agree" answers to indicate the percentage of students who *agreed* on a specific statement and "strongly disagree" and "disagree" answers to indicate the percentage of students who *disagreed* on a specific statement. "Do not know" answers were ignored. A *grand mean* (Webster, 1992) was calculated (see Appendix-K) from the *weighted-mean answers* of the questions in each part of the questionnaire to facilitate comparison between the responses collected from the two classes. The grand mean was scaled from 1 (the worst) to 5 (the best).

About course information – This part shows the students' impressions regarding the distance course using the TADV system. The grand mean was 3 for both classes. However, there were some positive differences, highlighted in Table 7.8, which indicate a *better impression from Class-2 respondents*. For example, the percentages of students who disagree on that working with TADV is better than the face-to-face lecture is 62% in Class-1 against only 29% in Class-2. This might be attributed to the availability of the advice and feedback from the facilitators, which was the only factor differentiating between the conditions of the control and the experimental groups.

Table 7.8 Class-1 vs. Class-2 - course information

No.	Question Subject (statement)	Class-1		Class-2	
		Agree	Disagree	Agree	Disagree
Q13	Gain Learning from the course	33%	58%	43%	43%
Q14	One hour working with TADV is better than one hour lecture	23%	62%	43%	29%
Q15	Will use TADV with other courses	38%	38%	50%	36%
Q16	TADV interface is easy	69%	31%	79%	21%

About advising and feedback information – The advising part was assessed only by Class-2 - students who received feedback from the facilitators. A summary of the results is shown in Table 7.9 and more details are presented in Appendix-K. The results show the following points:

- The students were interested to know how they were evaluated by their facilitators (Q19, Q22). This points to the students' need to receive feedback and get help from their teachers. This, in turns, showed the importance of providing support to teachers to give appropriate feedback to the students.
- The students felt that they were continuously guided by the facilitators (Q24). This means that TADV succeeded in giving the students the impression that the facilitators supervised them during the course.
- The availability of the advice reduced the students' need to contact their distant teachers (Q25).

The grand mean of the advising part is 4, which shows the *appropriateness* of this feature and its *importance* for distant students.

Table 7.9 Class-2 – advising and feedback information

No.	**Question Subject (statement)**	**Class-2**	
		Agree	**Disagree**
Q19	Always start sessions with checking of the feedback and help	69%	31%
Q20	Advice and help information are useful	54%	38%
Q22	Students' interest to know how his work is evaluated by TADV and the facilitator	62%	8%
Q23	The feedback and advice details are appropriate	38%	15%
Q24	The student feels that he is getting continuous guiding from the facilitator during the course	62%	8%
Q25	The advice lessens the need to contact with the facilitator	50%	17%

About social aspects – The most important result found in this part, summarised in Table 7.10, is the fact that the level of student satisfaction (in Class-2) with the level of contact they had with the facilitator was higher if compared to Class-1 (Q32). The students' satisfaction with the contact they have with their teachers is important for lessening the students' feeling of isolation in distance learning (see Chapter 2). The grand mean of Class-2 answers was 3 while it is only 2 for Class-1 which, probably, reflects *better social aspects of Class-2 students*.

Table 7.10 Class-1 vs. Class-2 – social aspects

No.	Question Subject (statement)	Class-1		Class-2	
		Agree	Disagree	Agree	Disagree
Q29	Student responded to e-mails quickly	8%	54%	8%	69%
Q30	The amount of interaction with other students is as expected by the student	0%	62%	0%	62%
Q31	Facilitator responded to e-mails promptly	31%	15%	29%	0%
Q32	The level of contact with the facilitator is sufficient	23%	38%	54%	15%
Q33	Seeing the teacher face-to-face is absolutely necessary	77%	23%	62%	38%

About the students' overall satisfaction – Several differences were found between the two classes. Table 7.11 shows that Class-2 responses appear more positive than Class-1 responses regarding issues like enjoyment while working with the system, self esteem, and recommending the course to other students. The students from the experimental group (Class-2) enjoyed studying with TADV more than Class-1 students. Moreover, the grand mean was 4 for Class-2 against only 3 for Class-1. These results indicate that Class-2 students were more satisfied than Class-1 students. Since the availability of the advice and feedback information from facilitators was the sole difference (i.e. a controlling variable) between the two classes, then it may be possible to relate the better satisfaction level of Class-2 students to the availability of advice and help coming from the facilitator.

Table 7.11 Class-1 vs. Class-2 – overall satisfaction part

No.	Question Subject (statement)	Class-1		Class-2	
		Agree	Disagree	Agree	Disagree
Q35	I have enjoyed studying with TADV	31%	38%	64%	21%
Q36	I will recommend the course to other students	54%	31%	79%	17%
Q37	I have Learnt a great deal in this course	38%	31%	71%	14%
Q38	The course was difficult than face-to-face courses	54%	38%	43%	36%
Q39	Weekly duties was clear	85%	0%	86%	0%
Q40	I have enjoyed taking an online course	31%	54%	77%	15%
Q41	I will take another online course	23%	38%	64%	14%
Q42	After this course I will recommend online courses to other students	42%	33%	71%	14%

7.8.2. Analysis of learning gains using pre/post tests

Students who participated in the evaluation study completed a pre-test and a post-test. Pre-test scores were used as an indication of the students' learning levels gained from face-to-face teaching prior to the experimental study. Topics included in the pre-test were different from those studied with TADV and examined by the post-test (functions and relations). Given the administrative constraints (see Section 7.5.2) the experimenter did not participate in conducting the tests. Appendix-H shows all scores of the pre- and post-tests. Pre-test scores, post-test scores, and learning gains (differences between post-test scores and pre-test scores) were used to compare between students in Class-1 and Class-2 to check for any significant difference due to the availability of advice/feedback information. We used two statistical techniques for this analysis:

- T-test (Webster, 1992): used to compare pre/post test scores of experimental and control groups in similar projects; see for example (Bastiaens et al., 1999; Dunlop & Scott, 2001; Hartly & Mitrovic, 2002; Mitrovic, 2003)
- Effect Size (Cohen, 1988): used by many researchers in the field of computer-based educational systems to compare learning gains, see for example (Heffernan, 2003; Mayo & Mitrovic, 2001; and Olson & Wisher, 2002)

The analysis shows the following results:

- For [*df* (degree of freedom) = 28, t = 2.763, α (the probability of error) = 1% i.e. 99% confidence level, d_c (critical difference) = ±22.377, and d_a (difference between means) = 0.3] we found that there was no significant difference in the pre-test scores of the two classes, which in turn indicated similarity between the control and experimental group with respect to the students' level in the Discrete Mathematics course.
- For [df = 28, t = 2.763, α = 1%, d_c = ±0.805, and d_a = 0.15] we found that there was no significant difference between GPA (General Point Average) grades. This reinforced the similarity between the students of the two classes before the experiment with respect to the students' general academic level.
- For [df = 28, t = 2.763, α = 1%, d_c = ±18.55, and d_a = -2.666] we found that there was no significant difference between the post-test scores of the two classes. This means that there was probably no significant effect on post-test scores due to the availability of advice/feedback directed to Class-2 students. As mentioned earlier, this result was expected due to the short time of the experimental study.
- Effect size was applied to the participants in both classes to evaluate whether the students' learning gain improved after using TADV. The resultant effect size is found to be 0.288. This means, according to Rosnow and Rosenthal (1996), that *there was a small improvement in learning gains for the students of Class-2*. It is important to acknowledge that this small improvement cannot certainly be attributed specifically to the availability of TADV advising features.

7.9. Summary

In this chapter, we have discussed the results of the evaluation of the prototype we have developed to demonstrate the TADV framework for generating advice to facilitators in distance education course delivered with WCMS.

A formative evaluation was conducted to assess the system's behaviour and to discover potential problems. The prototype was thoroughly tested during all development phases. Comments and suggestions were elicited from potential users (facilitators and students) to ensure appropriate system usability. The prototype was then modified to satisfy the users' requirements.

A summative evaluation was conducted to assess the usefulness and benefits of the overall approach. We used an experimental study methodology in this phase of the evaluation. A combination of different quantitative and qualitative methodologies enabled the examination of the collected data from different perspectives. The combination of these studies led to the investigation into the suitability of generated advice and benefits to facilitators and students. Despite the administrative constraints, we have shown that TADV provides a practical and effective advice generation system. It has allowed generating advice to distant facilitators, which in turn made it easy to send help and feedback to distant students. Generally, the facilitators who participated in the study appreciated the generated advice and confirmed its appropriateness. The facilitators felt that they gained considerable knowledge about the students' behaviour and the problems they faced during the study of the course. The facilitators stressed the necessity of such advice for them to be able to manage distance classes. The students appreciated the idea of receiving feedback from the facilitators. The analysis of the students' questionnaires showed a better overall satisfaction and satisfactory social aspects for the students who used TADV advising features (experimental group). Moreover, the analysis of the students' learning gains based on the pre/post-tests scores showed that the learning gains of experimental group were slightly higher than that of control group. The empirical study suggested ways to tune the TADV framework by adding filtering and aggregation features which will be discussed in Chapter 8.

Chapter 8

Conclusion

8.1. Introduction

The research presented in this thesis belongs to the broad area of using Artificial Intelligence techniques in building computer based educational systems to enhance the effectiveness of the whole educational process. In particular, the research is relevant to building effective tutoring systems capable of adapting to the needs and problems of their users. We have focused on supporting distant teachers in WBDE environments managed by WCMS platforms, and have presented an approach for supplying the teachers with appropriate advice and information about their distant students and classes. The thesis has examined a computer-based advising framework, called Teacher ADVisor (TADV), where a teacher is advised and provided with important information about the behaviour and state of individual students, as well as groups of students and the whole class. The advice generated was intended to facilitate the appropriate management of distance classes which can result in effective support to distant students. Our aim was to formalise the advice generation process by applying AI methods. The main contribution of this work lies in the description of the TADV framework and its integration within WCMS platforms, which can lead to more effective support for facilitators and can increase the effectiveness of WBDE environments.

This chapter presents a summary of the results. First, we will describe the main achievements of our work and will outline its contributions to relevant research fields. Then, we will describe limitations of our approach and sketch out areas for future work.

8.2. Summary of the Work

This work has elaborated a **computer-based advice generating framework** in WBDE environments, which enables the development of student modelling and advice generation modules based on student tracking data collected by WCMS. We have formalised three main aspects as the basis for the design of such framework. Specifically, we have proposed:

- *Courseware structuring mechanism and domain meta-knowledge base* (presented in Chapter 4). We have described the process of creation and organisation of the course knowledge in order to be used in the proposed framework, taking into account the generality, simplicity, and domain independence issues. We have also described the Domain Meta-Knowledge or the metadata that should be kept to describe the contents of the Domain Knowledge Base and to facilitate the student modelling and advice generation processes.
- *Mechanism for structuring and building of student, group, and class models* (presented in Chapter 4). We have described the parts of the proposed student models, their functions, and their structure. The process of building student models using student-tracking data is clarified along with a detailed description of the process of diagnosing students' knowledge and fuzzy techniques used to evaluate the cognitive status and the communicative behaviour of individual students, group of students, and the whole class.
- *Advice generation mechanism based on a taxonomy of advice types* (presented in Chapter 5). We have proposed a taxonomy of advice types based on a study conducted in order to investigate the facilitator's needs when they manage a distance course in WCMS platforms. We have described in detail criteria of advice generation and an algorithm used by the Advice Generator to compose advice based on information available in both the constructed student models and the domain meta-knowledge base.

The formalisation of the above aspects supports the implementation of computer-based advice generation systems in a variety of WCMS platforms. The thesis has demonstrated an application of the framework using one of the conventional WCMS. Following the framework defined here, we have developed a **TADV prototype** (described in Chapter 6). The TADV prototype exemplifies the main aspects described above. The proposed architecture was demonstrated within the CENTRA WCMS in a Discrete Mathematics course.

The TADV prototype has been used for a validation of the computer-based advice generation framework proposed in this thesis. An **experimental study** with the prototype (presented in Chapter 7) has been conducted in order to outline advantages and point out problems of the approach. The results of the experimental study allowed us to discuss practical issues of the current TADV implementation, the problems, and the possible improvements.

The experimental study with TADV prototype has shown that the advice generated enabled the facilitators to gain helpful and appropriate knowledge about cognitive, behavioural, and social aspects of their distant students. The advice generated helped the facilitators to know the students who had not started the course, delayed students, students who did not visit regularly the course material and assessment quizzes, students who did not communicate much in the course, excellent and weak students, and other important information about the groups and classes. The facilitators regarded the advice provided as useful for monitoring and managing successful distance education courses. The advice generated and the TADV feedback recommended to the students gave the facilitators the chance to appropriately help and guide their students without experiencing considerable loads. The study also confirmed the appropriateness of the advice types included in the proposed taxonomy and pointed out required enhancement for few advice subtypes. Furthermore, the experimental study showed the students' satisfaction with the feedback they received from their facilitators. Some improvements in the students' affective aspects and their overall satisfaction were noticed when they used TADV. The study also pointed at some required improvements and potential applications of the TADV architecture. These improvements and applications will be discussed in Section 8.5.1.

The results of the experimental study have allowed us to conclude that TADV is a useful framework which may be employed in WBDE environment implemented with WCMS platforms to support teachers to manage their distance courses in a more effective way, and to enable teachers to guide their students according to their behaviour and cognitive status. This, in turn, may improve the effectiveness of using WCMS in WBDE environments.

The **generality** of the approach presented in this thesis can be shown by considering the main components of the TADV framework:

- *The courseware structure and domain meta-knowledge:* The proposed courseware structure, described in Chapter 4, is domain independent and can be applied to any domain in a straightforward manner. The proposed concept maps used to show the relations between domain concepts could be easily applied to any course which is organised around a set of concepts to study. Moreover, this course structure is compatible with the methods used by content managers of the most conventional WCMS to represent course contents. We have followed the IEEE-LOM metadata standards to describe the domain learning objects and the assessments quizzes, which convey the generality of the attributes required to describe the course learning objects. The other attributes (not included in IEEE-LOM) proposed as a requirement for fuzzy calculations used by student modelling mechanisms can be acquired from teachers or experts of any domain. The database approach and the Web-based application used respectively to represent and enter the courseware structure information and the values of metadata attributes can be easily used to perform the same functions in any domain.

- *The student modelling features:* The proposed design of the student model parts, namely Student Profile Model, Student Behaviour Model, Student Knowledge Model, and Student Preferences Model is domain independent. The general structure of these models and the use of relational database modelling approach for their representation facilitate their implementation as an extension to any WCMS platform to keep information about learner (student, trainee, etc.). The algorithm used by Student Model Builder to construct student models (discussed in Section 4.5) is also domain independent. However, the process performed by the Interaction Interpreter, which uses the student tracking data provided by WCMS to create Student Behaviour Model is dependent on the data representation method and the structure used by a WCMS to store the student tracking data. This does not affect the generality of the framework because the TADV framework describes how such features can be added to conventional WCMS, which, of course, is implemented using different designs and different technologies on different platforms. The Interaction Interpreter can be easily designed if a straightforward format was used for the tracking data captured by the candidate WCMS (e.g. text files or relational tables). The other algorithms performed by the Student Model Builder are completely independent from the WCMS.
- *The taxonomy of advice types and advice generation mechanism:* The advice types and subtypes proposed in the advice taxonomy are fairly general. They are domain independent and also WCMS independent. The taxonomy can be applied to any WCMS and to any

domain. Similarly, the advice generation database model and the algorithm used by the Advice Generation module are also quite general and do not depend on any specific domain or WCMS. It is important to point out here that adding new advice types to the proposed taxonomy should require performing few simple actions: (1) define new stimulating evidence, (2) define possible reasons which might cause the evidence, (3) define advice templates and their parameters and relate advice to the evidence and reasons, (4) write the code necessary to check for each new piece of evidence and reasons, and (5) adjust the general advice generation module to call the appropriate checks necessary for the new advice. This fairly straightforward way of extending the advice taxonomy and generation shows that the TADV framework is flexible and can easily be enhanced to deal with additional advice categories.

8.3. Contributions

The work presented in this thesis resulted in a number of original contributions. In this section we will highlight the significance of the achievements with respect to the related research areas.

8.3.1. Contribution to Web-Based Distance Education

The increasing use of the WWW as a medium for implementing distance education programs has lead to a growing number of studies that attempt to point out problems of WBDE. On the other hand, studies are being conducted in order to address these problems and increase the effectiveness of WBDE environments. WBDE programs have changed the roles of students and teachers in the educational process. Because students are the primarily target of the educational process, most of the studies conducted in WBDE have tended to focus on how to help students get better understanding and become active learners. There are very few studies conducted to support teachers to perform their new role as facilitators in WBDE environments. It is expected that supporting distant teachers to effectively manage their duties will be reflected positively on the learning and social aspects of distant students. Teachers in WBDE environments have insufficient knowledge about the behaviour of their distant students and classes. Viewed from such perspectives, our computer based advice generation framework, designed to provide teachers with appropriate information about distant students and to support teachers to perform their role as facilitators, contributes to the research in Web-Based Distance Education.

The work presented in this thesis is a progression in the issue of supporting teachers in WBDE environments. More specifically, the approach discussed here explores the idea that facilitators in WBDE environments should be automatically provided with information about their classes which highlights cognitive, behavioural, and social aspects of students, groups and the whole class. Moreover, facilitators should be supported in the task of guiding and sending feedback to the students in an easy and quick manner.

Several projects consider providing support to teachers in Web-based learning environments, as discussed in Chapter 2. Our approach is different from the works of Delozanne et al. (2003) and Merceron & Yacef (2003) who apply data mining techniques to investigate students' answers to extract only common pedagogically relevant information and provide feedback to the teacher. Along the same road, the work of Chang (2003) proposes an evaluation mechanism to perform quantitative analysis of exam outcomes to allow teacher to choose different instruction sequences. Santos et al. (2003) focus on helping teachers to manage the collaborative tasks. In contrast to these works, which focus on a certain type of students' interactions, our work investigates all types of students' interactions and provides feedback to the teachers about a variety of cognitive, behaviour and social aspects.

The objectives behind our research are similar to the objectives of CourseVis (Mazza & Dimitrova, 2004), however, the approaches employed to achieve the goals are very different. Mazza & Dimitrova (2004) use information visualisation techniques to produce graphical representations of student tracking data. These graphical representations have to be interpreted by the teachers to draw knowledge about students' aspects and decide about the feedback and the necessary actions. In contrast, a distinctive feature was gained through the using of intelligent techniques in our work. This enabled the *automatic* generation of advice and, in some cases, feedback that could be sent to the students. By highlighting the important situations the teachers should be aware of and recommending actions, TADV provides appropriate support and, at the same time, lessens the teachers' cognitive and communication load. On the contrary, the effectiveness of CourseVis is dependent on the teacher's ability to understand the graphical information and recognise what is happening in their classes. Moreover, due to the lack of intelligent features (as those included in TADV), CourseVis cannot recommend appropriate actions, and may fail to reduce the cognitive and communication overload of the teachers.

8.3.2. Contributions to Artificial Intelligence in Education

One of the main goals behind the use of AI techniques in education is to build computer-based learning systems capable of adapting to the needs of students and therefore, capable of providing them with effective personalised instruction. Student models which effectively reflect different dimensions of students' aspects are usually constructed within such adaptive learning systems to support the process of students' learning and to provide direct help and support to the students during their interaction with the system. In intelligent distance education environments (e.g. WBITS), the system usually provides different types of support directly to the students without the teachers' intervention. In such environments, the teachers may not effectively manage and guide their students because they do not know what is happening in their distance classes. Within this context, our computational framework which constructs student models and uses advice generation techniques with the aim of supporting teachers in distance education environments through providing them with informative advice contributes to the research in Artificial Intelligence in Education.

More specifically, the approach explored here goes beyond the common idea of building student models just to support student learning. In this thesis, we have built student models mainly to support teachers playing their role as facilitators through providing them with appropriate information about what is happening in their distance classes and what problems students face. Moreover, in some situations, we have provided teachers with recommended remedial actions to give them the chance to guide their students in an effective and easy manner. In this way, the TADV framework provides support to both teachers and students in a more teacher-controlled process by providing teachers with supportive and informative advice to make them knowledgeable about their students. It also allows recommended feedback and guiding information to be sent via teachers to support students, and allows maintaining continuous links between teachers and students.

In our approach to model the students' knowledge, we have considered mainly information derived from different students' interactions described by tracking data stored by WCMS. In line with (Anjaneyulu, 1997; Capuano et al., 2000; Grigoriadou et al., 2002) we have considered the plausibly of certain information derived from students' answers to assessment quizzes that test different domain concepts. Moreover, similarly to ABITS (Capuano et al., 2000), InterBook (Brusilovsky et al., 1997), and

AHA (de Bra & Calvi, 1998), we have also considered the uncertain information derived from the student's interactions with the learning objects designed to teach different domain concepts. In contrast to these systems, we have tuned the effect of uncertain interactions with the learning objects according to the time a student has spent in visiting learning objects. Viewed from such a perspective, the fuzzy student modelling mechanism presented in Chapter 4 contributes to research in AIED.

8.3.3. Contributions to Intelligent Web Course Management Systems

The thesis has demonstrated an original approach to utilising intelligent modules to extend the capabilities and improve the functionalities of conventional WCMS. The work has contributed to the new emerging research area of intelligent WCMS (intelligent course management systems). Research in this new area can be classified into two categories. In the first category, researchers try to provide their views on intelligent WCMS through sketching out the main components of these systems and outline the main research directions they anticipate toward enhancing student learning in these environments, for example, Moodie & Kunz (2003), Schaverien (2003), and Yacef (2003). In the second category, researchers try to extend traditional WCMS by developing new models and systems with the aim of supporting future intelligent WCMS, for example, Brusilovsky (2003), Capuano et al. (2000), Santos et al. (2003), and Sánchez et al. (2003). The work presented in this thesis contributes to the second category through extending the functionality of WCMS by adding student modelling and advice generation modules. Using these intelligent modules to support teachers in WCMS platforms is considered to be our main contribution to the new area of intelligent WCMS.

8.4. Reflection on the Decisions Made and the Methodology Used

The general characteristics that shape WCMS environments, the issues considered in the development of the TADV framework (see Section 4.1), and the shortage of the time and resources available for the evaluation of TADV prototype have influenced the decisions made throughout this study. This section will discuss the limitations and constraints experienced and how these had affected the research objectives of this work. A more focused discussion with elaboration on future work will be provided in the next section.

8.4.1. Domain representation

A relatively simple approach was adopted for the building of the concept maps. The relations between the domain concepts were based on a hierarchical structure to show the prerequisite links. Similar approach was used in other research work (e.g. Goodkovsky (1996)). TADV used different levels (Strong, Moderate, and Weak) to represent the prerequisite relationships between concepts. This design choice was influenced by the discussions with teachers who worked with WCMS environments during the requirements capture phase. Most of the teachers using WCMS assumed the relationships of course concepts are defined within the course structure, i.e. at a prerequisite level. In addition, teachers were unfamiliar with building sophisticated concept maps which usually use advanced knowledge representation schemes and it was also considered as a difficult and time-consuming task. Therefore, the issues of simplicity and generality influenced greatly the choice of the TADV concept maps. Although improvements could be made to the representation of domain knowledge (e.g. using additional types of relationships such as a part of, is a, etc.) it remains a challenge to map teachers' knowledge on the concept maps.

8.4.2. The student modelling approach

The approach adopted by the TADV for student modelling was quite general and depended mainly on the data provided by the tracking features of the conventional WCMS. As such, it is constrained by the information provided by WCMS. The tracking data, as mentioned in Chapter 2, included students' logins, visited pages, times spent on pages, scores achieved in quizzes, postings to discussion forums, and so on but for example, did not include any information about the way by which students constructed their knowledge, i.e. their learning styles (e.g. serialist/holist, impulsive/reflective, etc.). The types of available data would inevitably affect the way the facilitators were informed about their students and would affect the effectiveness of help provided to the students. Conventional WCMS usually do not provide intelligent features that can be used to track the way by which student solve the given assessment quizzes. If such information were available, sophisticated language processing techniques could be used in diagnosing the student's level of understanding.

In addition to the constraints imposed by the adopted WCMS tracking data, the choice of student modelling approach was also affected by the design of the concept maps. For example, it was not sensible to propagate the change in one concept's certainty factor to its connecting concepts based on a simple prerequisite structure. Such propagation techniques require the design of more sophisticated concept maps which use stronger semantics between concepts. In this case, the TADV framework could be extended by adding propagation algorithms similar to those used in the Bayesian networks.

8.4.3. The advice taxonomy

As mentioned in Chapter 5, the proposed advice taxonomy was based on our analysis of the problems with Web-based distance learning courses as discussed in the literature and on interviews with a few teachers (see Chapter 2). Accordingly, the completeness of such advice taxonomy has not been assured and the likelihood of new needs for other types of advice is possible (e.g. advice that could be adapted to the progression of student, group, and class knowledge). Enlarging the sample of interviewees for requirements capture may result in a more comprehensive taxonomy. Further discussion on how this could be addressed in future work is given in Section 8.5. Secondly, with richer domain representation and suitable supporting WCMS, some of the other types of advice, which were not addressed in this research, might be possible to be generated.

8.4.4. The TADV evaluation

As mentioned in Chapter 7, conducting evaluative studies to identify the impact of educational systems is generally a challenging task. The circumstances in which we conducted the TADV evaluation, the constraints imposed by the administration of the university, and the shortage of resources and time available had affected the methods adopted for the evaluation and, hence, the results drawn from the evaluative study. The following points summarise the main constraints of the TADV evaluation process:

- Most of the students who participated in the evaluative study did not have any real experience in taking a course which depended solely on Web- based interaction with teaching material, facilitators, and other students. Although some of them had used course materials from WCMS as a supplementary feature, there were students who had not used WCMS before the study. Therefore, it was quite difficult for them to effectively compare between the normal features given by a conventional WCMS and those given by the TADV. Their inexperience with Web-based courses may have affected negatively their group activities (exchanging e-mails, participating in discussion forums, etc.) both with their teachers and with peers. This, in turn, restricted the possibility to compare between the control and experimental group regarding the effect of the TADV on the group activities.

- The settings of the TADV evaluation study, described in detail in Chapter 7, showed that we simulated an environment for Web-based distance learning in order to evaluate the prototype. Students, as well as teachers, originally came from a traditional face-to-face class. Because of this, the settings of the evaluative study were detected by some participants, as an artificial world. This, in turn, might have affected their normal behaviour. It would be more beneficial if the study was conducted in a real Web-based distance learning settings in which the students and the facilitators could use the system in their normal environment. More discussion is given in Section 8.5.
- The shortage of time allowed and the difficulties encountered to gain commitment from staff also affected the evaluation study. For example, it was difficult during the specified period to compare between the facilitators' workload while using WCMS with and without TADV. Although it was possible to convince the participating teachers to regularly attend the advising sessions in order to evaluate the new features provided by TADV and manage the students of the experimental group, it was not possible to force them to use the features provided by WCMS (e.g. online chatting, tracking features, etc.) to manage the students of the control group. In addition, it was difficult to measure effectively the students' affective aspects (e.g. feeling of isolation, frustration) for comparison between the control and experimental groups. It was not realistic to examine properly isolation and frustration when the students only use the system for two topics and could regularly meet with their peers. The ideal settings required to successfully measure these variables would be having two groups of facilitators teaching the same Web-based course (one group using TADV and the other working with normal WCMS) for two relatively similar groups (e.g. have same cultural, demographic, and academic aspects) of students working in normal Web-based distance learning environment for the whole period dedicated for the course. It will be possible in such settings to collect richer quantitative and qualitative data for the evaluation.

Some of the limitations and constraints discussed in this section have opened the door for a list of future work that would be explored in the next section.

8.5. Future Work

Having sketched out the achievements of this work, we will now propose possible applications and enhancements of this research. To avoid some of the limitations revealed during the TADV evaluative study, we will first outline our short-term goals that concern improvements and applications of the current TADV architecture. Then, we will propose further long-term studies that concern the enhancement and exploitation of TADV. Finally, in a more speculative spirit, we will propose a follow up of ideas discussed in the thesis that we expect to address in long-term research.

8.5.1. Improvements and applications of the current architecture

Lessening the amount of generated advice

The TADV evaluative study (presented in Chapter 7) showed the appropriateness and the importance of the proposed advice types. However, the need for further reduction in of the amount of generated advice in some situations was highlighted by the facilitators who participated in the evaluative study. This refers to using some filtering and aggregation mechanisms to reduce the amount of advice displayed to the facilitators.

As immediate improvements of TADV, we will complete the filtering program (discussed in Section 7.6.1) so that it will address other situations which cause the increase in the amount of the generated advice. These situations are discussed in detail in Section 7.6.2 and all of them are related to advice types concerned with the evaluation of students' knowledge status [Type1-1 (student knowledge status), Type2-1 (group knowledge status), and Type3-1 (class knowledge status)]. In some of these situations, all similar pieces of advice can be filtered and replaced by one combined piece of advice. For example, if the advice used to highlight the fact that a student should summon his courage to participate in the discussion forum of a certain domain concept is repeated for many times (e.g. more than three), then all such pieces of advice will be filtered and replaced by a single piece of advice which highlights that the student should be encouraged to generally participate in different discussion forums. A similar approach will be used to filter several pieces of advice generated to highlight that a weak student is struggling with domain concepts. Using such an approach at different levels (individual, group, and class) will significantly decrease the amount of generated advice and, at the same time, the facilitator will not lose the detailed information because he can use “View all advice” button to display all advice whenever he wishes.

Employing TADV in the AAST On-line Learning Portal

Universities sometimes develop their own WCMS following local research projects to implement innovative ideas. Examples of these WCMS are ARIADNE (Forte et al., 1996) and InterBook (Brusilovsky et al., 1998). Other universities support the implementation of well-developed and tested WCMS but with less technological features. For example, MALLARD from the University of Illinois at Urbana-Champaign (Graham et al., 1997) and Virtual-U from Simon Fraser University (Fisher et al., 1997).

AAST is currently running a project to internally develop a Web course management system, called AAST On-line Learning Portal (AASTOLP). The high price of the commercial WCMS licenses is one of the main reasons behind this project. The availability of AASTOLP will facilitate the distribution of free licences to different AAST branches and campuses in Egypt and other Arabic countries. The TADV architecture was discussed in detail with the project manager and the TADV prototype (presented in Chapter 6) was demonstrated to the members of the project team. Accordingly, it was decided to implement the ideas explored by TADV as a feature to AASTOLP. The main components required by TADV (e.g. Domain Meta-Knowledge model, student models, and Advice Generation model) are considered during the preparation of the overall system design. The physical implementation of the advising features is scheduled as part of the second phase of the project (expected in March 2005). Employing TADV in AASTOLP will give us the chance to use Arabic language in the advising features in addition to English language and to deploy TADV in real settings involving a significant number of students and staff members.

8.5.2. Feasible research directions with TADV

Evaluating TADV in long-term studies in real distance education environments

We have to acknowledge that in the TADV evaluative study (presented in Chapter 7), the experimental settings were constrained by two major limitations: the shortage of the time allowed for the experimental study and the simulated distance learning environment in which the experiment was conducted. Having improved the advice generation mechanisms to reduce the amount of generated advice and having implemented TADV architecture within the AAST learning management system, we will be able to use the system for further examination and conduct studies in more realistic situations. It will be possible to examine TADV in real distance learning environments with different courses and for long periods of time in which the courses are conducted. Accordingly, we will be able to collect more qualitative and quantitative data that will be gathered from different groups of students and teachers who will participate from different courses. Using the data that will be collected, we will be able to conduct improved analytical studies which may lead to more valid conclusions about the benefits and pitfalls of the TADV architecture.

Enhancing the reliability of the TADV student modelling mechanisms

The reliability of the TADV student modelling mechanisms (discussed in Chapter 4) is affected by two important factors. The first is the dependency of these mechanisms on the values of metadata attributes either required to describe the standard characteristics of the learning objects (IEEE LOM) or attributes and parameters used to run the fuzzy student modelling mechanism (e.g. measures of beliefs and disbeliefs, boundaries used to evaluate concepts-learning status, and boundaries used to generally evaluate students and their communicative status). Consequently, the mechanism adopted in this research is strongly dependent on the initial data supplied by the teachers. People usually tend to minimise their efforts supplying metadata which in turn may lead to incomplete and inconsistent metadata (Pinkwart et al., 2004). On the other hand, the assigned values of metadata attributes are usually subjective and present the view of a particular teacher about the course material he has developed. These problems are common in all projects which need to deal with metadata and a general solution seems out of reach. However, some solutions are being proposed, e.g. Pinkwart et al. (2004) describe an approach for partial automatic generation of metadata in a collaborative modelling environment to reduce the user's effort required to prepare metadata. In our case, the problem of the subjectivity of some metadata attributes (e.g. typical reading times for learning objects) and fuzzy parameters (e.g. learning status boundaries) can be solved by acquiring this data from several domain experts which may lead to more reasonable values. This, in turn, may increase the effort and time required to collect metadata. Sensitivity analysis methods may be used, depending on the availability of resultant data from several system runs, to fine-tune the values of some metadata attributes and fuzzy parameters. This, however, may need long term studies in real distance learning environments.

The second factor which affects the reliability of the TADV student modelling mechanisms is the sole dependence on the students' interactions with the system and students' performance at quizzes to assess the knowledge. The other potential sources for learning (e.g. reading the course topics using text book, solving quizzes from other references and supplementary material, etc.) are not considered in judging the students' knowledge. This may mislead the system's beliefs about the students' knowledge. A potential solution for this problem can be achieved through employing concepts of open and interactive student modelling (Dimitrova, 2003; Paiva & Self, 1994; Zapata-Rivera

& Greer, 2001). The main goal of open student modelling is to deal with the dynamics and inaccuracies of student models. To a degree this is related to dealing with the uncertainty in diagnosing students, which is the case in this thesis. By opening and externalising student models to students and/or teachers it is possible to promote reflection, interactive assessment, and collaborative creation of student models (Zapata-Rivera & Greer, 2001). Accordingly, one possible route to enhance the reliability of the TADV student modelling mechanisms is to study how to use the new concepts of opening and externalising student models within the TADV student modelling mechanisms to enable improving the reliability of the TADV student models, taking into account the students' view and, most importantly, to provide students with control over both their learning and the system's adaptivity.

Adding visualisation of student knowledge status

One of the features TADV offers to teachers while they are viewing the generated advice to individual students, groups, or classes is the possibility to view the knowledge status of individual students, groups, or the class. As mentioned in Section 6.5.1, this can be accomplished through a link named "View Knowledge Status" located in the screen used to display the advice to the teachers. In the current version, TADV presents the knowledge status in a simple tabular form (as shown in Figure 6.13) which categorises the course concepts according to their learning states. We have to acknowledge that this type of presentation is not the optimum type because it does not effectively help the teacher to identify the causal effects of, for example, the unlearned concepts on the other related concepts. This shows the need for a more informative and supportive way to present knowledge status. Moreover, as discussed earlier, we plan to use ideas such as externalising student modelling by giving the students an active role in the modelling process. In this case, it is important to ensure that both students and teachers will be able to easily understand the models presented. This factor also confirms the need for a significant student model visualisation technique to be employed in the future versions of TADV. Several authors have been working on questions related to find the appropriate kind of representations, e.g. textual, graphical, etc. For example, Zapata-Rivera & Greer (2000) present an integrated tool, called ViSMod, to graphically visualise and inspect distributed Bayesian student models. The authors reported that using ViSMod students can understand, explore, inspect, and modify their models. In line with this work, we would expect the usefulness of using graphical representation to enhance the visualisation of student knowledge status in the TADV as an alternative to the current tabular textual format. Potential future work in this area may include building a visualisation tool to project information derived from

Student Knowledge Model on the concept maps used to describe the relation between course concepts (see Chapter 4). As shown in Figure 8.1, the output of this tool is expected to use different colours to represent the knowledge status of the course concepts existing in the concept map and, accordingly, to facilitate the understanding of the cause-effect relationship among different concepts.

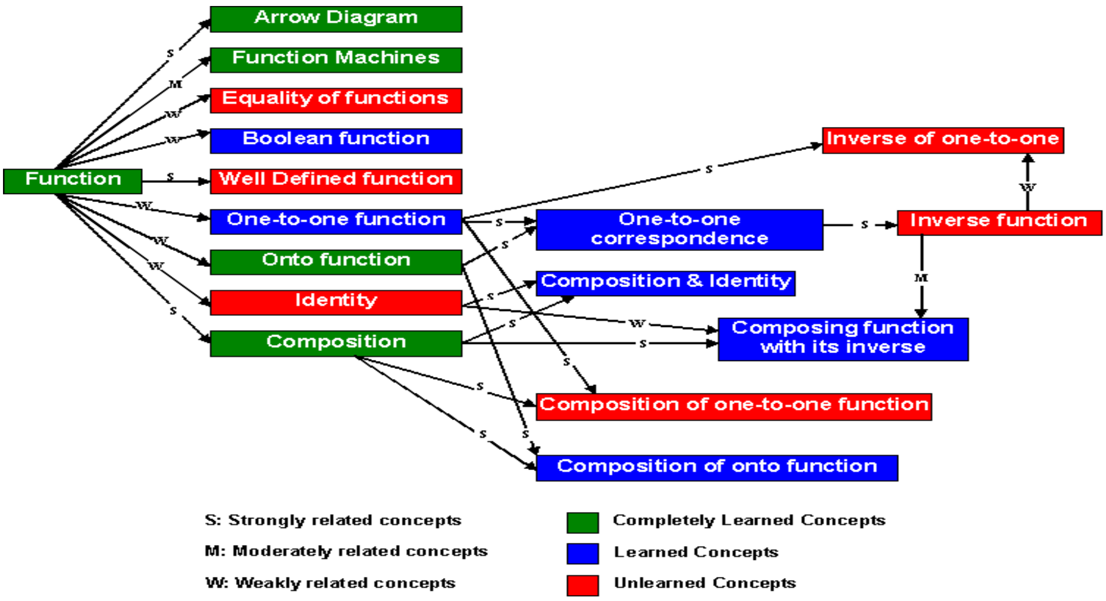


Figure 8.1 Possible output from a tool for visualising student knowledge status that can be integrated in TADV.

8.5.3. Long-term research directions

Studying the effects of advice on the students' behaviour

The work presented in this thesis opened the door for several research questions to emerge. One of these questions is related to student's motivational aspects. More specifically: do students follow the advice sent to them by the facilitators; what changes does this make; and does it affect the students' motivation and meta-cognition? To answer these questions, long-term research is required to examine the link between the TADV advising features and methods for improving the student’s motivation (de Vicente & Pain, 2002; del Soldato & du Boulay, 1995) and meta-cognition (Chi et al., 1989; Conati & VanLehn, 2000).

Another question has emerged: are there any relations between the students' learning styles and effective advising? Learning styles are the different ways students follow to gain learning. For example, a serialist student would concentrate on small, direct concept linkages, and a holist student who would prefer to inter-relate further and wider issues into a more complex view (Arshad et al., 1995; Pask, 1976). There are other classifications of learning styles, e.g. Impulsive/Reflective (Arshad et al., 1995; Kagan, 1965), or Convergent/Divergent styles (Arshad et al., 1995; Hudson, 1966). An interesting research point, for example, is how to adapt the TADV advising features according to the student's learning style. This will require studies of effective advising and student's learning style.

Exploring more general and cultural-based advice taxonomy

The study conducted to evaluate TADV (presented in Chapter 7) has shown the usefulness of the TADV framework for teachers and students. One of the important factors that affects the usefulness of the system is the types of advice that constitute the advice taxonomy used. The more appropriate the advice types are and the more important problems they highlight to the teachers, the more useful and beneficial the advice generation approach will be. The advice taxonomy proposed in this thesis is based on a limited study including both a review of related literature and interviews with several distance learning teachers with some experience in teaching using WCMS environments. This taxonomy described in Chapter 5 may not be considered as the most comprehensive and general advice taxonomy. However, this taxonomy gives a general model for advice generating which may facilitate capturing of more advice types. Accordingly, one possible long-term research direction emerging from this thesis is to develop a more general and comprehensive advice taxonomy based on the one proposed here. The new taxonomy should be based on extensive studies that consider large numbers of distant teachers with considerable experience in this type of teaching and educational specialists with academic and research experience in this field.

It is worthwhile for the new taxonomy to consider improving the pedagogical actions recommended by the system with different advice types. In the taxonomy proposed in this thesis, there are many advice situations, especially at a class level (Type-3) in which the system is not able to recommend the best feedback to the student and the action is left for the teachers' decision. Based on large-scale studies, it is possible to identify more pedagogical actions accepted by many teachers. Considering this issue would help in the formalisation of an improved and fairly complete taxonomy which, in turn, may increase the effectiveness of the advising features.

An important outcome that emerged from the TADV evaluation is the obvious relation between the appropriateness of the advice type and some cultural aspects of the participating students (e.g. the advice related to the social behaviour). Therefore, further studies are required to more deeply consider those cultural aspects that may affect the structure of the advice taxonomy. It is necessary for the taxonomy to include different types of advice that cope with different groups of students from different cultures. Some cultural aspects may be reflected in the phrasing (language) of the advice templates. For example, in some cultures it may be useful for the advice to motivate and encourage the students, while in other cultures advice may be more useful when it gives the students the impression that they are being continuously supervised and guided by their teachers.

And finally, we have started this work with the view that providing help and advising teachers is an important factor in the creation of more effective Web-based distance education environments. We have argued in favour of integrating intelligent techniques within such environments, more specifically, those maintained with Web course management systems. The variety of aspects we needed to study and the knowledge we gained in several theoretical areas made our work on this dissertation an exciting research endeavour. We believe that future research on intelligent Web course management systems will benefit from the formalisation described in this thesis. Potential extension and practical application of the work presented in this thesis has already been considered in AASTOLP and will enable extensive, long-term studies of the potential of our approach. Furthermore, recent discussions with researchers involved in the PROLEARN EU Network of excellence and with university teachers using the MOODLE course management system within the Edukalibre project have highlighted the need for providing intelligent tools to support teachers to manage on-line classes. The TADV framework was considered as a valuable contribution in that direction.

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Appendix A

Domain Meta-Knowledge Detailed Specifications

This appendix presents the detailed specifications of the entities included in the data model of the domain meta-knowledge base. The Appendix includes:

- Figure A.1 shows the Crow's foot notations used to draw data models presented through this thesis.
- Figure A.2 shows the proposed data model of domain meta-knowledge.
- Tables from A.1 to A.14 show the attributes proposed in each entity along with their descriptions and specifications. The abbreviations O, Q, D are used to denote learning **O**bjects, assessment **Q**uizzes, and communication activities (**D**iscussion forums) respectively.

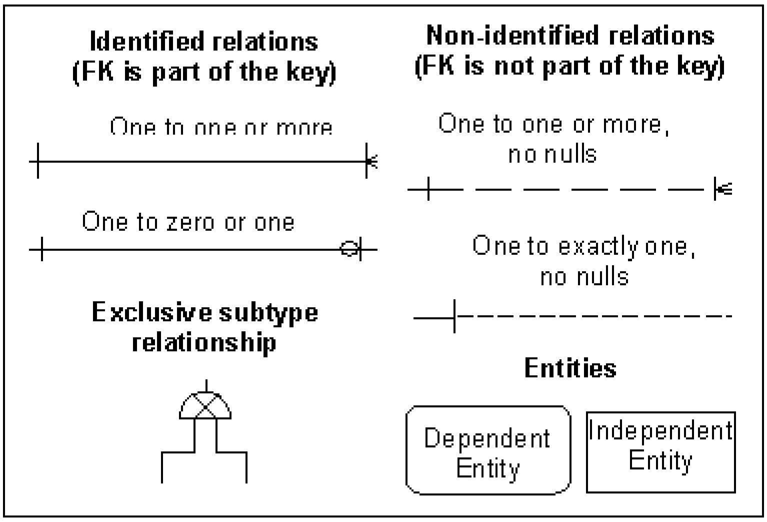

Figure A.1 Crow's foot notations used for drawing data models.

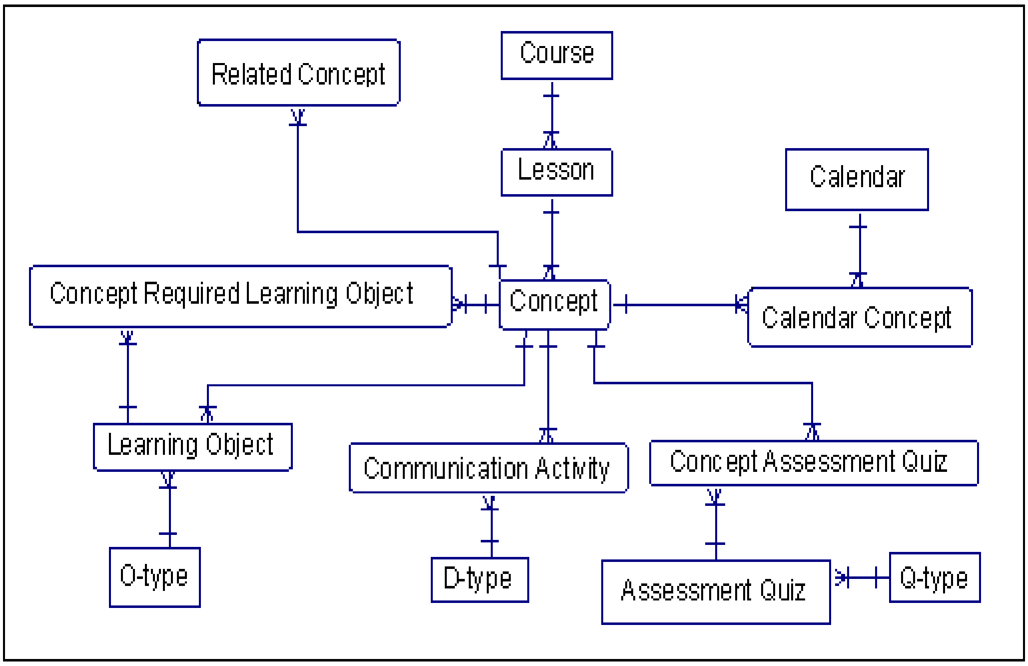

Figure A.2 Data model of the proposed Domain Meta-Knowledge.

Table A.1 Specifications of "COURSE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**COURSE-ID**	Course Identification code	Char	5	Primary Key
2	**COURSE-NAME**	Course Name	Char	100	
3	**COURSE-DESC**	Course short Description	Char	500	
4	**COURSE-OBJ**	Course objectives and goals	Char	1000	
5	**START-DATE**	Course start date	date		
6	**END-DATE**	Course end date	date		

Table A.2 Specifications of "LESSON" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**LESSON-ID**	Lesson identification			Primary Key
1.1	COURSE-ID	Course Identification code	Char	5	Exists in COURSE
1.2	LESSON-NO	Lesson number	Char	5	
2	**LESSON-NAME**	LESSON Name	Char	100	
3	**LESSON-DESC**	Lesson short Description	Char	500	
4	**LESSON-OBJ**	Lesson objectives and goals	Char	1000	

Table A.3 Specifications of "CONCEPT" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CONCEPT-ID**	Concept Identification			Primary Key
1.1	LESSON-ID	Lesson identification	Char	10	Exists in LESSON
1.2	CONCEPT-NO	Concept number	Char	5	
2	**CONCEPT-NAME**	Concept name	Char	100	
3	**CONCEPT-DESC**	Concept short description	Char	1000	
4	**CONCEPT-WEIGHT**	The weight of the concept in relation to the other concepts of the course.	Int	2	The sum of all concept weights is 100.

Table A.4 Specifications of "RELATED-CONCEPT" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**R-CONCEPTS**				Primary key
1.1	CONCEPT-ID1	1st Concept identification	Char	15	Exists in CONCEPT
1.2	CONCEPT-ID2	2nd concept identification	Char	15	Exists in CONCEPT
2	**R-TYPE**	Type of relation between the concept and the second one.	Char	1	‘S’: Strong ’M’: Moderate ‘W’: Weak

Table A.5 Specifications of "CALENDAR" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CAL-ENTRY-NO**	Calendar entry serial number	char	5	Primary key
2	**CAL-ENTRY-DESC**	Calendar entry description. The calendar entry should be defined to the interval dedicated for studying a group of concepts.	Char	100	Example: First period, second period, or first week, second week, etc.
3	**CAL-ENTRY-START-DATE**	The interval start date	Date		
4	**CAL-ENTRY-END-DATE**	The interval end date	Date		

Table A.6 Specifications of "CALENDAR-CONCEPT" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CALENDAR-CONCEPT**	Calendar entry serial number			Primary key
1.1	CAL-ENTRY-NO	Calendar entry number	Char	5	Exists in CALENDAR
1.2	CONCEPT-ID	The identification of a concept belonging to the group of concepts dedicated in the interval defined for CAL-ENTRY-NO.	Char	15	Exists in CONCEPT
2	**CONCEPT-START-DATE**	The concept interval start date	Date		Valid within the interval defined for CAL-ENTRY-NO.
3	**CONCEPT-END-DATE**	The concept interval end date	Date		Valid within the interval defined for CAL-ENTRY-NO.

Table A.7 Specifications of "Q-TYPE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**Q-TYPE-ID**	Assessment quiz type identification	Char	2	Primary key
2	**Q-TYPE-DESC**	The description of Assessment quiz type	Char	50	

Table A.8 Specifications of "ASSESSMENT-QUIZ" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**Q-ID**	Assessment quiz identification			Primary key
1.1	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.2	Q-NO	Assessment quiz number	Char	5	Quiz serial no.
2	**Q-NAME**	The name of assessment quiz	Char	100	
3	**Q-TYPE-ID**	The type of the quiz	Char	2	Exists in Q-TYPE
4	**Q-CORRECT-MB**	The measure of belief that the student has understood the concept when he correctly solves this assessment.	Dec	(3,2)	Ranges from 0 to 1
5	**Q-WRONG-MD**	The measure of disbelief that student has understood the concept when he erroneously solves this assessment.	Dec	(3,2)	Ranges from 0 to 1
6	**Q-NO-MD**	The measure of disbelief that student has understood the concept when he did not solve this assessment.	Dec	(3,2)	Ranges from 0 to 1

Table A.9 Specifications of "CONCEPT-ASSESSMENT-QUIZ" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**C-Q-ID**	Concept-Q identification			Primary key
1.1	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.2	Q-NO	Assessment quiz number	Char	5	Quiz serial no.

Table A.10 Specifications of "D-TYPE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**D-TYPE-ID**	Communication activity type identification	Char	2	Primary key
2	**D-TYPE-DESC**	The description of communication activity type	Char	50	

Table A.11 Specifications of "COMMUNICATION-ACTIVITY" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**D-ID**	Communication activity identification			Primary key
1.1	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.2	D-NO	Communication activity number	Char	5	Communication activity serial no.
2	**D-NAME**	The name of Communication activity	Char	100	
3	**D-TYPE-ID**	The type of Communication activity	Char	2	Exists in D-TYPE

Table A.12 Specifications of "O-TYPE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**O-TYPE-ID**	Learning object type identification	Char	2	Primary key
2	**O-TYPE-DESC**	The description of the learning object type	Char	50	

Table A.13 Specifications of "CONCEPT-REQUIRED-LEARNING-OBJECT" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CRO-ID**	The identification of the required learning objects of a concept.			Primary key
1.1	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.2	SER-NO	Serial no.	Char	5	
2	O-NO	Learning object serial no.	Char	5	Exists in LEARNING-OBJECT
3	**CONNECTOR**	Type of the connector	Char	3	OR, AND, …

Table A.14 Specifications of "LEARNING-OBJECT" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**O-ID**	Learning object unique identification			Primary key
1.1	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.2	O-NO	Learning object serial no.	Char	5	
2	**IDENTIFIER**	Global unique label See IEEE 1484.12.1-2002			IEEE LOM General category
2.1	CATALOG	Cataloging scheme See IEEE 1484.12.1-2002	Char	1000	IEEE LOM General category
2.2	ENTRY	Value within cataloging scheme See IEEE 1484.12.1-2002	Char	1000	IEEE LOM General category
3	**TITLE**	Name given to O See IEEE 1484.12.1-2002	Char	1000	IEEE LOM General category
4	**DESCRIPTION**	A textual description of the O contents. See IEEE 1484.12.1-2002	Char	2000	IEEE LOM General category
5	**KEYWORD**	A Keyword describing the topic of this O. See IEEE 1484.12.1-2002	Char	1000	IEEE LOM General category
6	**FORMAT**	Technical data type of O. See IEEE 1484.12.1-2002	Char	500	IEEE LOM technical category
7	**SIZE**	The size of O in bytes See IEEE 1484.12.1-2002	Char	30	IEEE LOM technical category

Table A.14 Specifications of "LEARNING-OBJECT" Table (Cont'd).

No.	Attribute	Description	Type	Size	Validation / Notes
8	**LOCATION**	A string that used to access the O. See IEEE 1484.12.1-2002	Char	1000	IEEE LOM Technical category
9	**REQUIREMENT**	The technical capabilities necessary for using this O. See IEEE 1484.12.1-2002	Char	300	IEEE LOM Technical category
10	**O-TYPE-ID**	Specific type of Learning Object. (This attribute is equivalent to LEARNING RESOURCE TYPE specified in IEEE LOM, Educational category)	Char	2	Exists in O-TYPE
11	**DIFFICULTY**	How hard it is to work with or through this O. Vocabulary enumerated See IEEE 1484.12.1-2002	Char	2	IEEE LOM Educational category
12	**O-FILE-NAME**	The name of the file that contains the learning object	Char	100	
13	**T-MIN**	The minimum time required for the system to consider that student has started the visit to this O.	Int	2	Time in minutes
14	**TYPICAL-LEARNING-TIME-INTERVAL**	Approximate or typical time interval it takes to work with or through this O.			This attribute replaces the TYPICAL-LEARNING-TIME attribute mentioned in IEEE LOM.
14.1	T1	The lower limit of the typical learning time interval.	Int	2	Time in minutes Greater than MIN-T
14.2	T2	The upper limit of the typical learning time interval.	Int	2	Time in minutes Greater than T1
15	**T-MAX**	The time after which there is no impact for the time on the understanding measure of belief.	Int	2	Time in minutes Greater than O-T2
16	**MB**	The measure of belief assigned during T1:T2 time interval.	Dec	(3,2)	Ranges from 0 to 1
17	**MBMAX**	The measure of belief assigned at T-MAX.	Dec	(3,2)	Ranges from 0 to 1
18	**MD**	the measure of disbelief assigned when there is no visits to the chunk K.	Dec	(3,2)	Ranges from 0 to 1

Appendix B

Student, Group, and Class Models Detailed Specifications

This appendix presents the detailed specifications of the entities included in the data model of the student, group, and class models. The Appendix includes:

- Figure B.1 shows the proposed data model of individual student, group, and class models (see Appendix-A for the notations used).
- Tables from B.1 to B.14 show the attributes proposed in each entity along with their descriptions and specifications.

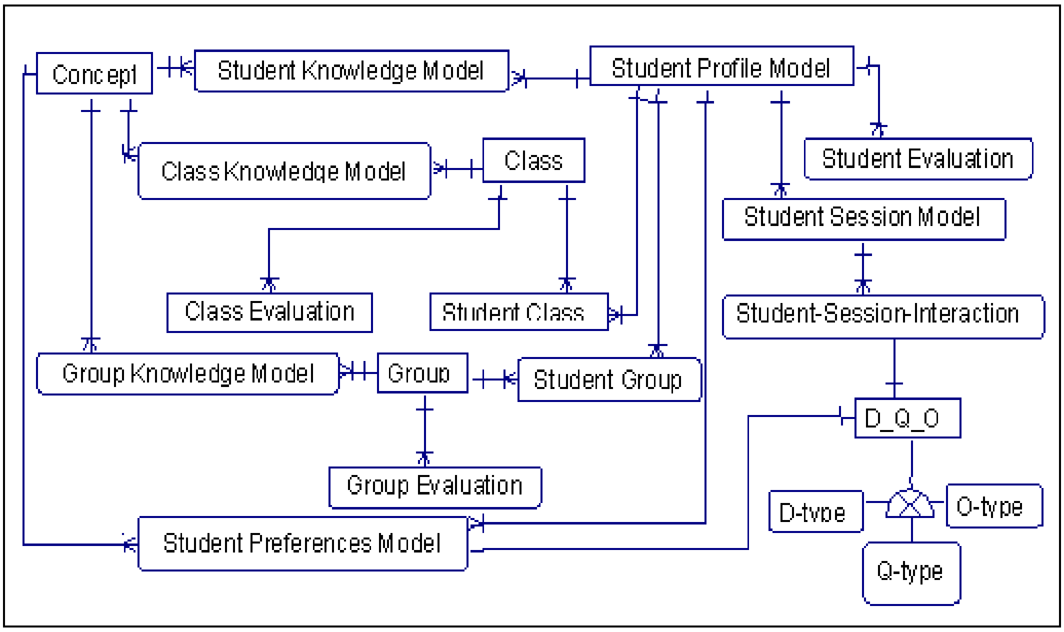

Figure B.1 Data Model of Student, Group, and Class models.

Table B.1 Specifications of "STUDENT PROFILE MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**STUDENT-ID**	Student Identification number	Char	5	Primary Key
2	**STUDENT-NAME**	Student full name			
2.1	FIRST-NAME	Student's first name	Char	25	
2.2	MIDDLE-NAME	Student's middle name	Char	25	
2.3	LAST-NAME	Student's last name	Char	25	
3	**STUDENT-NATIONALITY**	Student's nationality	Char		
4	**STUDENT-SEX**	Student gender	Char	1	M: Male F: Female
5	**STUDENT-BIRTH-DATE**	Student's date of birth	Date		
6	**STUDENT-ADDRESS**	Student's address of residence (post address)			
6.1	STREET-ADDRESS	Student's street address	Char	50	
6.2	CITY-AREACODE	Student's city or area code	Char	50	
6.3	COUNTRY	Student's country of residence	Char		
7	**STUDENT-PHONE**	Student's phone number	Char		
8	**STUDENT-FAX**	Student's fax number	Char		
9	**STUDENT-EMAIL**	Student's email address	Char	100	
10	**STUDENT-GSSG**	Student's General Secondary School Grade	Dec	(5,2)	percentage
11	**STUDENT-FDG**	Student's first degree grade	Dec	(3,2)	For students who already finished their first university degree.
12	**STUDENT-GPA**	Student's current General Point Average.	Dec	(3,2)	For University students
13	**STUDENT-PREF**	Up to what level student prefers the type of the course that he will study in distance.	Char	1	P: Prefer N: Neutral D: Dislike

Table B.2 Specifications of "STUDENT SESSION MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**SESSION-ID**	Session identification			Primary Key
1.1	STUDENT-ID	Student Identification number	Char	5	Exist in SPM
1.2	SESSION-NO	Session serial number	Char	5	
2	**SESSION-DATE**	Session's date	Date		
3	**SESSION-START-TIME**	Session's start time	Time		
4	**SESSION-END-TIME**	Session's end time	Time		

Table B.3 Specifications of "STUDENT-SESSION-INTERACTION" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**INTERACTION-ID**	Interaction identification			Primary Key
1.1	SESSION-ID	Session Identification number	Char	10	Exists in SSM
1.2	INTERACTION-NO	Interaction serial number	Char	5	
2	**INTERACTION-TYPE**	To which type of knowledge this interaction was made	Char	2	'O': Learning Object 'D' Communication Activity 'Q': Assessment quiz
3	**INTERACTED-ITEM**	The identification of the learning object, assessment quiz, or communication activity interacted by this interaction.	Char	20	Foreign Key from LEARNING-OBJECT, ASSESSMENT-QUIZ, or COMMUNICATION-ACTIVITY
4	**INTERACTION-ACTIVITY**	Describes student activity during this interaction	Char	2	In O case: 'RT': Reading Text 'RE': Reading Example, etc. In D case: 'PO': Posting 'RE': Replay, etc. In Q case: 'MC': solving multiple choice quiz 'TF': solving True/false quiz, etc.
5	**INTERACTION-SCORE**	Describes the student's answer (correct/wrong) in the case of assessment quiz.	BOL	1	Has value only case of INTERACTION-TYPE= 'Q'
6	**INTERACTION-ELAPSED-TIME**	The time spent by the student in this interaction	Dec	(5,2)	

Table B.4 Specifications of "STUDENT KNOWLEDGE MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**SKM-ID**	SKM identification			Primary Key
1.1	STUDENT-ID	Student identification	Char	5	Exists in SPM
1.2	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
2	**SKM-MB**	Aggregate measure of belief that the student understands the concept.	Dec	(3,2)	Ranges from 0 to 1
3	**SKM-MD**	Aggregate measure of disbelief that the student understands the concept.	Dec	(3,2)	Ranges from 0 to 1

Table B.5 Specifications of "STUDENT EVALUATION" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**SEVAL-ID**	Student evaluation identification			Primary Key
1.1	STUDENT-ID	Student identification	Char	5	Exists in SPM
1.2	SEVAL-DATE	Date and time of evaluation	Char		
2	**WAVG-CERTAINTY-FACTOR**	Weighted average of student's concepts understanding certainty factors.	Dec	(3,2)	Ranges from -1 to 1
3	**ACC-COMM-INTERACTIONS**	Accumulated communication interactions	Int	5	

Table B.6 Specifications of "STUDENT PREFERENCES MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**PREFERENCE-ID**	Student's preference identification			Primary Key
1.1	STUDENT-ID	Student identification	Char	5	Exists in SPM
1.2	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
1.3	PREFERENCE-TYPE-ID	The identification of the preference type.	Char	2	Exists in O-TYPE, Q-TYPE, or D-TYPE.
2	**PREFERENCE-NO-OF-HITS**	The number of times in which student use this type of preference in dealing with the specified concept.	Int	5	

Table B.7 Specifications of "GROUP" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GROUP-ID**	The identification of a group of the students	Char	5	Primary Key
2	**GROUP-DESC**	Group description	Char	1000	
3	**GROUP-KEYWORD**	A keyword that best defines the group.	Char	25	

Table B.8 Specifications of "STUDENT GROUP" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**STUDENT-GROUP-ID**	Identify student belonging to a certain group			Primary Key
1.1	GROUP-ID	Group identification	Char	5	
1.2	STUDENT-ID	Student Identification	Char	5	

Table B.9 Specifications of "GROUP KNOWLEDGE MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GKM-ID**	GKM identification			Primary Key
1.1	GROUP-ID	Group identification	Char	5	Exists in GROUP
1.2	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
2	**GKM-MB**	Aggregate measure of belief that the group understands the concept.	Dec	(3,2)	Ranges from 0 to 1
3	**GKM-MD**	Aggregate measure of disbelief that the group understands the concept.	Dec	(3,2)	Ranges from 0 to 1

Table B.10 Specifications of "GROUP EVALUATION" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GEVAL-ID**	Group evaluation identification			Primary Key
1.1	GROUP-ID	Group identification	Char	5	Exists in GROUP
1.2	GEVAL-DATE	Date and time of evaluation	Char		
2	**GAVG-CERTAINTY-FACTOR**	The average concepts understanding certainty factors of the students in the group.	Dec	(3,2)	Ranges from -1 to 1
3	**GACC-COMM-INTERACTIONS**	Group accumulated communication interactions	Int	5	

Table B.11 Specifications of "CLASS" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CLASS-ID**	The identification of a class of the students	Char	5	Primary Key
2	**CLASS-DESC**	Class description	Char	1000	
3	**CLASS-KEYWORD**	A keyword that best defines the class.	Char	25	

Table B.12 Specifications of "STUDENT CLASS" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**STUDENT-CLASS-ID**	Identify student belonging to a certain class.			Primary Key
1.1	**CLASS-ID**	Group identification	Char	5	
1.2	**STUDENT-ID**	Student Identification	Char	5	

Table B.13 Specifications of "CLASS KNOWLEDGE MODEL" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CKM-ID**	GKM identification			Primary Key
1.1	CLASS-ID	Group identification	Char	5	Exists in CLASS
1.2	CONCEPT-ID	Concept identification	Char	15	Exists in CONCEPT
2	**CKM-MB**	Aggregate measure of belief that the class understands the concept.	Dec	(3,2)	Ranges from 0 to 1
3	**CKM-MD**	Aggregate measure of disbelief that the class understands the concept.	Dec	(3,2)	Ranges from 0 to 1

Table B.14 Specifications of "CLASS EVALUATION" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**CEVAL-ID**	Class evaluation identification			Primary Key
1.1	CLASS-ID	Group identification	Char	5	Exists in GROUP
1.2	CEVAL-DATE	Date and time of evaluation	Char		
2	**CAVG-CERTAINTY-FACTOR**	The average concepts understanding certainty factors of the all students in the class.	Dec	(3,2)	Ranges from -1 to 1
3	**CACC-COMM-INTERACTIONS**	Class accumulated communication interactions	Int	5	

Appendix C

The Proposed Advice Types and Subtypes

This appendix presents the complete list of the proposed advice types and subtypes (the taxonomy of advice types). The notations used to describe advice types are defined in details in Chapter 5. The Appendix includes:

- Table C.1, which shows the proposed Type-1 advice
- Table C.2, which shows the proposed Type-2 advice.
- Table C.3, which shows the proposed Type-3 advice.

Table C.1 Type-1 Advice (generated about individual students).

Advice Type	Stimulating Evidence (E)	Investigated Reasons (R)	Advice from TADV to Facilitator (A)	Recommended advice from facilitator to the student (T)	IMP.	Next AG Action
1-1-1	**(S, c_b, UL)**	*(c_b, learning objects and/or assessment quizzes are not activated by the student S)*	Student S should be advised to work on the available learning objects and assessment quizzes related to c_b	In order for you to understand c_b we suggest you refer to its available learning objects and solve related assessment quizzes.	VI	Look for new stimulating evidence
1-1-2		*(c_a, Strong, UL)*	Student S should be advised to study c_a	In order for you to master c_b, it is highly recommended to study c_a first.	VI	Look for new stimulating evidence
1-1-3		*(c_a, Moderate, UL)*	It may be useful to advise student S to study c_a	In order for you to master c_b, it may be useful to study c_a first.	I	Look for other reasons
1-1-4		*(c_a, Strong, L)*	Student S should be advised to work more with concept c_a	In order for you to master c_b, it is preferred to work more on c_a.	VI	Look for other reasons
1-1-5		*(c_a, Weak, UL)*	It might be useful to advise student S to study c_a	In order for you to master c_b, it might be useful to study c_a.	I	Look for other reasons
1-1-6		*(c_b, Uncommunicative or normally communicated)*	Student S should be encouraged to participate effectively in the communication activities related to c_b. Students $\{S_1, S_2, S_3\}$ are communicative and have already mastered concept c_b	We note that you did not participate effectively in the c_b discussion forum. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact S_1, S_2 or S_3 to discuss c_b.	I	Look for new stimulating evidence
1-1-7		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is unlearned by student S, TADV is unable to find the reason. It might be useful to talk directly with the student and discuss the problem.	Facilitator should take the necessary actions	VI	Look for new stimulating evidence
1-1-8	**(S, c_b, L)**	*(c_b, some learning objects and/or assessment quizzes are not activated by the student S)*	Student S should be advised to complete his/her work on the available learning objects and assessment quizzes related to concept c_b	In order for you to completely understand c_b we suggest you refer to its available learning objects and solve related assessment quizzes.	I	Look for new stimulating evidence
1-1-9		*(c_a, Strong, UL)*	Student S should be advised to study c_a	In order for you to completely understand c_b, we suggest you study c_a first.	I	Look for new stimulating evidence
1-1-10		*(c_a, Moderate, UL)*	It may be useful to advise student S to study c_a	In order for you to completely master c_b, it is preferred to study c_a first.	I	Look for other reasons
1-1-11		*(c_a, Strong, L)*	Student S should be advised to work more on c_a	In order for you to completely master c_b, it is preferred to work more on c_a	I	Look for other reasons
1-1-12		*(c_b, Uncommunicative or normally communicated)*	Student S should be encouraged to participate effectively in the communication	We note that you did not participate effectively in the c_b discussion forum. It	I	Look for new stimulating

			activities related to c_b. Students {S_1, S_2, S_3} are communicative and have already mastered concept c_b	might be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact S_1, S_2 or S_3 to discuss c_b.		evidence
1-1-13		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is moderately learned by the student *S*; TADV is unable to find the reason. If necessary, talk directly with the student and discuss the problem.	Facilitator should take the necessary actions)	LI	Look for new stimulating evidence
1-2	**Student *S* does not start study concept c_a on the time specified by course calendar.**	*(S, c_a, Delayed)*	Student S is delayed in studying concept c_a, he should be advised to start studying this concept.	You are delayed in studying the topic of c_a, you should start work on this topic as soon as possible. Take care time is going.	VI	Look for new stimulating evidence
1-3-1 **1-3-2** **1-3-3**	**Weak student**	*(S, Weak)*	Student *S* is evaluated by TADV as Weak and uncommunicative. Student *S* is evaluated by TADV as Weak and normally communicative. Student *S* is evaluated by TADV as Weak and highly communicative.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
1-4-1 **1-4-2** **1-4-3**	**Excellent student**	*(S, Excellent)*	Student *S* is evaluated by TADV as Excellent and uncommunicative. Student *S* is evaluated by TADV as Excellent and normally communicative. Student *S* is evaluated by TADV as Excellent and highly communicative.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
1-5	**Student did not start the course**	*(S, Did not start the course)*	Student *S* has not started course yet	You have not started the course yet. You should start the course as soon as possible	VI	Look for new stimulating evidence

Table C.2 Type-2 Advice (generated about groups of students).

Advice Type	Stimulating Evidence (E)	Investigated Reasons (R)	Advice from TADV to Facilitator (A)	Recommended advice from facilitator to the student (T)	IMP.	Next AG Action
2-1-1	**(G, c_b, UL)**	*(c_b, learning objects and/or assessment quizzes are not activated by all or some of the group G members)*	G members should be advised to work on the available learning objects and assessment quizzes related to c_b	c_b appears to be a common problem for students in G. For those students who do not start working with c_b, please refer to its available learning objects and solve related assessment quizzes.	VI	Look for new stimulating evidence
2-1-2		*(c_a, Strong, UL)*	G members should be advised to study c_a	c_b appears to be a common problem for students in G. For those students who do not master c_a, it is highly recommended to study the perquisite c_a first.	VI	Look for new stimulating evidence
2-1-3		*(c_a, Moderate, UL)*	It may be useful to advise G members to study concept c_a	c_b appears to be a common problem for students in G. For those students who do not master c_a, it may be useful to study the perquisite c_a first.	I	Look for other reasons
2-1-4		*(c_a, Strong, L)*	G members should be advised to work more with concept c_a	c_b appears to be a common problem for students in G. It is preferred to work more on c_a.	VI	Look for other reasons
2-1-5		*(c_a, Weak, UL)*	It might be useful to advise G members to study c_a	c_b appears to be a common problem for students in G. It might be useful to study c_a	I	Look for other reasons
2-1-6		*(c_b, Uncommunicative or normally communicated)*	G members should be encouraged to participate effectively in the communication activities related to c_b.	We note that some students of G members did not participate effectively in the c_b discussion forum. It is recommended to participate together in c_b discussion forum. You can post your questions there.	I	Look for new stimulating evidence
2-1-7		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is unlearned by group G, TADV is unable to find the reason. It might be useful to talk directly with the student and discuss the problem.	Facilitator should take the necessary actions)	VI	Look for new stimulating evidence
2-1-8	**(G, c_b, L)**	*(c_b, some learning objects and/or assessment quizzes are not activated by all or some of the group G members)*	G members should be advised to complete their work on the available learning objects and assessment quizzes related to concept c_b	c_b is not completely mastered by G members. For those who do not complete work on c_b, please read its available learning objects and solve related assessment quizzes.	I	Look for new stimulating evidence
2-1-9		*((c_a, Strong, UL)*	G members should be advised to study c_a	c_b is not completely mastered by G members. The perquisite c_a is not	I	Look for new stimulating

				mastered by *G* members. For those who did not study c_a, it is highly recommended to study and master c_a first.		evidence
2-1-10		*(c_a, Moderate, UL)*	It may be useful to advise G members to study c_a	c_b is not completely mastered by *G* members. The perquisite c_a is not mastered by *G* members. For those who did not study c_a, it is suggested to study and master c_a first.	I	Look for other reasons
2-1-11		*(c_a, Strong, L)*	It might be useful to advise *G* members to work more on c_a	c_b is not completely mastered by *G* members. The perquisite c_a is also not completely mastered by *G* members. For those who did not completely mastered c_a, it might be useful to work more on c_a	LI	Look for other reasons
2-1-12		*(c_b, Uncommunicative or normally communicated)*	It might be useful to encourage *G* members to participate more effectively in the communication activities related to c_b.	We note that some students of *G* members did not participate effectively in the c_b discussion forum. It might be useful to participate together in c_b discussion forum. You can post your questions there.	LI	Look for new stimulating evidence
2-1-13		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is moderately learned by *G* members; TADV is unable to find the reason. If necessary, talk directly with the student and discuss the problem.	Facilitator should take the necessary actions.	I	Look for new stimulating evidence
2-2	**Weak Group**	*(G, Weak)*	Group *G* is evaluated by TADV as Weak and uncommunicative group. Group *G* is evaluated by TADV as Weak and normally communicative group. Group *G* is evaluated by TADV as Weak and highly communicative group.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
2-3	**Excellent Group**	*(G, Excellent)*	Group *G* is evaluated by TADV as Excellent and highly communicative group. Groups *G* is evaluated by TADV as Excellent and normally communicative group. Groups *G* is evaluated by TADV as Excellent and uncommunicative group.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
2-4	**Most of the group members did not start the course**	*(G, Most of group G members Did not start the course)*	TADV can not evaluate group Group1 because most of its members have not started course yet	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence

Table C.3 Type-3 Advice (generated about class of students).

Advice Type	Stimulating Evidence (E)	Investigated Reasons (R)	Advice from TADV to Facilitator (A)	Recommended advice from facilitator to the student (T)	IMP.	Next AG Action
3-1-1	**(C, c_b, UL)**	*(c_b, learning objects and/or assessment quizzes are not activated by all or some of the class C members)*	c_b appears to be a common problem for students in C. It seams that most of them does not visit learning objects and assessment quizzes related to c_b.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
3-1-2		*(c_a, Strong, UL)*	c_b appears to be a common problem for students in C. The perquisite c_a is not mastered by the class members. It is highly recommended to advise class members to study c_a	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
3-1-3		*(c_a, Moderate, UL)*	c_b appears to be a common problem for students in C. The perquisite c_a is not mastered by the class members. It may be useful to advise class members to study c_a	Facilitator should take the necessary actions.	I	Look for other reasons
3-1-4		*(c_a, Strong, L)*	c_b appears to be a common problem for students in C. The perquisite c_a is not completely mastered by the class members. It might be useful to advise class members to study c_a	Facilitator should take the necessary actions.	I	Look for other reasons
3-1-5		*(c_b, Uncommunicative or normally communicated)*	c_b appears to be a common problem for students in C. TADV notes that class members are not participated effectively in the c_b discussion forum. C members should be encouraged to participate effectively in the communication activities related to c_b.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
3-1-6		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is "Unlearned" by class C, TADV is unable to find the reason. It might be useful to talk directly with the student and discuss the problem.	Facilitator should take the necessary actions.	VI	Look for new stimulating evidence
3-1-7	**(C, c_b, L)**	*(c_b, learning objects and/or assessment quizzes are not activated by all or some of the class C members)*	c_b is not completely mastered by class C. It seams that some students do not complete working on the learning objects and assessment quizzes related to c_b.	Facilitator should take the necessary actions.	I	Look for new stimulating evidence
3-1-8		*(c_a, Strong, UL)*	c_b is not completely mastered by class C. The perquisite c_a is not mastered by the class members. It is recommended to advise class members to study c_a first.	Facilitator should take the necessary actions.	I	Look for new stimulating evidence

3-1-9		*(c_a, Moderate, UL)*	c_b appears to be a common problem for students in *C*. The perquisite c_a is not mastered by the class members. It might be useful to advise class members to study c_a	Facilitator should take the necessary actions.	I	Look for other reasons
3-1-10		*(c_a, Strong, L)*	c_b appears to be a common problem for students in *C*. The perquisite c_a is not completely mastered by the class members. It is preferred to advise class members to study c_a	Facilitator should take the necessary actions.	LI	Look for other reasons
3-1-11		*(c_b, Uncommunicative or normally communicated)*	It might be useful to encourage *C* members to participate more effectively in the communication activities related to c_b.	Facilitator should take the necessary actions.	LI	Look for new stimulating evidence
3-1-12		TADV cannot investigate about the reasons behind this stimulating evidence.	Concept c_b is moderately learned by *C* members; TADV is unable to find the reason. If necessary, talk directly with the student and discuss the problem.	Facilitator should take the necessary actions.	I	Look for new stimulating evidence
3-2	Excellent and Weak students relative to the class	*(C, Excellent & Weak Students relative to the class)*	Students S_1, S_2, and S_3 are the most Excellent students relative to the whole class, while Students S_4, S_5, and S_6 are the weakest students.	Facilitator should take the necessary actions.	VI	NA
3-3	Most comm. and most uncomm. Students relative to the class.	*(C, Highly communicative and uncommunicative students relative to the class)*	Relative to the whole class, students S_1, S_2, and S_3 are the top highly communicative students while Students S_4, S_5, and S_6 are the most uncommunicative students.	Facilitator should take the necessary actions.	VI	NA
3-4	Most active and most inactive students.	*(C, Most active and inactive students relative to the whole class)*	Students S_1, S_2, and S_3 are the most active students relative to the whole class, while Students S_4, S_5, and S_6 are the most inactive students.	Facilitator should take the necessary actions.	VI	NA
3-5	Most of the class *C* members does not start the course	*(C, Most of the student did not start the course)*	TADV can not evaluate class *C* because most of its students have not started course yet.	Facilitator should take the necessary actions.	VI	NA

Appendix D

Advice Generation Data Model Detailed Specifications

This appendix presents the detailed specifications of the entities included in the data model of the advice generation module. The Appendix includes:

- Figure D.1, which shows the proposed data model of advice generation (see Appendix-A for the notations used).
- Tables from D.1 to D.9 that show the attributes proposed in each entity along with their descriptions and specifications.

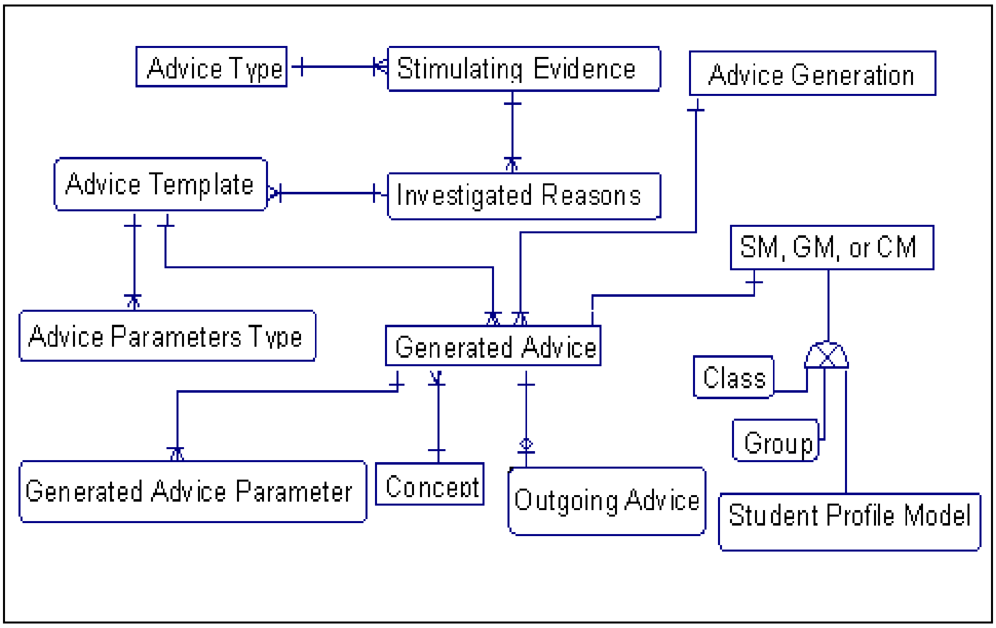

Figure D.1 Advice Generation Data Model.

Table D.1 Specifications of "ADVICE TYPE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**ADVICE-ID**	Advice Identification			Primary Key
1.1	ADVICE-TYPE	Student, group, or class advice	Int	2	
1.2	ADVICE-SUBTYPE	The advice number in the main type (e.g., 1-1, 1-2,..)	Int	2	
2	**ADVICE-DESC**	Advice description	Char	250	
3	**ADVICE-STATUS**	Suppressed or not	Int	2	1: To Appear 2: Suppressed

Table D.2 Specifications of "STIMULATING EVIDENCE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**EVIDENCE-ID**	Evidence Identification			Primary Key
1.1	ADVICE-ID	Advice Identification			Exists in ADVICE TYPE
1.2	EVIDENCE-NO	Serial number assigned to the evidence	Int	2	
2	**EVIDENCE-DESC**	Evidence description e.g., (***S***, ***c_b***, ***UL***)	Char	100	

Table D.3 Specifications of "INVESTIGATED REASONS" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**REASON-ID**	Reason Identification			Primary Key
1.1	EVIDENCE-ID	Evidence Identification			Exists in STIMULATING EVIDENCE
1.2	REASON-NO	Serial number assigned to the reason	Int	2	
2	**REASON-DESC**	Reason description e.g., (c_b, c_a, Strong) and (S, c_a, UL)	Char	100	

Table D.4 Specifications of "ADVICE TEMPLATE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**TEMPLATE-ID**	Template Identification			Primary Key
1.1	REASON-ID	Reason Identification			Exists in INVESTIGATED REASONS
1.2	TEMPLATE-DESTINATION	To facilitator or student	Int	2	1: To Facilitator 2: To Student
2	**TEMPLATE-MSG**	Message	Char	500	

Table D.5 Specifications of "ADVICE PARAMETERS TYPE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**PARAMETER-ID**	Parameter Identification			Primary Key
1.1	TEMPLATE-ID	Template Identification			Exists in ADVICE TEMPLATE
1.2	PARAMETER-SER	The serial number assigned to the parameter inside the template.	Int	2	
2	**PARAMETER-TYPE**	The Type of data carried by the parameter	Int	2	1: Concept 2: Student name 3: Group name 4: Class name

Table D.6 Specifications of "ADVICE GENERATION" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GENERATION-SER**	The serial number given to each advice generation execution	Int	4	Primary Key
2	**GENERATION-DATE**	Date of advice generation execution	Datetime	8	

Table D.7 Specifications of "GENERATED ADVICE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GEN-ADVICE-ID**	Generated Advice Identification (serial no.)	Int	8	Primary Key
2	**TEMPLATE-ID**	Template Identification			Exists in ADVICE TEMPLATE
3	**GENERATION-SER**		Int	4	Exists in ADVICE GENERATION
4	**STUDENT-GROUP-CLASS-ID**	Advice is for which student, group or class.	Char	32	
5	**CONCEPT-ID**	The concerned concept	Char	32	
6	**SEND-STATUS**		Int	2	1: SEND 2: DON'T SEND

Table D.8 Specifications of "GENERATED ADVICE PARAMETER" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GEN-ADVICE-PARAMETER-ID**				Primary Key
1.1	GEN-ADVICE-ID	Generated Advice ID			Exists in GENERATED ADVICE
1.2	FACILITATOR-STUDENT	Advice is to the facilitator or to a student			
1.3	PARAMETER-SER	Parameter serial number	Int	2	
2	**PARAMETER-VALUE**	The value carried by the parameter			

Table D.9 Specifications of "OUTGOING ADVICE" Table.

No.	Attribute	Description	Type	Size	Validation / Notes
1	**GEN-ADVICE-ID**				Exists in GENERATED ADVICE
2	**MESSAGE**	The protected advice message to the facilitator or the modifiable recommended advice message to the student, group, or class.	Char	500	

Appendix E

Algorithm for Generating Type-1 Advice

This appendix presents an algorithm to illustrate the process of advice generation. The shown algorithm describes the criteria used by TADV to generate Type-1 advice (see Appendix-C). The algorithm is presented using Decision Tree notation in four parts A, B, C, and D shown in Figures E.1, E.2, E.3, and E.4 respectively. The following abbreviations are used through out the algorithm:

S – Student

c – Concept

CL – Completely Learned   L – Learned   UL – Unlearned concept

HC – Highly Communicative   NC – Normally Communicative

UN – Uncommunicative

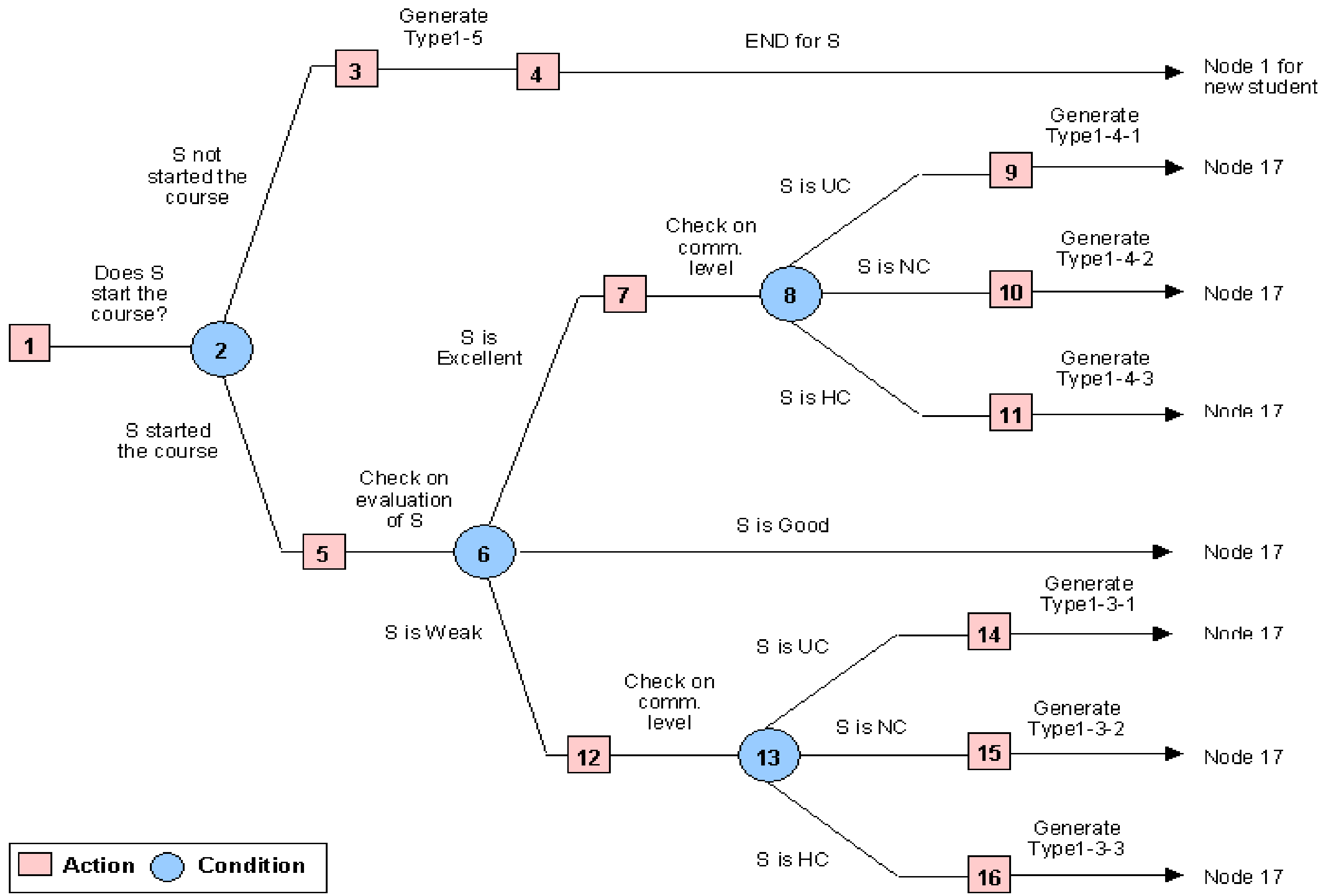

Figure E.1 Algorithm for generating Type-1 Advice (Part A).

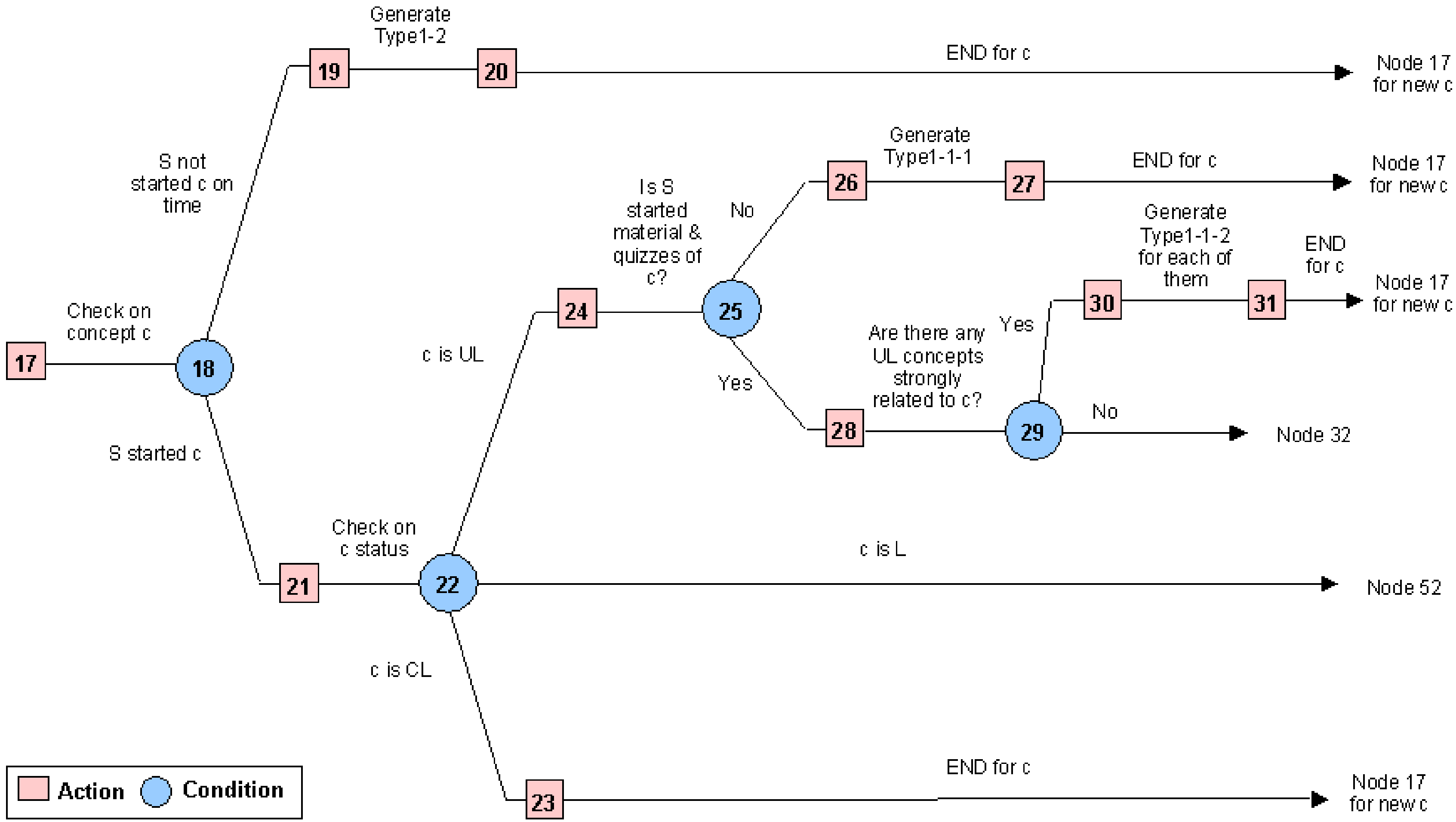

Figure E.2 Algorithm for generating Type-1 Advice (Part B).

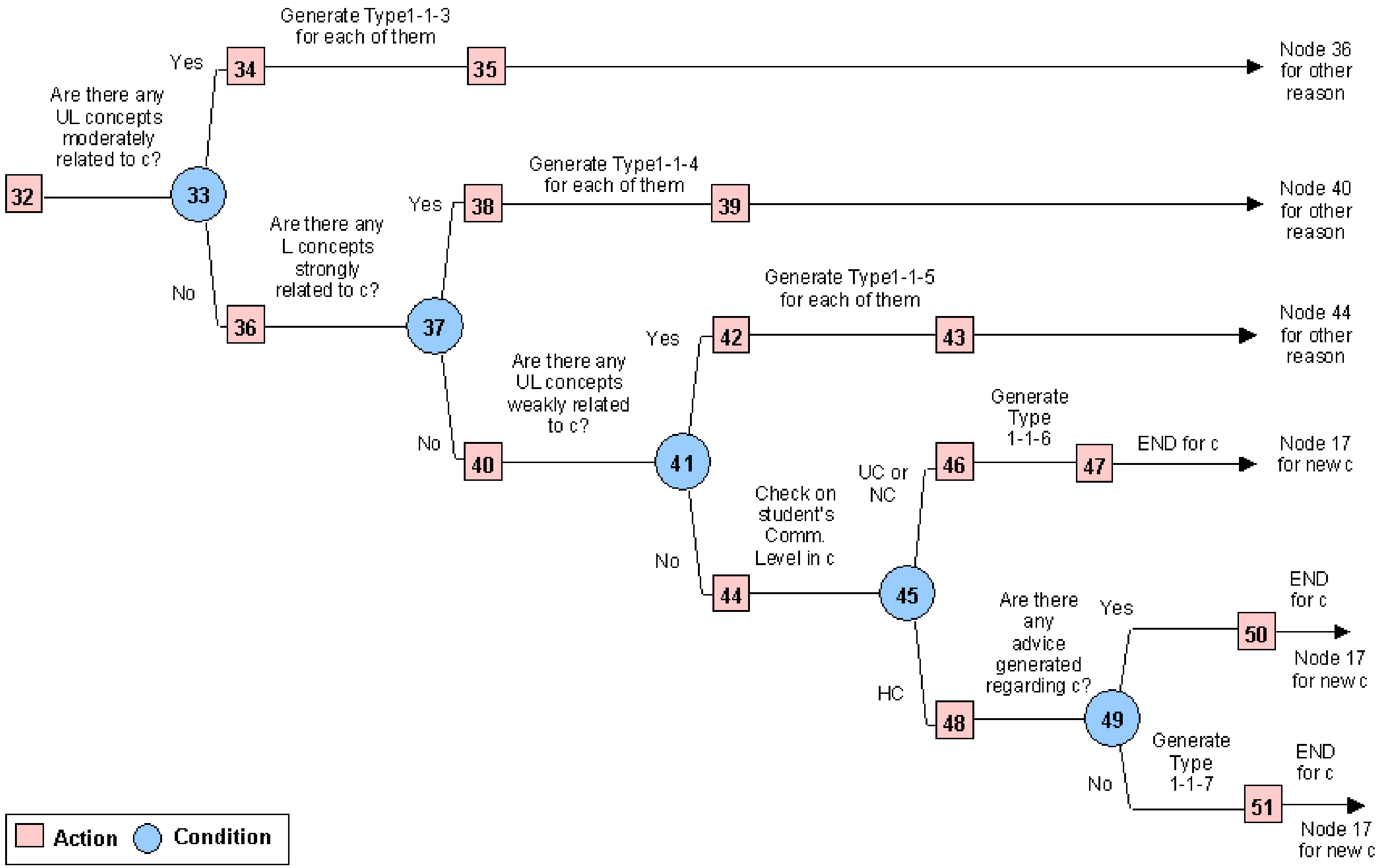

Figure E.3 Algorithm for generating Type-1 Advice (Part C).

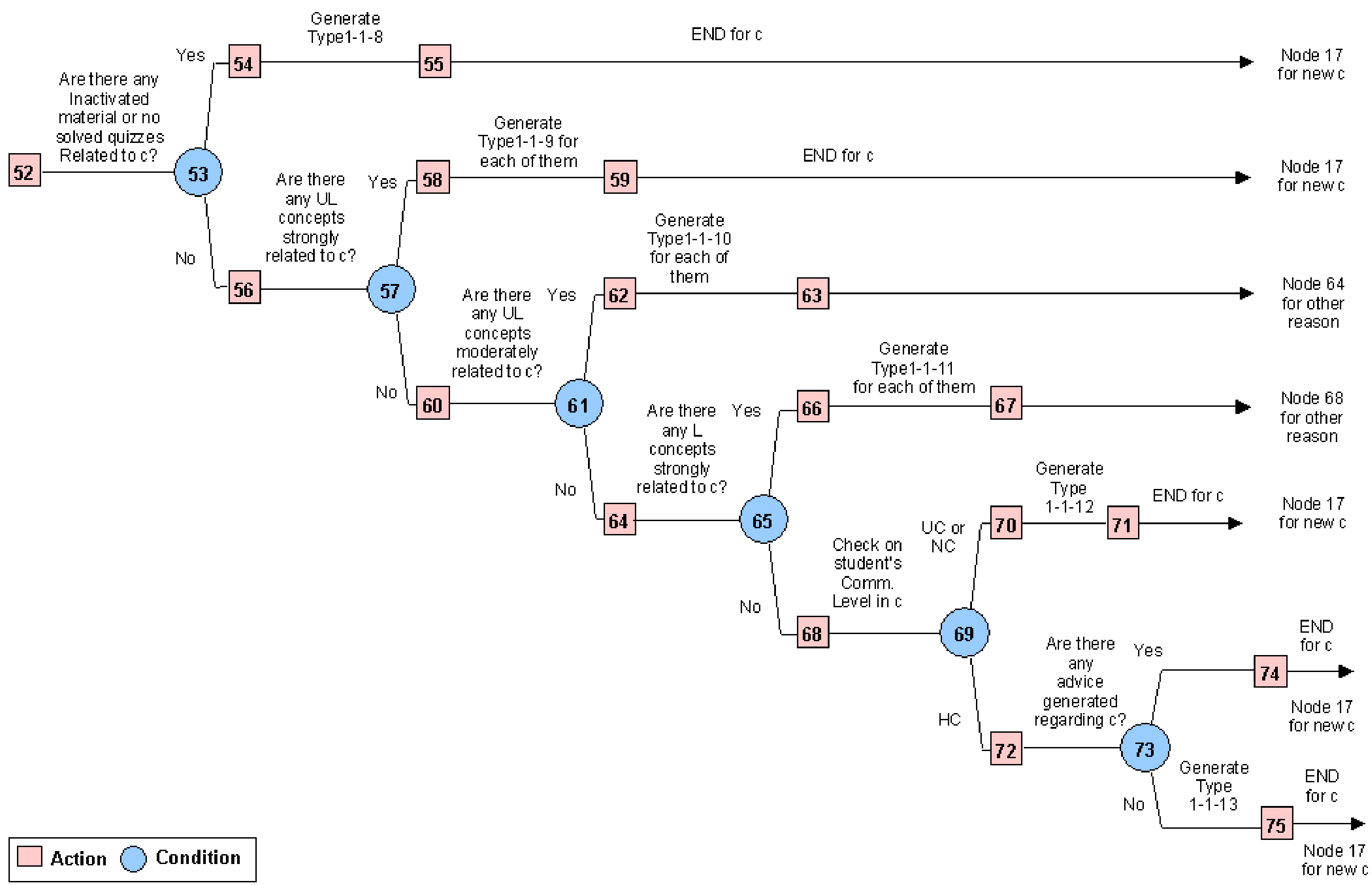

Figure E.4 Algorithm for generating Type-1 Advice (Part D).

Appendix F

Metadata and Course Calendar

This appendix presents samples of the metadata acquired from the domain expert to describe the course concepts and how they are related, the course learning objects, and the assessment quizzes. The Appendix also presents the course calendar prepared by the course teacher. The Appendix includes:

- Table F.1 presents course concept list.
- Figures F.1 and F.2 show the concept map of the functions and relations lessons.
- Table F.2 presents the difficulty levels and weights assigned to course concepts.
- Table F.3 presents sample of the metadata of the course learning objects.
- Table F.4 presents sample of the metadata of the assessment quizzes.
- Table F.5 presents the course calendar.

Note: The symbols used to denote the difficulty levels of the learning object are VE: Very Easy, E: Easy, M: Medium, D: Difficult, and VD: Very Difficult.

Table F.1 The concepts list.

Lesson-1 (Functions)		**Lesson-2 (Relations)**	
C_ID	**Concept name**	**C_ID**	**Concept name**
101	Function	201	Relation
102	Arrow diagram	202	Binary relation
103	Function machine	203	Function and relation
104	Equality of functions	204	Arrow diagram
105	Boolean function	205	Inverse relation
106	Well defined function	206	Binary relation on a set
107	One-to-one function	207	Directed graph
108	Onto function	208	N-ary relation
109	One-to-one correspondence	209	Reflexive Property
110	Inverse function	210	Symmetric property
111	Inverse of one-to-one	211	Transitive property
112	Identity	212	Transitive closure
113	Composition	213	Equivalence relation
114	Composition and identity	214	Relation and set partitions
115	Composing function with its inverse	215	Equivalence class
116	Composing of one-to-one function	216	Anti-symmetric
117	Composing of onto function	217	Partial order relation

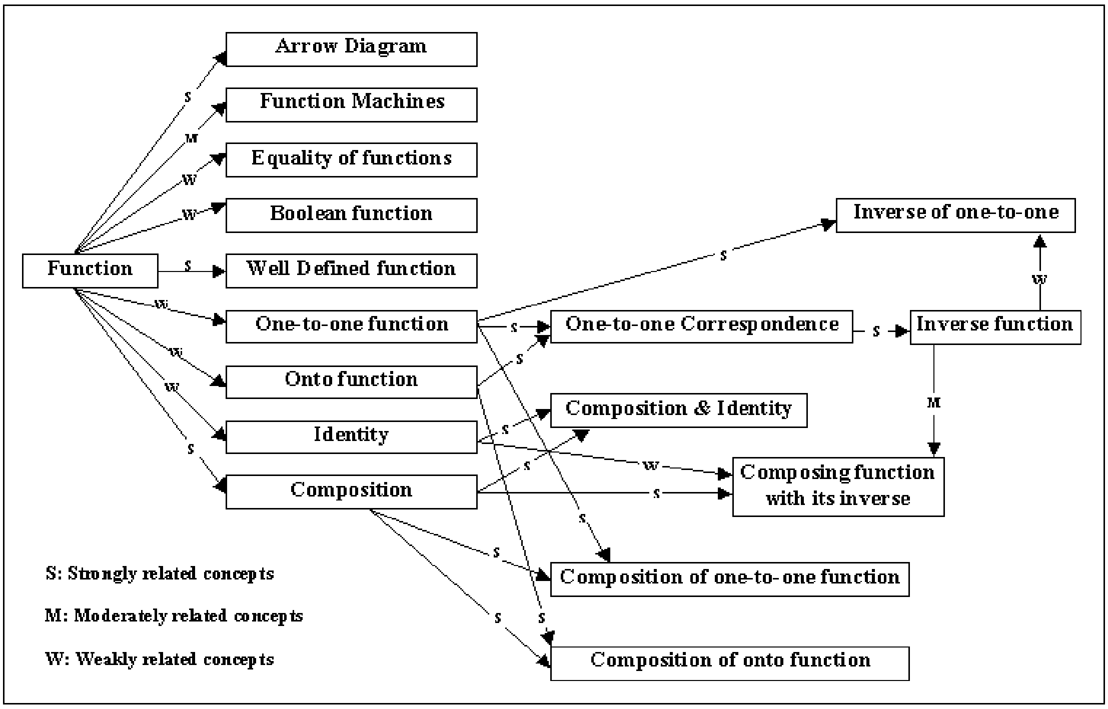

Figure F.1 The concept map of the Functions lesson.

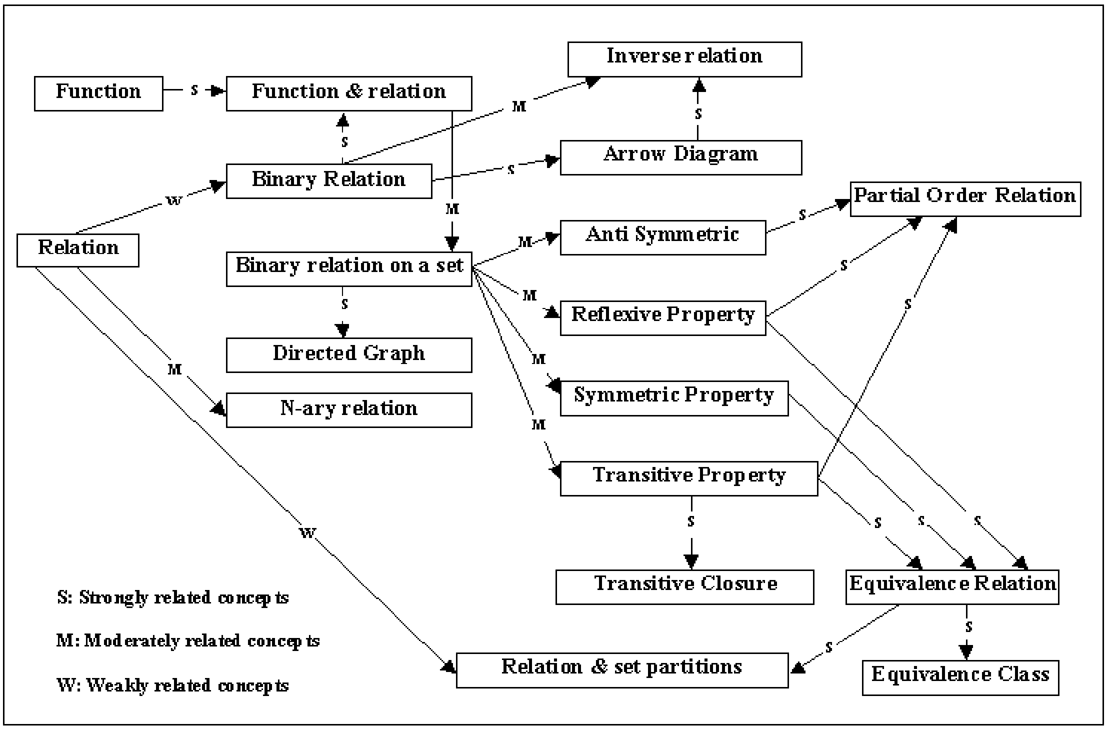

Figure F.2 The concept map of the Relations lesson.

Table F.2 Concepts' weights and difficulty levels.

C_ID	Concept name	Difficulty	Weight
101	Function	M	2.7
102	Arrow diagram	E	1.3
103	Function machine	E	1.3
104	Equality of functions	E	1.3
105	Boolean function	D	4
106	Well defined function	D	4
107	One-to-one function	D	4
108	Onto function	D	4
109	One-to-one correspondence	D	4
110	Inverse function	M	2.7
111	Inverse of one-to-one	M	2.7
112	Identity	M	2.7
113	Composition	M	2.7
114	Composition and identity	D	4
115	Composing function with its inverse	M	2.7
116	Composition of one-to-one function	D	4
117	Composition of onto function	VD	5.3
201	Relation	E	1.3
202	Binary relation	E	1.3
203	Function and relation	M	2.7
204	Arrow diagram	E	1.3
205	Inverse relation	M	2.7
206	Binary relation on a set	E	1.3
207	Directed graph	E	1.3
208	N-ary relation	E	1.3
209	Reflexive Property	M	2.7
210	Symmetric property	M	2.7
211	Transitive property	D	4
212	Transitive closure	D	4
213	Equivalence relation	D	4
214	Relation and set partitions	D	4
215	Equivalence class	D	4
216	Anti-symmetric	M	2.7
217	Partial order relation	VD	5.3
		Total Weights	**100**

Table F.3 Sample of the learning objects metadata.

ID	Concept name / learning object title	Identifier Cat./Entry	Format	Size bytes	page/ Slides	DIFF Level	T1	T2	MB	MD
101	Function									
	101_Function_T	CC318/070101	text/html	28,344	1	M	6	10	0.3	0.1
	101_Function_T	CC318/070102	text/doc	62,464	1	M	6	10	0.3	0.1
	101_Function_T	CC318/070103	Pres/cpf	388,033	5	M	10	15	0.3	0.1
102	Arrow diagram									
	102_Arrow_diagram_T	CC318/070201	text/html	12,346	1	E	4	7	0.3	0.1
	102_Arrow_diagram_T	CC318/070202	text/doc	27,136	1	E	4	7	0.3	0.1
	102_Arrow_diagram_T	CC318/070203	Pres/cpf	221,953	3	E	6	8	0.3	0.1
	102_Arrow_diagram_E1	CC318/070204	text/html	21,129	1	E	5	7	0.4	0.2
	102_Arrow_diagram_E1	CC318/070205	text/doc	33,280	1	E	5	7	0.4	0.2
	102_Arrow_diagram_E1	CC318/070206	Pres/cpf	293,763	7	E	5	8	0.4	0.2
	102_Arrow_diagram_E2	CC318/070207	text/html	11,407	1	E	3	6	0.4	0.2
	102_Arrow_diagram_E2	CC318/070208	text/doc	29,184	1	E	3	6	0.4	0.2
	102_Arrow_diagram_E2	CC318/070209	Pres/cpf	201,282	3	E	3	7	0.4	0.2
	102_Arrow_diagram_E3	CC318/070210	text/html	24,512	1	E	5	7	0.4	0.2
	102_Arrow_diagram_E3	CC318/070211	text/doc	35,840	1	E	5	7	0.4	0.2
	102_Arrow_diagram_E3	CC318/070212	Pres/cpf	182,428	3	E	5	8	0.4	0.2
201	Relation									
	201_Relation_T	CC318/100101	text/html	28,373	3	E	15	20	0.3	0.1
	201_Relation_T	CC318/100102	text/doc	390,144	3	E	15	20	0.3	0.1
	201_Relation_T	CC318/100103	Pres/cpf	432,605	6	E	15	20	0.3	0.1
202	Binary relation									
	202_Binary_Relation_T	CC318/100201	text/html	7,886	1	E	4	6	0.3	0.1
	202_Binary_Relation_T	CC318/100202	text/doc	20,480	1	E	4	6	0.3	0.1
	202_Binary_Relation_T	CC318/100203	Pres/cpf	161,051	1	E	4	6	0.3	0.1
	202_Binary_Relation_E1	CC318/100204	text/html	18,534	2	E	8	10	0.4	0.2
	202_Binary_Relation_E1	CC318/100205	text/doc	32,256	2	E	8	10	0.4	0.2
	202_Binary_Relation_E1	CC318/100206	Pres/cpf	240,281	4	E	10	12	0.4	0.2

Table F.4 Sample of the assessments quizzes metadata.

Assessment name (file name)	Type	Related Concepts	DIFF Level	MBC	MDW	MDN
FUNCTION_ASSESSMENT_01	Multiple Choice	101	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_02	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_03	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_04	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_05	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_06	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_07	Multiple Choice	101, 102, 103	M	0.8	0.4	0.2
FUNCTION_ASSESSMENT_08	Multiple Choice	104	E	0.7	0.5	0.2
FUNCTION_ASSESSMENT_09	Multiple Choice	105	D	0.8	0.3	0.1
FUNCTION_ASSESSMENT_10	Multiple Choice	105	D	0.8	0.3	0.1
RELATION_ASSESSMENT_01	Multiple Choice	203	M	0.8	0.4	0.2
RELATION_ASSESSMENT_02	Multiple Choice	201,202,206	M	0.8	0.4	0.2
RELATION_ASSESSMENT_03	Multiple Choice	201,202,205,206, 208	M	0.8	0.4	0.2
RELATION_ASSESSMENT_04	Multiple Choice	201,202,205,206,208	M	0.8	0.4	0.2
RELATION_ASSESSMENT_05	Multiple Choice	204, 207	E	0.7	0.5	0.2
RELATION_ASSESSMENT_06	Multiple Choice	216	M	0.8	0.4	0.2
RELATION_ASSESSMENT_07	Multiple Choice	216	M	0.8	0.4	0.2
RELATION_ASSESSMENT_08	Multiple Choice	209,210,211	D	0.8	0.3	0.1
RELATION_ASSESSMENT_09	Multiple Choice	209,210,211	D	0.8	0.3	0.1
RELATION_ASSESSMENT_10	Multiple Choice	212	D	0.8	0.3	0.1

Table F.5 The course calendar.

ENTRY NO.	DESCRIPTION	START DATE	END DATE	CONCEPTS & ASSESSMENTS	START DATE	END DATE
W1	1st WEEK	30/11/03	6/12/03			
				101_Function FUNCTION_ASSESSMENT_01	30/11/03	30/11/03
				102_Arrow diagram		
				103_Function machine FUNCTION_ASSESSMENT_02 FUNCTION_ASSESSMENT_03 FUNCTION_ASSESSMENT_04 FUNCTION_ASSESSMENT_05 FUNCTION_ASSESSMENT_06 FUNCTION_ASSESSMENT_07		
				104_Equality of functions FUNCTION_ASSESSMENT_08		
				105_Boolean function FUNCTION_ASSESSMENT_09 FUNCTION_ASSESSMENT_10		
				106_Well defined function FUNCTION_ASSESSMENT_11 FUNCTION_ASSESSMENT_12	1/12/03	1/12/03
				107_One-to-one function FUNCTION_ASSESSMENT_13 FUNCTION_ASSESSMENT_14 FUNCTION_ASSESSMENT_15 FUNCTION_ASSESSMENT_16		
				108_Onto function FUNCTION_ASSESSMENT_17	2/12/03	2/12/03
				109_One-to-one correspondence FUNCTION_ASSESSMENT_28		
				110_Inverse function FUNCTION_ASSESSMENT_31	3/12/03	3/12/03
				111_Inverse of one-to-one		
				112_Identity FUNCTION_ASSESSMENT_18		
				113_Composition FUNCTION_ASSESSMENT_19 FUNCTION_ASSESSMENT_20 FUNCTION_ASSESSMENT_21 FUNCTION_ASSESSMENT_22 FUNCTION_ASSESSMENT_23 FUNCTION_ASSESSMENT_24 FUNCTION_ASSESSMENT_25 FUNCTION_ASSESSMENT_26	4/12/03	4/12/03

				FUNCTION_ASSESSMENT_27 FUNCTION_ASSESSMENT_32 FUNCTION_ASSESSMENT_33 FUNCTION_ASSESSMENT_34		
				114_Composition and identity	5/12/03	5/12/03
				115_Composing function with its inverse FUNCTION_ASSESSMENT_35	6/12/03	6/12/03
				116_Composition of one-to-one function FUNCTION_ASSESSMENT_29		
				117_ Composition of onto function FUNCTION_ASSESSMENT_30		
W2	2nd WEEK	7/12/03	13/12/03			
				201_Relation	7/12/03	7/12/03
				202_Binary relation		
				203_Function and relation RELATION_ASSESSMENT_01		
				204_Arrow diagram	8/12/03	8/12/03
				205_Inverse relation		
				206_Binary relation on a set RELATION_ASSESSMENT_02	9/12/03	9/12/03
				207_Directed graph RELATION_ASSESSMENT_05		
				208_N-ary relation RELATION_ASSESSMENT_03 RELATION_ASSESSMENT_04		
				209_Reflexive Property	10/12/03	10/12/03
				210_Symmetric property		
				211_Transitive property RELATION_ASSESSMENT_08 RELATION_ASSESSMENT_09		
				212_Transitive closure RELATION_ASSESSMENT_10		
				213_Equivalence relation		
				214_Relation and set partitions RELATION_ASSESSMENT_11	11/12/03	11/12/03
				215_Equivalence class RELATION_ASSESSMENT_12		
				216_Anti-symmetric RELATION_ASSESSMENT_06 RELATION_ASSESSMENT_07	12/12/03	12/12/03
				217_Partial order relation RELATION_ASSESSMENT_13 RELATION_ASSESSMENT_14		

Appendix G

Entity Relationship Diagrams

This appendix depicts the Entity Relationship Diagrams (ERDs) which represent the databases designed and implemented to hold the data of domain meta-knowledge, students, groups, and class models, and advice generation model. The Appendix includes:

- Figures G.1 and G.2 show the parts A & B of the ERD of the database designed to hold data of DMK
- Figures G.3, G.4, and G.5 show the parts A, B & C of the ERD of the database designed to hold data of students, groups, and class models.
- Figure G.6 shows the ERD of the database designed to hold data of the advice generation model.

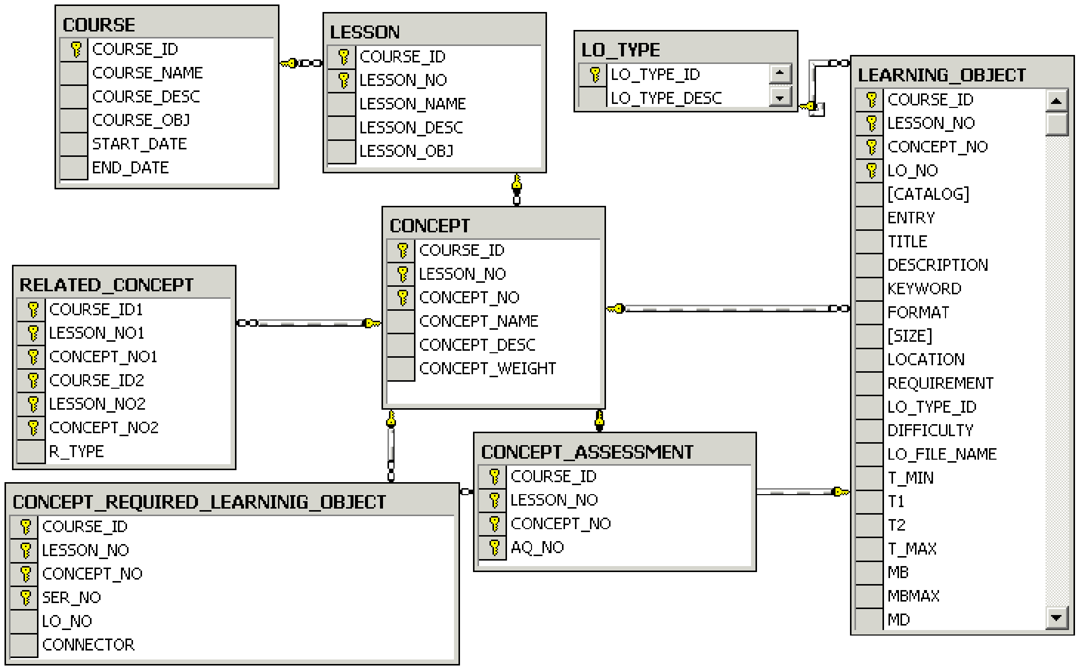

Figure G.1 Domain Meta-Knowledge ERD – Part A.

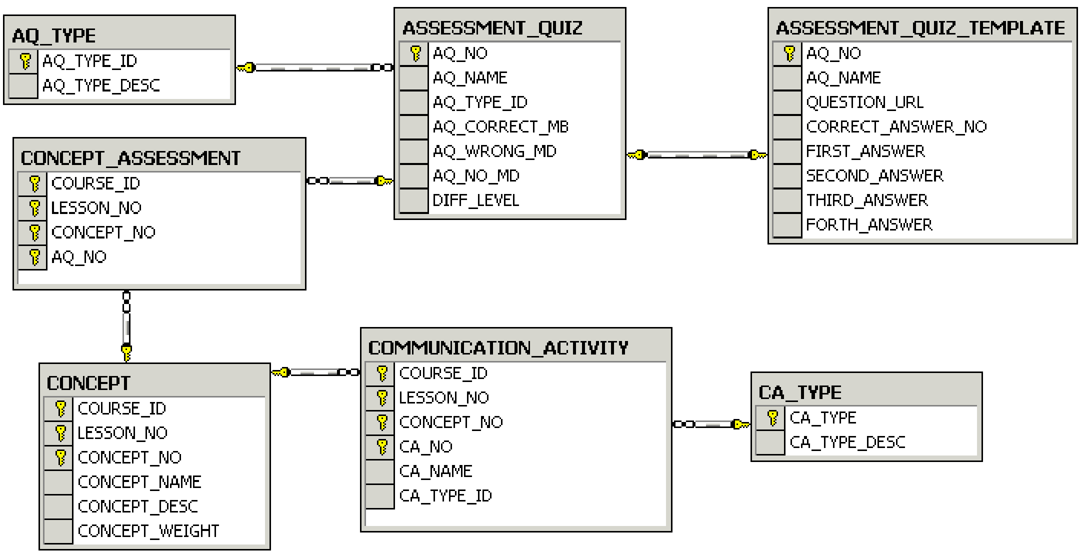

Figure G.2 Domain Meta-Knowledge ERD – Part B.

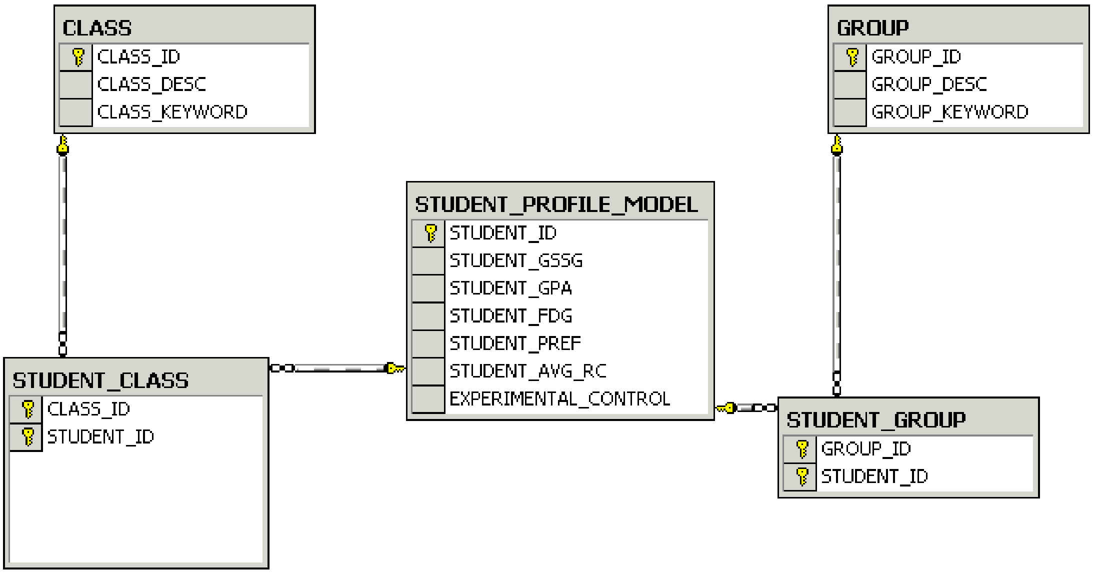

Figure G.3 Student, Group, and Class Models ERD – Part A.

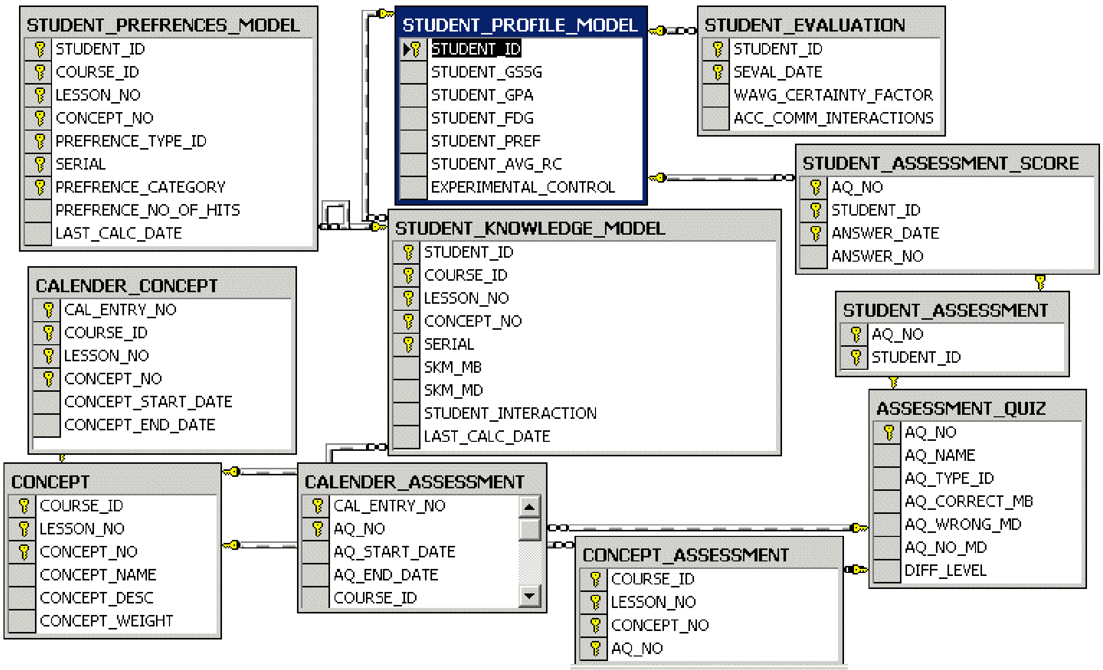

Figure G.4 Student, Group, and Class Models ERD – Part B.

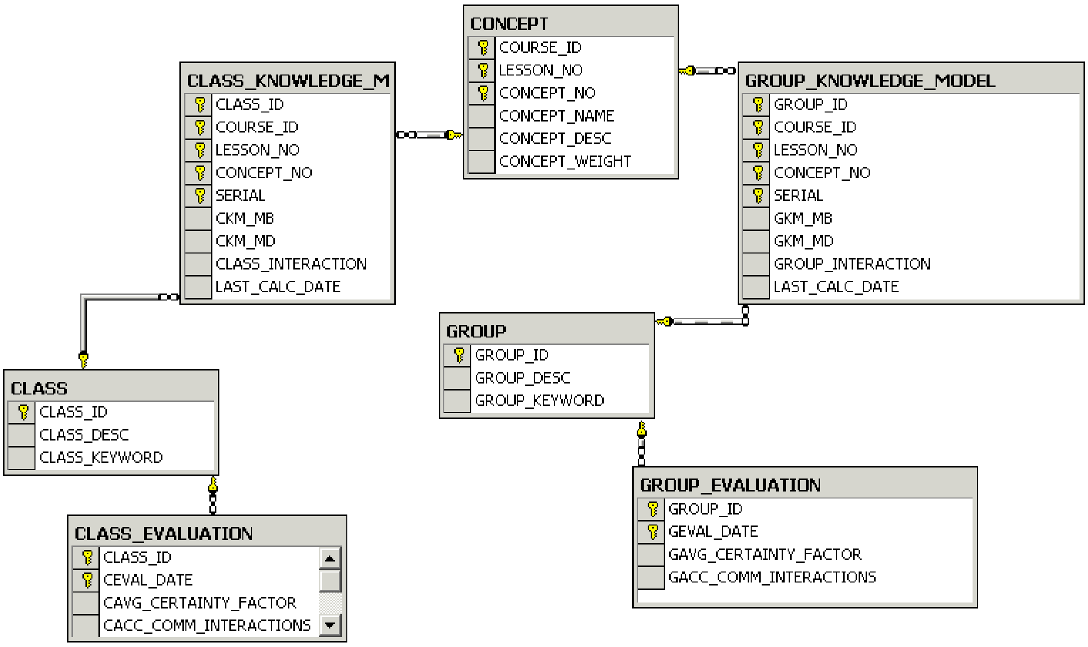

Figure G.5 Student, Group, and Class Models ERD – Part C.

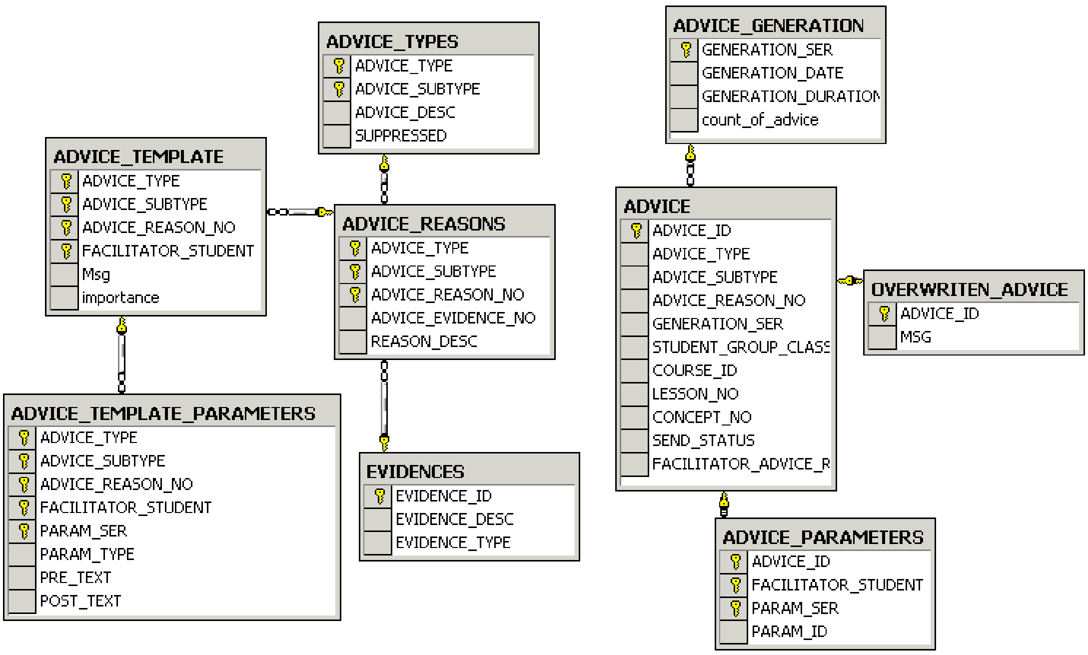

Figure G.6 Advice Generation ERD.

Appendix H

Information about Control and Experimental Groups

This appendix depicts information about the students assigned to control and experimental groups. This information is used to compare between the two groups during the phase of TADV evaluation. The Appendix depicts the following tables:

- Tables H.1 and H.2 show some demographic and academic information about the students in the control (Class-1) and the experimental (Class-2) groups respectively. In these tables the symbol "M" is used to denote Male and "F" to denote Female. Students' ages are computed at 1/12/2003. GPA (General Point Average) is the student's general grade. GPA is calculated by the assessment information system used in AAST registration department. The maximum value of GPA is 4. There are two groups defined within Class-2: Group1- contains two students with high GPA and other two with low GPA. Group2 – contains the non-Egyptian students.
- Tables H.3 and H.4 present information about pre/post test scores for students in Class-1 and Class-2 respectively. Information about students who did not worked on the system is not included. Tables H.3 and H.4 present GPA, Pre-test and post-test scores (out of 100), and learning gains (the differences between post-test and pre-test scores). The average and the standard deviation (SDEV) of each column are presented.

Table H.1 Information about the students of the control group (Class-1).

Student ID	Nationality	Gender	Age	GPA
Student1	Egyptian	M	20.1	3.96
Student2	Egyptian	M	19.75	3.83
Student3	Egyptian	M	19.5	3.63
Student4	Egyptian	M	19	3.33
Student5	Egyptian	M	20.8	3.21
Student6	Egyptian	M	20.8	3.03
Student7	Egyptian	F	20	2.81
Student8	Egyptian	M	19.5	2.59
Student9	Egyptian	M	24.75	2.28
Student10	Jordanian	M	23.5	2.23
Student11	Syrian	M	21.8	2.23
Student12	Egyptian	F	19.5	2.23
Student13	Egyptian	M	24.7	2.12
Student14	Egyptian	M	23	2.07
Student15	Egyptian	M	19.5	1.98
Student16	Egyptian	F	24.1	1.94
Student17	Egyptian	M	20.5	1.87
Student18	Egyptian	M	20.25	1.62
Student19	Saudi	M	22.5	1.6
Student39	Saudi	M	23.8	1.53
		Average	**21.37**	**2.504**
		STDEV	**1.909**	**0.737**

Table H.2 Information about the students of the experimental group (Class-2).

Student ID	Nationality	Gender	Age	GPA	Group
Student20	Egyptian	M	19.5	3.92	Group1
Student21	Egyptian	M	19.8	3.84	Group1
Student22	Egyptian	M	19.8	3.21	
Student23	Egyptian	M	21.75	3.2	
Student24	Egyptian	M	20.3	3.19	
Student25	Egyptian	F	20.3	2.83	
Student26	Egyptian	F	19.4	2.78	
Student27	Egyptian	M	22	2.58	
Student28	Egyptian	M	21.5	2.33	
Student29	Egyptian	M	19.5	2.3	
Student30	Egyptian	M	20.8	2.23	
Student31	Syrian	M	22.25	2.12	Group2
Student32	Egyptian	M	24.1	2.08	
Student33	Egyptian	M	19.8	2.06	
Student34	Egyptian	M	23.1	1.99	Group1
Student35	Egyptian	M	19.7	1.9	Group1
Student36	Palestinian	M	21.25	1.6	Group2
Student37	Sudanese	M	26	1.37	Group2
Student38	Egyptian	F	20.8	2.16	
Student40	Egyptian	M	21	2.3	
		Average	**21.13**	**2.499**	
		STDEV	**1.676**	**0.671**	

Table H.3 Class-1 pre/post-test scores.

Student ID	**GPA**	**Pre-test**	**Post-test**	**Gain**
Student1	3.96	83	90	7
Student2	3.83	77	80	3
Student3	3.63	73	90	17
Student4	3.33	90	90	0
Student5	3.21	87	80	-7
Student7	2.81	77	70	-7
Student8	2.59	73	70	-3
Student10	2.23	37	75	38
Student11	2.23	87	85	-2
Student12	2.23	63	50	-13
Student14	2.07	73	30	-43
Student17	1.87	27	65	38
Student18	1.62	63	55	-8
Student19	1.6	23	30	7
Student39	1.53	50	55	5
Average	**2.583**	**65.533**	**67.667**	**2.133**
SDEV	**0.832**	**21.742**	**20.077**	**19.701**

Table H.4 Class-2 pre/post-test scores.

Student ID	**GPA**	**Pre-test**	**Post-test**	**Gain**
Student20	3.92	80	75	-5
Student21	3.84	90	80	-10
Student22	3.21	90	70	-20
Student23	3.2	57	90	33
Student28	2.33	77	55	-22
Student29	2.3	77	80	3
Student30	2.23	77	55	-22
Student32	2.08	67	75	8
Student33	2.06	70	60	-10
Student34	1.99	13	90	77
Student35	1.9	60	90	30
Student36	1.6	30	30	0
Student37	1.37	37	65	28
Student38	2.16	70	60	-10
Student40	2.3	43	80	37
Average	**2.433**	**62.533**	**70.333**	**7.800**
SDEV	**0.761**	**22.608**	**16.526**	**27.934**

Appendix I

Students Questionnaire

This appendix depicts a copy of the questionnaire submitted to the students participated in the experimental study. This questionnaire is used to evaluate the effects of TADV on the participated students. Its main aim is to compare between the responses collected from the students in control group (students in Class-1 who used TADV without advising features) and students in the experimental group (students in Class-2 who used TADV with advising features). There are six different parts in the questionnaire. Each part contains a number of open and closed questions. Table I.1 shows the names of the different parts and the numbers and types of the questions in each part.

Table I.1 Number and type of questions in the questionnaire parts.

No.	Part Name	Open Questions	Closed Questions	Total
1	Student's general information	0	6	6
2	Student's interaction information	0	6	6
3	Course information (how student evaluate the course)	2	4	6
4	Advising and feedback information (how student evaluate the advising features)	4	6	10
5	Social information	1	5	6
6	Student's overall satisfaction	1	8	9
Total No. of questions in the questionnaire		**8**	**35**	**43**

The same questionnaire is used to collect responses from students in both groups except that part four (advising and feedback information) is required only from students in the experimental group (Class-2) and therefore it was not included in the questionnaire submitted to students in the control group (Class-1).

TEACHER ADVISOR (TADV) PROJECT

DISCRETE MATHEMATICS COURSE

STUDENT QUESTIONNAIRE

INSTRUCTIONS

Please respond to all items in the all parts.

In all questions please circle only one choice unless otherwise specified.

Through out this questionnaire, the word "course" always refers to the web-based Discrete Mathematics course (Functions and Relations lessons).

Facilitator is the teacher who supervised you during the course period.

PART 1: GENERAL INFORMATION

Q1- My Gender is

a) Male
b) Female

Q2- My secondary school was

a) Governmental Arabic school with English as an additional language
b) English private school
c) IGCSE or American Diploma
d) Other ________________________________ (Please specify)

Q3- Rate your previous experience with numeric and mathematics courses:

a) Excellent
b) Good
c) Fair
d) Poor

Q4- Rate your previous experience with the subject of Discrete Mathematics:

a) Excellent
b) Good
c) Fair
d) Poor

Q5- Rate your Internet skills:

a) Excellent (You have used the Internet for more than two years more or less on a daily base)
b) Good (You have used the Internet for just six months more or less on a daily base)
c) Fair (You have used the Internet for just six months but not on a regular base)
d) Poor (You are not completely familiar with the Internet)

Q6- Have you participated before in any Web-based online distance courses?

a) Yes
b) No

PART 2: INTERACTION INFORMATION

Q7- I did found it easy to learn how to deal with the course using TADV features

a) Strongly agree
b) Agree
c) Do not know
d) Disagree
e) Strongly disagree

Q8- I have accessed the course most frequently from

a) Home
b) Academy's laboratories and/or cyber café
c) Other ______________________________ (Please specify)

Q9- The connection speed to the Internet on the computer from which I have frequently accessed the course is

a) Very slow
b) Slow
c) Do not know
d) Fast
e) Very fast

Q10- I have experienced technical difficulties with the course (please specify if any)

a) Not at all
b) Few
c) I do not know
d) Frequently
e) Too much

Q11- The time I spent on the web site of this course during a week is approximately

a) One hour or less
b) One to two hours
c) Two to three hours
d) Three to four hours
e) More than four hours

Q12- Specify roughly the percentage of time you have spent in each of the following tasks during your interaction with the course

a) Reading learning objects and solving assessment quizzes [%]
b) Opening learning object just to print it [%]
c) Trying to know how the system works [%]
d) Reviewing feedback and help information coming from the facilitator [%]
e) Other tasks [%]

PART 3: COURSE INFORMATION

Q13- Do you feel that you learnt about "Functions" and "Relations" of the Discrete Mathematics course from using TADV?

a) Nothing
b) Some things learnt
c) Do not know
d) I feel that I learnt most of the material
e) I feel that I learnt the material and I am very confident now

Q14- For me, one hour working with this course is more valuable than one hour of lectures

a) Agree
b) Do not know
c) Disagree

Q15- Would you like to use TADV with other courses? (Please specify reasons)

a) Yes
b) Do not know
c) No

Q16- Did you find the TADV interface easy to use? (Please specify reasons)

a) Not at all
b) Some what easy
c) Do not know

d) Easy
e) Very easy

Q17- What do you like in particular about TADV?

Q18- Is there anything you found frustrating with using TADV?

PART 4: ADVISING AND FEEDBACK INFORMATION

Q19- I have started my sessions usually by checking the incoming feedback and help information from facilitator

a) Agree
b) Disagree

Q20- Did you find advice and help messages useful? (Specify the reasons)

a) Not helpful at all
b) Somehow helpful
c) Do not know
d) Helpful
e) Very helpful

Q21- Please specify examples for useful and helpful type of advice you have received from TADV (in other words, advice that you have followed)

Q22- It was interesting to know how my work in the course was continuously evaluated by TADV and the facilitator

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q23- The details in the advice and in the feedback messages are appropriate?

a) Yes
b) Do not know
c) No

Q24- During the course period, I felt that I was constantly guided by the facilitator

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree

e) Strongly agree

Q25- The availability of the advice and help information reduced the need to frequently contact the facilitator with questions

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q26- Is there anything you found surprising about the TADV advising part? Please specify

Q27- Is there anything you found frustrating about the TADV advising part? Please specify

Q28- How can the advising part of the system be improved for you?

PART 5: SOCIAL INFORMATION

Q29- How quickly did you respond to e-mails related to this course?

a) Never responded
b) Responded with some delay
c) Immediately

Q30- The amount of contact/interaction with the other students in the course is

a) Less than what I needed
b) Close to what I needed
c) More than what I needed

Q31- The facilitator responds to email promptly

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q32- I feel satisfied with the level of contact I had with the facilitator

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree

e) Strongly agree

Q33- During the session with TADV, I have missed my teacher. Seeing the teacher face-to-face was absolutely necessary

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q34- Is there anything you found frustrating about the course in general?

PART 6: STUDENT OVERALL SATISFACTION

Q35- Did you enjoy studying with this Web-based course?

a) Not at all
b) Little enjoyment
c) Neutral
d) I have enjoyed
e) I have very much enjoyed

Q36- Would you recommend this course to other students? (Please specify reasons)

a) Yes
b) Do not know
c) No

Q37- I have learned a great deal in this course

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q38- For me, the course was more difficult than face-to-face courses

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q39- For each week of the course it was clear what I was supposed to learn

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q40- Overall, I enjoyed taking a class online

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q41- After this course, I would take another class online

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q42- After this course, I would recommend online classes to other students

a) Strongly disagree
b) Disagree
c) Do not know
d) Agree
e) Strongly agree

Q43- How can this course be improved for you?

Appendix J

Interview Conducted with the Facilitators

This appendix is dedicated to report the details of the interview conducted with the facilitators participated in the experimental study. The interview was conducted on 1/14/2004 with the aim of gathering facilitators' impressions, opinions, and comments regarding the TADV system. The three facilitators participated in the experimental study were asked to attend this group interview; the domain expert, the course teacher, and the teacher assistant.

The following eight dimensions were addressed during this interview:

- **Dimension-1:** What the facilitators wanted their students to gain from the course.
- **Dimension-2:** Up to what level they felt that the students gained what was required.
- **Dimension-3:** How the facilitators evaluated the process of preparing the course using the TADV proposed structure.
- **Dimension-4:** How the facilitators evaluated the TADV advising features.
- **Dimension-5:** How the advising features may be improved.
- **Dimension-6:** What difficulties the facilitators had faced while teaching this course.
- **Dimension-7:** What the facilitators wanted to tell us about this course.
- **Dimension-8:** What the facilitators thought that we should know about the TADV.

The facilitators' views and attitudes regarding these dimensions are presented in the following parts of this appendix.

Dimension-1: What the facilitators wanted their students to gain from the course

The participants agreed on that the students should:

1- Gain reasonable level of learning in the basic concepts of functions and relations lessons of discrete mathematics course. Students should be able to solve related applications to these concepts.

2- Learn how to communicate with each other, how to manage the suggested course plan and how to be autonomous students.

Dimension-2: Up to what level they felt that the students gained what was required

Course teacher said *"The level of achieving our goals is actually differs from one student to another. Regarding the first goal, I can say that learning gain is relatively good for both classes. As it is clear from the post-test scores of both classes, learning gain for Class-2 is a little bit better than of Class-1. Similar to all distance learning environments, we cannot attribute the achieved learning gains solely to students' working with the system. As it clear from our monitoring to the students in Class-2, there are some students who depended mainly on the TADV, others used TADV just to solve the given assessments, and probably used the available textbook to read the assigned chapters. I think that this is also true for the students in the Class-1. Regarding the second goal, it is clear that the level of communication between students is low for both classes as it is for the case of traditional face-to-face learning in our Egyptian culture. Most students did not follow the course plan and this is clear from the high frequency of the delay advice. A considerable number of students started the course near to its end and this reflects a common behaviour of our students, which is studying just before the exam. However, I would like to conclude that the experiment showed that our students could be autonomous if they offered the chance to learn on their own"*

Domain expert said "*I think course teacher and his assistant could give accurate answer to this question, but I would like to mention that many students talked to me about this issue and most of them appreciated the idea of having online distance courses with the condition of starting them from the beginning of the term to its end. This appreciation means that they like to be more autonomous and that they have the ability to mange courses themselves if they got the chance*"

Teacher assistant said "*I think that students gained learning level relatively similar to what they normally gain during face-to-face approach. There are of course some* *students who resist these ideas but we have to recognize that we have students who also resist sitting in the class for face-to-face learning. If we need our students to be more autonomous and self motivated we have to give them the chance to prove that. For this experiment, I believe that the students gained some experience in studying alone and independently managed this part of the course*"

Dimension-3: How the facilitators evaluated the process of preparing the course using the TADV proposed structure

Participants left the answer of this question to the domain expert because he was the only person participated in this task. He said "*I can divide the process of course preparation into three phases: The first phase was concerned with dividing the course into concepts and determining the text and examples that describe each of these concepts. There were not any difficulties in this phase because we got the material and examples from the textbook and we just put it in different formats (html pages, word documents, and power point presentations) with the help provided from data entry people. The second phase was concerned with preparing of the assessment quizzes. The only difficulty we have faced during this phase is how to formulate discrete mathematics problems in the form of multiple choices questions. The third phase was concerned with the preparation of course metadata. Drawing the lessons' concept map and determining the type of relation between related concepts were very straightforward tasks. The process of determining the values of MBs, MDs, and reading times of learning objects required first a good understanding of the proposed membership function and what is meant by measure of belief and measure of disbelief. Once the idea of these issues were clear it was easy for me to set the required metadata*"

Course teacher added "*I liked the way by which material and assessment were prepared*"

Dimension-4: How the facilitators evaluated the TADV advising features

Domain expert said "*In general, the feedback from the TADV system is excellent. Delivering of such information to the facilitator is very useful in distance learning environments. I felt that most of the advice was generated to let us know about the problems that exist regarding individual students, groups or the whole class and I think that this is very useful for distance teacher to early solve these problems and take suitable educational actions. No doubts that advice provided me with very important knowledge about the students in class-2. I got to know about their study behaviours – who followed the course calendar, who is delayed, who has worked just before the end of the course, etc. Lessening the amount of advice generated for all levels (student, group, and class) as I have suggested during the advising sessions will greatly increase the effectiveness of the TADV advising features*"

Course teacher said "*I think that teacher advising feature is necessary for any distance learning environment. I can now feel the difference between my knowledge about Class-1 and Class-2. Class-2 seems clear to me - I can easily know who is delayed, who did not start the course, who is good and who is weak. I can also know what concepts students are struggling with. I have liked the features, which give me the chance to directly send feedback to the students, modify it before sending, or completely skipping it. The types and contents of the advice generated for all levels were generally good. Advice revealed most of the problems that usually happen in the distance learning courses. My major concern is that in some cases amount of advice is somewhat high. The reason behind this problem, from my point of view, is the repetition of a certain type of advice for many concepts. For example, in one of the advising sessions we got an advice which says that one of the students is uncommunicative, this is good, after that we got many pieces of advice which said that this student should participate effectively in discussion forums related to different concepts. I think it will be better if system can combine these messages in one advice which encourage student to be communicative*"

Teacher assistant said "*Overall evaluation of the advising feature is good. I really appreciate the advice generated for groups and class. For me, advice that provided information like who are the most excellent or weak students, communicative or uncommunicative students, etc. is really very useful. I am agreeing with Dr. Khaled* (he means domain expert) *that we got useful knowledge from the system about students in class-2, while on the other hand, we do not know anything about the other class. I could understand that the increasing number of generated advice in the last two sessions,* *especially for group and class levels, is because that most students started interaction with the course just before its end which makes most of them evaluated by the system as weak students and accordingly the evaluation of the groups and class. I think that if the students follow the course calendar in their study then the amount of advice should be less. But this is difficult to happen and some actions should be taken to reduce amount of advice. So, I suggest that, for example, when most students in the class are weak and many concepts are unlearned by the whole class, then system should summarize this status in one advice to the teacher without mentioning this for each individual concept. Do not forget that TADV enabled us to see knowledge models of any individual student, group, or class from which we can know exactly about the status of each concept. I would like here to appreciate this feature that helped us during the advice sessions to validate some of the generated advice. Finally, I would like to say that it is preferred to enhance the advising feature by lessening the number of generated advice without affecting the amount of knowledge delivered from the system*"

Dimension-5: How the advising features may be improved

Course teacher answered "*our comments regarding this point were clearly mentioned during advising sessions*"

Ok, but are there any new advice types you see them important and should be included in next implementations of TADV?

Domain Expert said "*I think this group of advice is good especially if our comments are considered in the next implementations of TADV*"

Course teacher added "*if it is possible to let me know that a student opened and viewed the feedback we have sent, this is will be useful because in the case if he did not reviewed the feedback then we can told him to do that by sending e-mail for example*"

Teacher assistant said "*I am agree with Dr. Houssam* (he means course teacher) *and I would prefer, in the case if there is new feedback from the facilitator, highlighting the entry of - Review feedback from facilitator - in the student's interface by different colour or by any symbol that attract student to open this entry. It is also possible to automatically deliver a statement to the student upon his login saying that there is a feedback coming from the teacher and asking him to open the feedback entry*"

Dimension-6: What difficulties the facilitators had faced while teaching this course

Facilitators agreed on the following points:

1) The system provided some information about what happened in the class-2 throughout the generated advice but for class-1 there is no information about the students during the experiment period.

2) The period of time in which course conducted is very short.

3) Some students are not interested in working on the system because:

- Students felt that this is just part of the whole course and accordingly there is no need to direct much attention to it.
- Motivation and incentives were low.

Domain expert added "*it was difficult for me to mange the attendance of advice generation sessions during the work time*"

Dimension-7: What the facilitators wanted to tell us about this course

Course teacher said "*The web-based course was mainly dependent on text pages copied from the discrete mathematics book. Using presentations and other multimedia sources is absolutely better"*

Domain expert replayed to this problem and said "*presentations were prepared but it was difficult to upload it to the CENTRA course management system*"

Dimension-8: What the facilitators thought that we should know about the TADV

Domain expert said "*I am really pleased with my participation in this research from its beginning phases. It was very interesting to see the idea after implementation in a real setting. I think this is just a step toward providing distance instructors with effective help while they are teaching their distance classes. I would like to say that making a considerable advancement in this area may lead to lessening the resistance we usually face from teachers when they are required to switch to distance approach*"

Course teacher said "*I appreciate my participation in this experiment. Believe me I have learnt many useful issues about the behaviour and attitudes of my students regarding this type of teaching. I would be very happy if you kept us informed with the results of this project*"

At the end of the interview

At the end of interview, course teacher asked about the possibility of taking a copy of the course learning objects and assessments to use it in his lectures for the next term and said "*this material is very well organized*" The course teacher said before leave the meeting "*would you please give me information about the excellent and good students in Class-1 to decide about their bonus score as we promised them*"

I responded: ok, what about Class-2

He replayed: "*I think I have enough information about students in this class*"

Appendix K

Results of Students Questionnaire

In this appendix, the results of questionnaire submitted to participant students are reported. The charts and tables depicted in this Appendix are used to elicit some of the results and conclusions reported in chapter seven. In the first part of this appendix, the questions of each part are tabulated along with questions types and the answers' weights. In the rest of the appendix, each question of the questionnaire is recalled and their answers (from Class-1 and Class-2) are then presented in tabular and/or graphical form.

K.1. Questions and Answers' Weights

The following Tables, from K.1 to K.6, show for each of the questionnaire parts the subject of each question along with question type and the answers' weights. The rows of open (Essay) questions are marked with grey shadow. Answer weight cell with zero value means that the corresponding answer is not available. Answer weight cell with N value means that weight is not applicable to the corresponding answer.

Table K.1 Questions in Part 1 – General Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q1	Gender	Closed	N	N	0	0	0
Q2	Type of secondary school	Closed	1	3	5	1	0
Q3	Previous experience with numeric and mathematics courses	Closed	5	4	2	1	0
Q4	Previous experience with the subject of Discrete Mathematics	Closed	5	4	2	1	0
Q5	Internet skills	Closed	5	4	2	1	0
Q6	Previous participation in Web-based online distance courses	Closed	5	1	0	0	0

Table K.2 Questions in Part 2 – Interaction Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q7	The easiness of learning how to deal with TADV	Closed	5	4	3	2	1
Q8	The place from which course is accessed	Closed	5	3	1	0	0
Q9	The speed of the connection to the Internet	Closed	1	2	3	4	5
Q10	Technical difficulties with the course	Closed	5	4	3	2	1
Q11	The approximate time of working with the system per week	Closed	1	2	3	4	5
Q12	Time spent in different tasks	Closed	N	N	N	N	N

Table K.3 Questions in Part 3 – Course Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q13	Learning level gained from the course	Closed	1	2	3	4	5
Q14	One hour working with the TADV compared to 1 hour lecture	Closed	5	3	1	0	0
Q15	Using TADV with other courses	Closed	5	3	1	0	0
Q16	The easiness of the TADV interface	Closed	1	2	3	4	5
Q17	What student liked in particular about TADV	Opened					
Q18	What student found it frustrating with using TADV	Opened					

Table K.4 Questions in Part 4 – Advising and Feedback Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q19	Starting sessions with checking of the feedback and help	Closed	5	1	0	0	0
Q20	The usefulness of the advice and help information	Closed	1	2	3	4	5
Q21	Examples for useful and helpful type of advice student received	Opened					
Q22	Student's interest in knowing how his/her work is evaluated by TADV and the facilitator	Closed	1	2	3	4	5
Q23	The appropriateness of the feedback and advice details	Closed	5	3	1	0	0
Q24	The feeling of continuous guiding by the facilitator	Closed	1	2	3	4	5
Q25	The advice lessen the need to contact with the facilitator	Closed	1	2	3	4	5
Q26	What is founded surprising about the TADV advising part	Opened					
Q27	What is founded frustrating about the TADV advising part	Opened					
Q28	How can the advising part of the system be improved	Opened					

Table K.5 Questions in Part 5 – Social Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q29	The student's response to e-mails	Closed	1	3	5	0	0
Q30	The amount of interaction with other students	Closed	1	3	5	0	0
Q31	The Facilitator's response to e-mails	Closed	1	2	3	4	5
Q32	Satisfaction with the level of contact with the facilitator	Closed	1	2	3	4	5
Q33	Up to what level student missed the teacher	Closed	5	4	3	2	1
Q34	What is founded frustrating about the course in general	Opened					

Table K.6 Questions in Part 6 – Student Overall Satisfaction Information.

No.	Question Subject	Type	Answers Weights				
			a	b	c	d	e
Q35	The enjoyment with studying with TADV	Closed	1	2	3	4	5
Q36	Recommending the course to other students	Closed	5	3	1	0	0
Q37	Learning a great deal in this course	Closed	1	2	3	4	5
Q38	Course difficulty	Closed	5	4	3	2	1
Q39	The clearness of weekly duties	Closed	1	2	3	4	5
Q40	The enjoyment with taking online course	Closed	1	2	3	4	5
Q41	The possibility of taking another online course	Closed	1	2	3	4	5
Q42	Recommending online courses to other students	Closed	1	2	3	4	5
Q43	How course can be improved for student	Opened					

K.2. Questionnaire Results

In this section the answers collected from the participants are presented. The answers are presented for the control group (Class-1) and for the experimental group (Class-2). There are **13** respondents from Class-1 denoted $\mathbf{R_{1,1}}$ to $\mathbf{R_{1,13}}$ and **14** respondents from Class-2 denoted $\mathbf{R_{2,1}}$ to $\mathbf{R_{2,14}}$. Non-response items are denoted by (*). The answers of all closed questions are presented in Table K.7 for Class-1 and in Table K.8 for Class-2. Answers of questions were weighted according to the weights defined in Tables from K.1 to K.6. Weights are from 1(the worst) to 5 (the best). For each class, answers of each question are used to calculate the *weighted-mean answer* of the question (its value is from 1 to 5). The weighted-mean answers of all questions in one part of the questionnaire are then used to calculate the *grand mean* – the mean of the weighted-mean answers (its value is from 1 to 5). A grand mean indicates how a whole part of questions is evaluated by the students of the class and facilitates comparison between the responses from the two classes with respect to different parts of the questionnaire. To be indicative, all weighted-means and grand means are rounded to nearest integer.

To illustrate how the weighted-mean answers of the questions are calculated, consider, for example, the answers of Q3 shown in Table K.7:

The weighted-mean answer of Q3 = (5+5+5+4+4+4+5+5+5+5+4+5)/12 = 4.67 ≈ 5

Now, to illustrate how the grand means of the questionnaire parts are calculated, consider, for example, the weighted-mean answers of the question in the general information part shown in Table K.7:

Grand mean = (3*13+5*12+4*12+5*13+1*13)/(13+12+12+13+13) = 3.57 ≈ 4

Table K.7 Answers of closed questions - Class-1 respondents.

Question	$R_{1,1}$	$R_{1,2}$	$R_{1,3}$	$R_{1,4}$	$R_{1,5}$	$R_{1,6}$	$R_{1,7}$	$R_{1,8}$	$R_{1,9}$	$R_{1,10}$	$R_{1,11}$	$R_{1,12}$	$R_{1,13}$	Weighted Mean	Grand Mean
	GENERAL INFORMATION PART														
Q2	5	5	5	3	1	1	1	1	1	5	1	5	1	**3**	
Q3	5	5	5	4	4	4	5	5	5	5	4	5	*	**5**	
Q4	5	5	5	2	4	2	5	5	1	4	2	4	*	**4**	**4**
Q5	5	5	5	5	5	5	5	2	5	5	5	5	5	**5**	
Q6	1	1	1	1	1	1	1	1	5	1	1	1	1	**1**	
INTERACTION INFORMATION PART															
Q7	4	4	5	3	2	4	4	2	2	4	4	4	5	**4**	
Q8	5	5	5	5	3	5	5	3	5	5	5	5	5	**5**	
Q9	2	2	4	2	1	4	2	4	1	2	4	2	2	**2**	**4**
Q10	4	4	4	4	3	4	4	4	4	4	4	3	2	**4**	
Q11	1	4	3	4	1	3	1	2	1	4	3	4	2	**3**	
COURSE INFORMATION PART															
Q13	4	2	4	1	3	2	2	2	2	5	4	2	*	**3**	
Q14	5	1	5	1	3	1	1	3	1	5	1	1	1	**2**	**3**
Q15	3	1	5	5	5	1	1	1	3	5	1	5	3	**3**	
Q16	4	4	5	4	2	4	4	2	2	4	5	4	1	**3**	
SOCIAL INFORMATION PART															
Q29	1	3	1	1	1	3	3	3	1	5	1	3	1	**2**	
Q30	1	3	1	3	1	3	1	1	1	3	1	3	1	**2**	
Q31	3	2	5	4	3	3	3	1	3	5	3	4	3	**3**	**2**
Q32	3	1	5	4	3	3	3	1	2	5	1	3	2	**3**	
Q33	5	2	2	1	5	1	1	1	1	2	1	5	1	**2**	
STUDENT OVERALL SATISFACTION INFORMATION PART															
Q35	2	4	4	3	3	2	1	3	2	4	4	2	3	**3**	
Q36	5	1	5	5	3	1	1	5	1	5	5	5	3	**3**	
Q37	4	2	5	3	4	3	2	2	2	4	4	3	3	**3**	
Q38	4	4	4	2	3	2	2	1	2	4	2	4	2	**3**	**3**
Q39	4	5	5	3	4	4	4	4	5	4	4	4	3	**4**	
Q40	4	4	3	4	1	2	4	2	1	4	4	4	3	**3**	
Q41	4	1	3	4	3	1	3	2	3	2	2	4	3	**3**	
Q42	4	1	3	4	3	2	3	2	4	4	2	4	*	**3**	

Table K.8 Answers of closed questions - Class-2 respondents.

Question	$R_{2,1}$	$R_{2,2}$	$R_{2,3}$	$R_{2,4}$	$R_{2,5}$	$R_{2,6}$	$R_{2,7}$	$R_{2,8}$	$R_{2,9}$	$R_{2,10}$	$R_{2,11}$	$R_{2,12}$	$R_{2,13}$	$R_{2,14}$	Weighted Mean	Grand Mean
	GENERAL INFORMATION PART															
Q2	1	1	3	1	3	1	1	1	5	5	3	3	5	3	**3**	**4**
Q3	4	5	5	4	5	5	4	5	5	4	4	4	5	5	**5**	
Q4	2	4	4	4	4	1	5	1	4	4	2	4	5	5	**4**	
Q5	5	5	5	5	4	5	5	4	5	5	5	5	2	5	**5**	
Q6	1	1	5	5	1	1	1	1	1	1	1	1	1	1	**2**	
INTERACTION INFORMATION PART																
Q7	4	4	4	4	2	2	5	2	3	5	5	5	4	4	**4**	**4**
Q8	5	1	5	5	5	5	5	5	5	3	5	5	5	5	**5**	
Q9	2	2	4	4	4	4	4	1	2	4	4	2	2	2	**3**	
Q10	4	3	4	1	4	4	5	2	4	4	4	4	4	4	**4**	
Q11	1	1	3	4	1	3	3	5	3	1	1	2	4	4	**3**	
COURSE INFORMATION PART																
Q13	4	2	4	2	4	2	4	1	3	4	1	3	4	2	**3**	**3**
Q14	5	3	5	5	3	1	5	1	3	5	1	3	1	5	**3**	
Q15	5	1	5	5	1	1	5	1	3	5	3	1	5	5	**3**	
Q16	4	4	4	2	5	4	4	2	5	4	1	5	4	4	**4**	
ADVISING AND FEEDBACK INFORMATION PART																
Q19	5	5	5	5	1	5	5	*	1	5	1	1	5	5	**4**	**4**
Q20	4	2	4	1	1	4	4	*	2	3	1	4	5	4	**3**	
Q22	3	4	4	3	3	4	4	*	4	4	2	4	4	3	**4**	
Q23	3	3	3	1	3	5	3	*	3	5	1	5	5	5	**3**	
Q24	4	4	4	4	3	5	4	*	3	4	2	3	4	3	**4**	
Q25	3	3	4	4	3	*	4	*	4	3	2	2	4	4	**3**	
SOCIAL INFORMATION PART																
Q29	1	1	1	1	1	*	1	1	3	1	1	5	3	3	**2**	**3**
Q30	1	3	1	3	1	*	1	1	3	3	1	1	3	1	**2**	
Q31	3	3	3	3	3	3	3	3	3	3	4	5	4	4	**3**	
Q32	3	3	3	4	1	4	3	*	4	4	2	4	5	4	**3**	
Q33	1	4	4	2	1	2	4	*	2	2	1	2	5	5	**3**	
STUDENT OVERALL SATISFACTION INFORMATION PART																
Q35	2	4	4	4	3	4	4	1	3	4	1	4	5	4	**3**	**4**
Q36	1	5	5	5	5	3	5	1	5	5	5	5	5	5	**4**	
Q37	2	4	4	4	4	3	4	2	4	4	4	3	5	5	**4**	
Q38	3	4	4	2	2	2	4	2	3	3	2	2	4	4	**3**	
Q39	4	5	5	3	5	4	5	3	4	4	4	5	5	4	**4**	
Q40	4	4	5	3	4	*	5	1	4	5	2	4	4	4	**4**	
Q41	3	4	4	4	3	3	4	1	4	5	2	4	5	4	**4**	
Q42	3	4	4	4	4	4	4	1	4	5	3	4	4	2	**4**	

K.2.1. Results of Q1

Q1- My Gender is a) Male b) Female

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
Male	11	84.61	13	92.86
Female	2	15.39	1	7.14

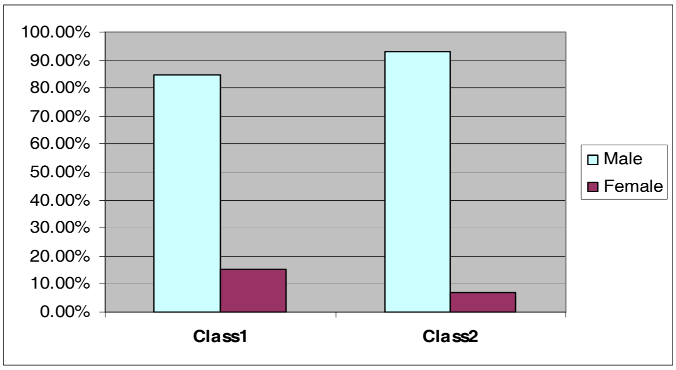

Figure K.1 Percentage of males and females in Class-1 and Class-2.

K.2.2. Results of Q2

Q2- My secondary school was

a) Governmental Arabic school with English as an additional language

b) English private school c) IGCSE or American Diploma d) Other _____

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	2	15.39	4	28.57
b	1	7.69	5	35.71
c	5	38.46	3	21.43
d	5	38.46	2	14.29

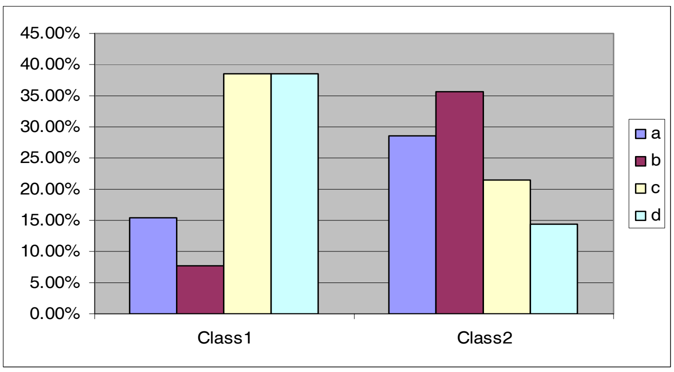

Figure K.2 English language skills in Class-1 and Class-2.

K.2.3. Results of Q3

Q3- Rate your previous experience with numeric and mathematics courses:

a) Excellent b) Good c) Fair d) Poor

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	8	66.67	8	57.14
b	4	33.33	6	42.86
c	0	0	0	0
d	0	0	0	0

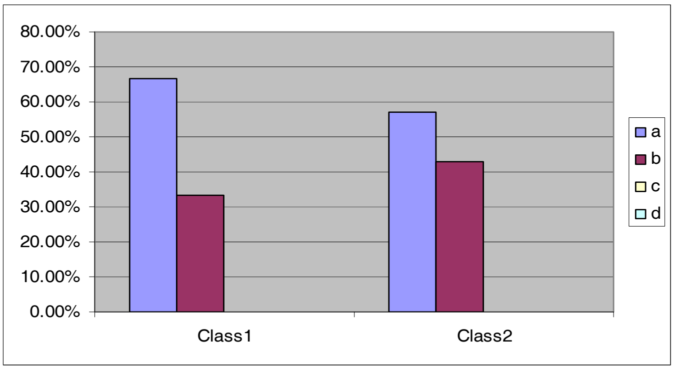

Figure K.3 Numeric and Mathematics Skills in Class-1 and Class-2.

K.2.4. Results of Q4

Q4- Rate your previous experience with the subject of Discrete Mathematics:

a) Excellent b) Good c) Fair d) Poor

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	5	41.67	3	21.44
b	3	25.00	7	50.00
c	3	25.00	2	14.28
d	1	8.33	2	14.28

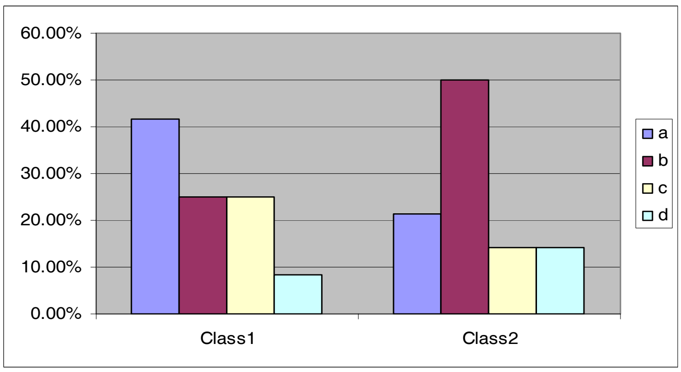

Figure K.4 Discrete Mathematics Skills in Class-1 and Class-2.

K.2.5. Results of Q5

Q5- Rate your Internet skills:

a) Excellent b) Good c) Fair d) Poor

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	12	92.31	11	78.57
b	0	0	2	14.29
c	1	7.69	1	7.14
d	0	0	0	0

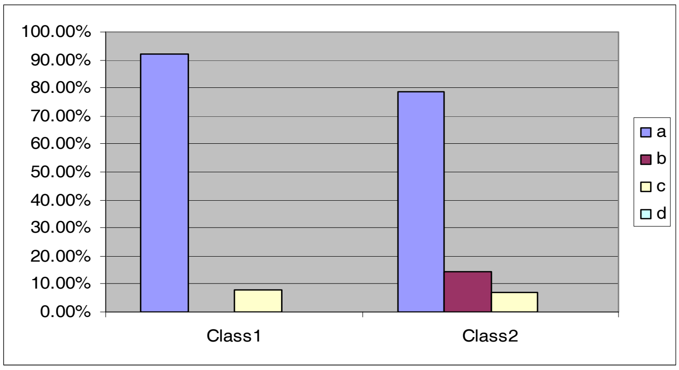

Figure K.5 Internet Skills in Class-1 and Class-2.

K.2.6. Results of Q6

Q6- Have you participated before in any Web-based online distance courses?

a) Yes b) No

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
Yes	1	7.69	2	14.29
No	12	92.31	12	85.71

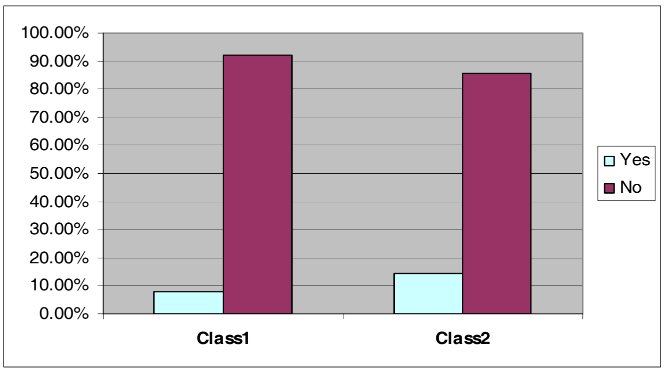

Figure K.6 Previous Participation in Web-based Courses.

K.2.7. Results of Q7

Q7- I did found it easy to learn how to deal with the course using TADV features

a) Strongly agree b) Agree c) Do not know d) Disagree e) Strongly disagree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	2	15.38	4	28.57
b	7	53.85	6	42.86
c	1	7.69	1	7.14
d	3	23.08	3	21.43
e	0	0	0	0

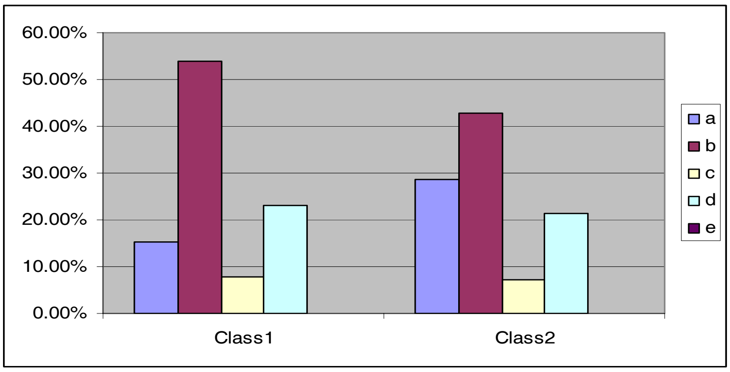

Figure K.7 The Easiness of learning how TADV works.

K.2.8. Results of Q8

Q8- I have accessed the course most frequently from

a) Home b) Academy's laboratories and/or cyber café c) Other

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
Home	11	84.62	12	85.72
Academy Labs	2	15.38	1	7.14
Others	0	0	1	7.14

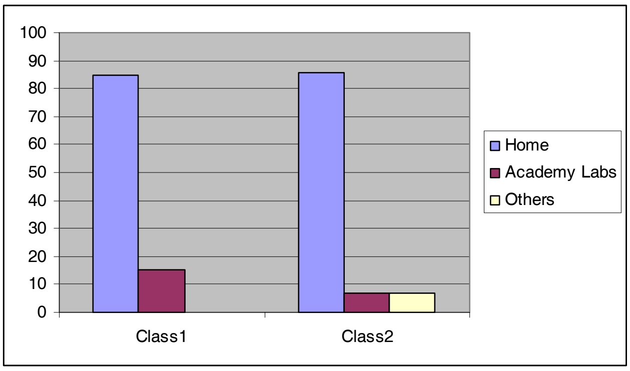

Figure K.8 Places from which course was accessed.

K.2.9. Results of Q9

Q9- The connection speed to the Internet on the computer from which I have frequently accessed the course is

a) Very slow b) Slow c) Do not know d) Fast e) Very fast

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	2	15.38	1	7.14
b	7	53.85	6	42.86
c	0	0	0	0
d	4	30.77	7	50.00
e	0	0	0	0

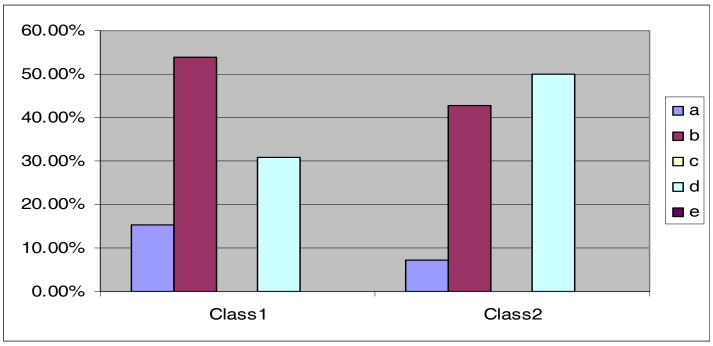

Figure K.9 Speed of Internet connection.

K.2.10. Results of Q10

Q10- I have experienced technical difficulties with the course (please specify if any)

a) Not at all b) Few c) I do not know d) Frequently e) Too much

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	0	0	1	7.14
b	10	76.92	10	71.44
c	2	15.39	1	7.14
d	1	7.69	1	7.14
e	0	0	1	7.14

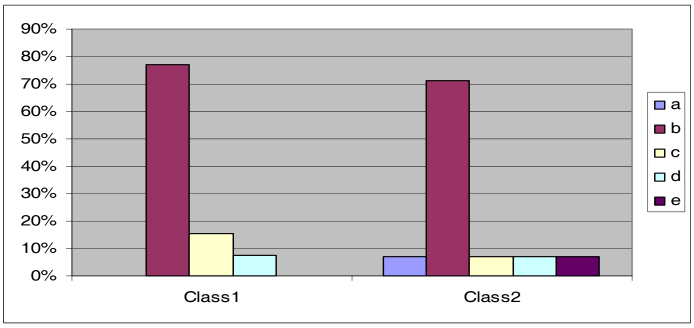

Figure K.10 Technical difficulties experienced with the course.

K.2.11. Results of Q11

Q11- The time I spent on the web site of this course during a week is approximately

a) One hour or less b) One to two hours c) Two to three hours
d) Three to four hours e) More than four hours

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	4	30.77	5	35.72
b	2	15.38	1	7.14
c	3	23.08	4	28.57
d	4	30.77	3	21.43
e	0	0	1	7.14

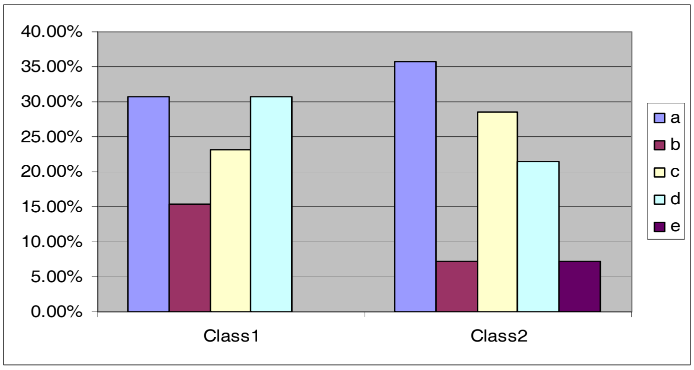

Figure K.11 Weekly working time with the course.

K.2.12. Results of Q12

Q12- Specify roughly the percentage of time you have spent in each of the following tasks during your interaction with the course

a) Reading learning objects and solving assessment quizzes [%]
b) Opening learning object just to print it [%]
c) Trying to know how the system works [%]
d) Reviewing feedback and help information coming from the facilitator [%]
e) Other tasks [%]

Only **9** participants from Class-1 answered this question. The following data is collected:

a) [95, 60, 70, 70, 50, 60, 15, 50, 10] b) [0, 10, 10, 0, 0, 0, 20, 10, 20]
c) [0, 5, 5, 0, 10, 30, 10, 5, 70] d) [0, 5, 5, 10, 10, 0, 25, 10, 0]
e) [5, 20, 10, 20, 30, 10, 30, 25, 0]

Only **8** participants from Class-2 answered this question. The following data is collected:

a) [80, 40, 15, 40, 60, 60, 70, 60] b) [0, 15, 20, 15, 10, 5, 10, 10]
c) [0, 25, 10, 20, 5, 10, 10, 10] d) [10, 20, 30, 5, 10, 15, 0, 0]
e) [10, 0, 25, 20, 15, 10, 10, 20]

Response	CLASS-1	CLASS-2
	%	%
Reading	53.33	53.13
Printing	7.77	10.62
Knowing TADV	15	11.25
Reviewing feedback	7.2	11.25
Other works	16.7	13.75

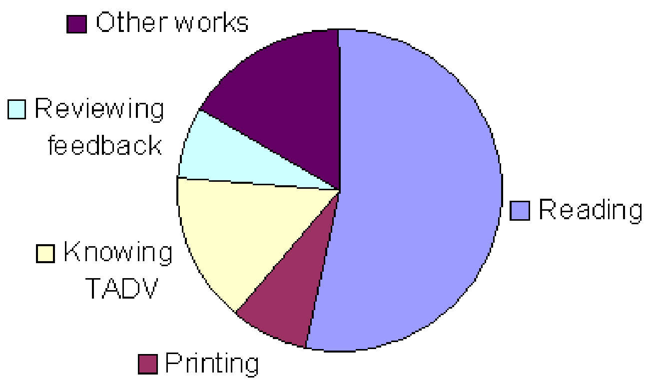

Figure K.12 Average time spent in different tasks (Class-1).

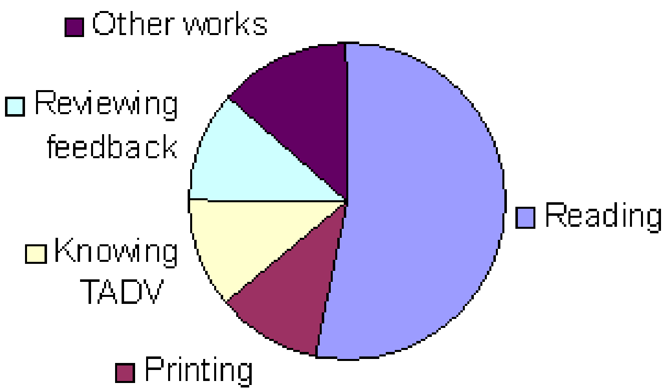

Figure K.13 Average time spent in different tasks (Class-2).

K.2.13. Results of Q13

Q13- Do you feel that you learnt about "Functions" and "Relations" of the Discrete Mathematics course from using TADV?

a) Nothing b) Some things learnt c) Do not know
d) I feel that I learnt most of the material
e) I feel that I learnt the material and I am very confident now

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	1	8.33	2	14.29
b	6	50	4	28.57
c	1	8.33	2	14.29
d	3	25	6	42.85
e	1	8.33	0	0

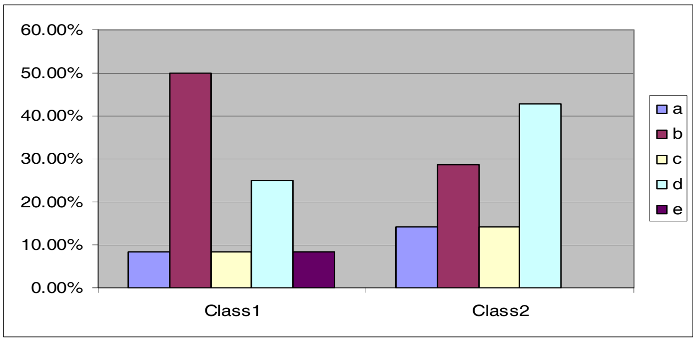

Figure K.14 Learning gains in Class-1 and Class-2.

K.2.14. Results of Q14

Q14- For me, one hour working with this course is more valuable than one hour of lectures: a) Agree b) Do not know c) Disagree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	3	23.08	6	42.86
b	2	15.38	4	28.57
c	8	61.54	4	28.57

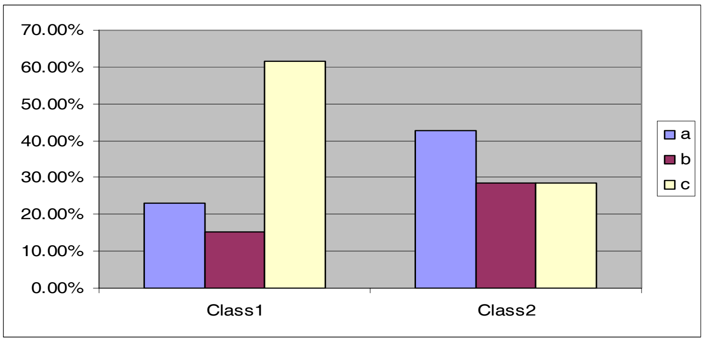

Figure K.15 Work with TADV vs. normal lectures.

K.2.15. Results of Q15

Q15- Would you like to use TADV with other courses? (Please specify reasons)

a) Yes b) Do not know c) No

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	5	38.46	7	50.00
b	3	23.08	2	14.29
c	5	38.46	5	35.71

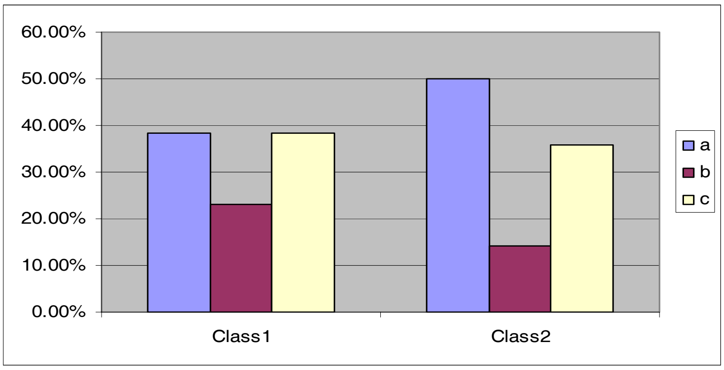

Figure K.16 The likelihood to use TADV with other courses.

Reasons specified by Class-1 students
"Yes, but as a supplementary part"
"No, because it requires me to study daily; the course does not deserve daily work"
"Yes, because time required to understand the course depends on the student"
"Yes, under one condition, do not use the same material from the text book on the site"
"Yes, but it is necessary to improve the course by using video, audio, simulation, etc."

Reasons specified by Class-2 students
"Yes, if the course material become better"
"Yes, but for the easy courses"
"Lectures are better"

K.2.16. Results of Q16

Q16- Did you find the TADV interface easy to use? (Please specify reasons)

a) Not at all   b) Some what easy   c) Do not know   d) Easy   e) Very easy

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	1	7.69	1	7.14
b	3	23.08	2	14.29
c	0	0.0	0	0.0
d	7	53.85	8	57.14
e	2	15.38	3	21.43

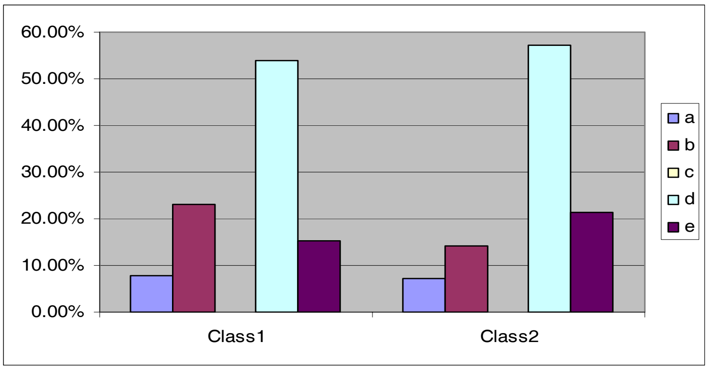

Figure K.17 Easiness of TADV interface.

K.2.17. Results of Q17

Q17- What do you like in particular about TADV?

Class-1

"A new way of learning"
"I liked the way in which course is divided"
"Easy to have, easy to read, it makes student want to learn"
"I liked the information I got it online, it is hard to forget"

Class-2

"The thing that I have liked too much is the studying from home"
"The system is quite interesting and user friendly"
"I can access the course when I am ready to do that"
"The idea is new but it needs longer time"
"The feedback from the teacher"
"It was not enough to just use the system, in the class teacher explain every things, I have a problem in the English language"

"I can study at anytime depending on myself"

K.2.18. Results of Q18

Q18- Is there anything you found frustrating with using TADV?

Class-1

"Working with the Centra CMS frustrated me, I prefer multimedia interactions"
"The material are copied from the book"
"It is not started from the beginning of the term, it is first time to use system like that so it need much more time"
"There is no details for the subject…it was just copy from the book"
"Nothing new, there is no big difference between online material and the text book"

Class-2

"The net was slow"
"I faced lot of problems during editing of the profile"
"Using the start button instead of clicking on the learning object directly"
"Since the learning objects are copied from the text book, I have studied from my book"
"The part of my learning is not easy and this should be highly considered"
"The text in the learning object is same like the book"
"No, the system was good but the course was just like the book"
"Text is same like the book"

K.2.19. Results of Q19

Q19- I have started my sessions usually by checking the incoming feedback and help information from facilitator

a) Agree b) Disagree

Response	CLASS-2	
	Number	%
Agree	9	69.23
Disagree	4	30.77

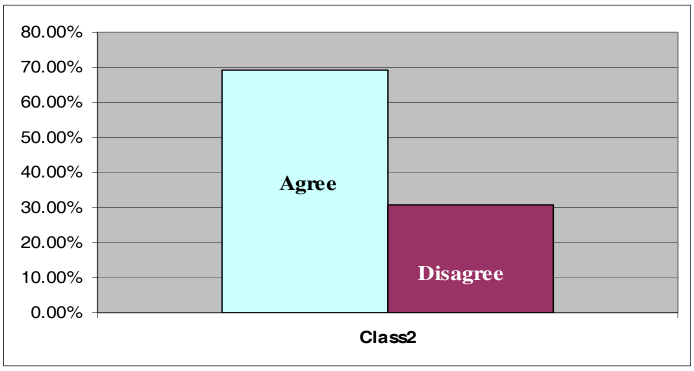

Figure K.18 Starting sessions with checking of the feedback/help.

K.2.20. Results of Q20

Q20- Did you find advice and help messages useful? (Specify the reasons)

a) Not helpful at all b) Somehow helpful c) Do not know
d) Helpful e) Very helpful

Response	CLASS-2	
	Number	%
a	3	23.08
b	2	15.39
c	1	7.69
d	6	46.15
e	1	7.69

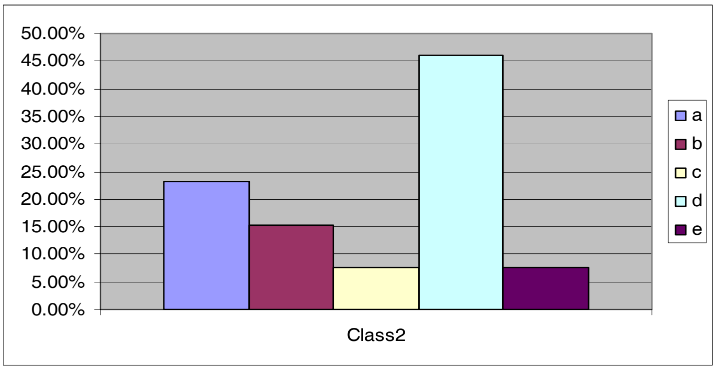

Figure K.19 The usefulness of the advice and help messages.

K.2.21. Results of Q21

Q21- Please specify examples for useful and helpful type of advice you have received from TADV (in other words, advice that you have followed)

Class-2
"It told me about the parts of the course that I am not good at" *"I liked the advice coming when I am delayed"* *"All are good"*

K.2.22. Results of Q22

Q22- It was interesting to know how my work in the course was continuously evaluated by TADV and the facilitator

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-2	
	Number	%
a	0	0.0
b	1	7.69
c	4	30.77
d	8	61.54
e	0	0.0

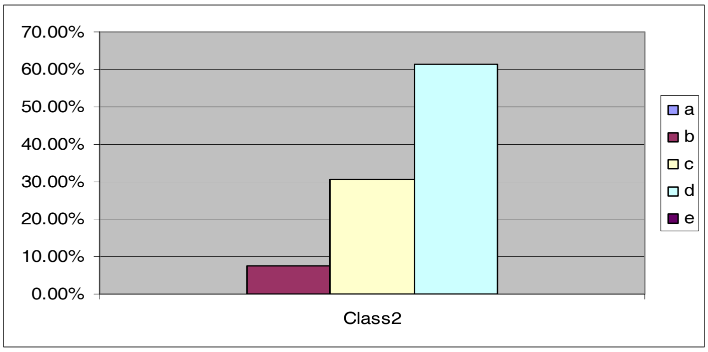

Figure K.20 Students' interest in knowing how work is evaluated by TADV and the facilitator.

K.2.23. Results of Q23

Q23- The details in the advice and in the feedback messages are appropriate?

a) Yes b) Do not know c) No

Response	CLASS-2	
	Number	%
a	5	38.46
b	6	46.15
c	2	15.39

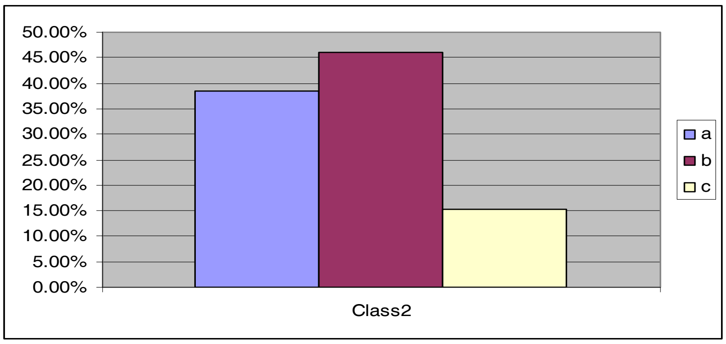

Figure K.21 Evaluation of advice details.

K.2.24. Results of Q24

Q24- During the course period, I felt that I was constantly guided by the facilitator

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-2	
	Number	%
a	0	0.0
b	1	7.69
c	4	30.77
d	7	53.85
e	1	7.69

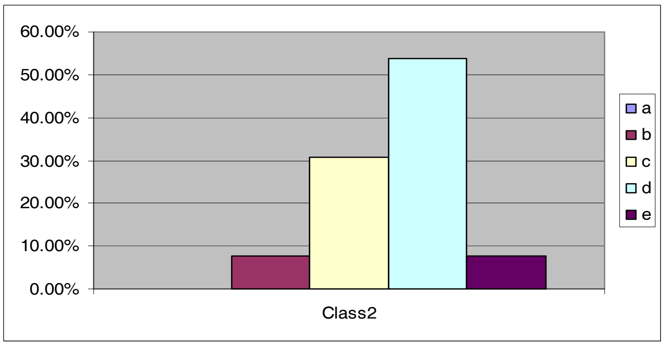

Figure K.22 The feeling of continuous guiding by the facilitator.

K.2.25. Results of Q25

Q25- The availability of the advice and help information reduced the need to frequently contact the facilitator

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-2	
	Number	%
a	0	0.0
b	2	16.67
c	4	33.33
d	6	50.00
e	0	0.0

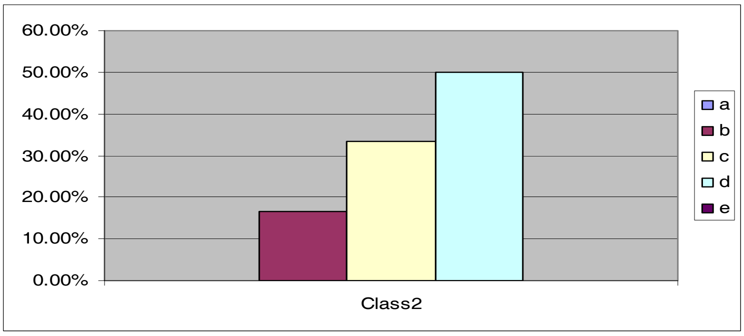

Figure K.23 The effect of advice on the students' need to contact the facilitator

K.2.26. Results of Q26

Q26- Is there anything you found surprising about the advising part? Please specify

Class-2
"It was normal" *"The existence of messages from teacher"* *"The existence of course calendar"*

K.2.27. Results of Q27

Q27- Is there anything you found frustrating about the advising part? Please specify

Class-2
"Messages are sometimes difficult to understand. Why don't you use Arabic?" *"There is no new feedback for two or three days"*

K.2.28. Results of Q28

Q28- How can the advising part of the system be improved for you?

Class-2
"The use of Arabic language, if possible" *" Take online advice directly from the teacher"* *" Advice in Arabic"*

K.2.29. Results of Q29

Q29- How quickly did you respond to e-mails related to this course?

a) Never responded b) Responded with some delay c) Immediately

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	7	53.85	9	69.23
b	5	38.46	3	23.08
c	1	7.69	1	7.69

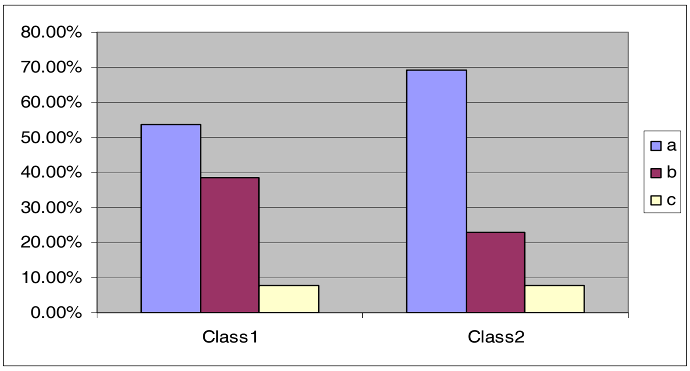

Figure K.24 How students responded to e-mails.

K.2.30. Results of Q30

Q30- The amount of contact/interaction with the other students in the course is

a) Less than what I needed b) Close to what I needed c) More than what I needed

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	8	61.54	8	61.54
b	5	38.46	5	38.46
c	0	0.0	0	0.0

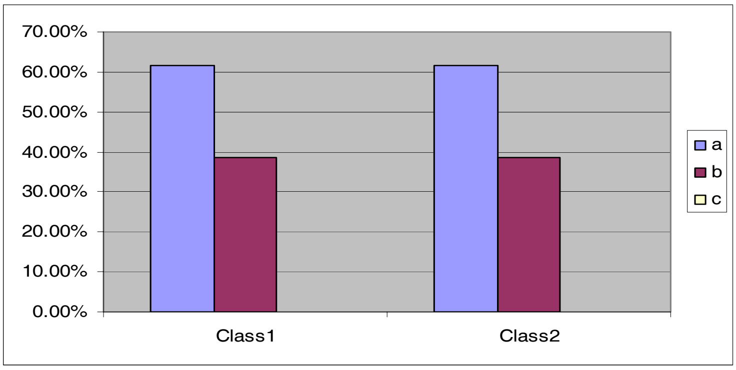

Figure K.25 Evaluating interactions between students.

K.2.31. Results of Q31

Q31- The facilitator responds to email promptly

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	1	7.69	0	0.0
b	1	7.69	0	0.0
c	7	53.86	10	71.43
d	2	15.38	3	21.43
e	2	15.38	1	7.14

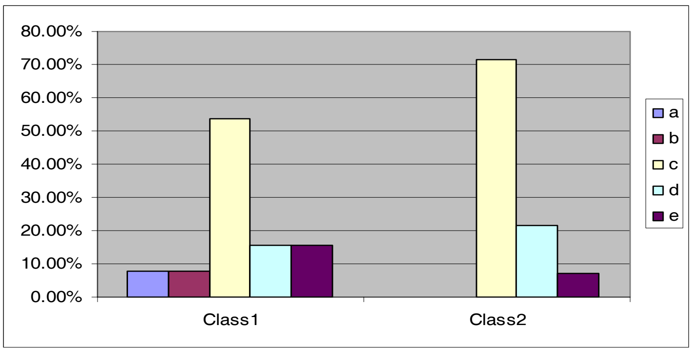

Figure K.26 How facilitators responded to e-mails.

K.2.32. Results of Q32

Q32- I feel satisfied with the level of contact I had with the facilitator

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	3	23.08	1	7.69
b	2	15.38	1	7.69
c	5	38.46	4	30.77
d	1	7.69	6	46.16
e	2	15.38	1	7.69

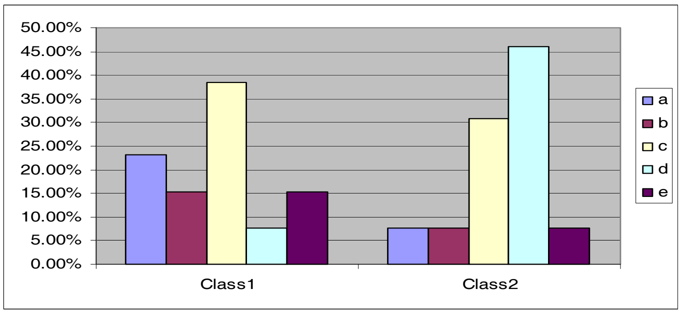

Figure K.27 Satisfaction with the level of contact with the facilitator.

K.2.33. Results of Q33

Q33- During the session with TADV, I have missed my teacher. Seeing the teacher face-to-face was absolutely necessary

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	3	23.08	2	15.38
b	0	0.0	3	23.08
c	0	0.0	0	0.0
d	3	23.08	5	38.46
e	7	53.84	3	23.08

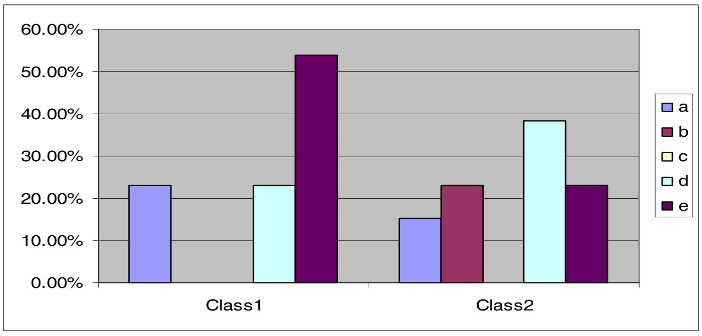

Figure K.28 How students missed the teacher.

K.2.34. Results of Q34

Q34- Is there anything you found frustrating about the course in general?

Class-1

"We missed a lot of lectures, it is better if there is a coordination between lectures and the on line system"
"It is necessary to add multimedia"
"The time is short; it must be for the whole term because we depend on it without waiting lecture or section"

Class-2

"Questions are not clear and text is not enough"
" There is no multimedia used"
" Time is very short"

K.2.35. Results of Q35

Q35- Did you enjoy studying with this Web-based course?

a) Not at all b) Little enjoyment c) Neutral
d) I have enjoyed e) I have very much enjoyed

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	1	7.69	2	14.29
b	4	30.77	1	7.14
c	4	30.77	2	14.29
d	4	30.77	8	57.14
e	0	0.0	1	7.14

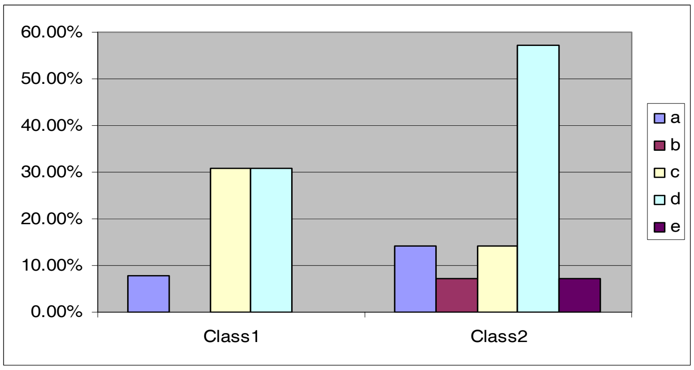

Figure K.29 Students' level of enjoyment.

K.2.36. Results of Q36

Q36- Would you recommend this course to other students? (Please specify reasons)

a) Yes b) Do not know c) No

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	7	53.85	11	78.57
b	2	15.38	1	7.14
c	4	30.77	2	14.29

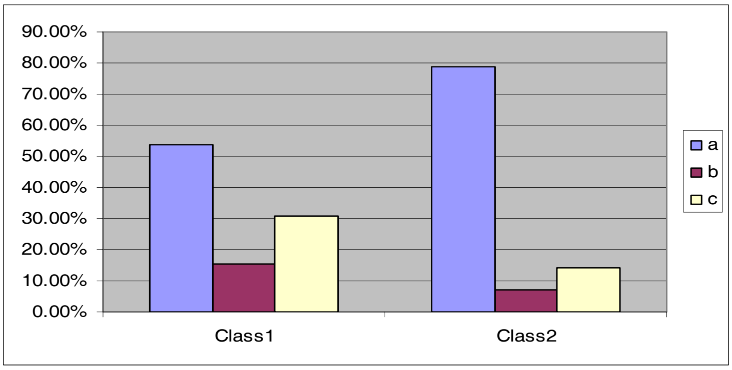

Figure K.30 Recommending the course to other students.

K.2.37. Results of Q37

Q37- I have learned a great deal in this course

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	0	0.0	0	0.0
b	4	30.77	2	14.29
c	4	30.77	2	14.29
d	4	30.77	8	57.14
e	1	7.69	2	14.29

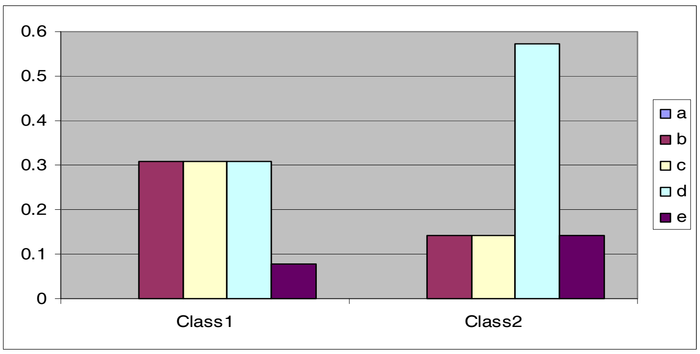

Figure K.31 How students evaluated their gained learning.

K.2.38. Results of Q38

Q38- For me, the course was more difficult than face-to-face courses

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	0	0.0	0	0.0
b	5	38.46	5	35.71
c	1	7.69	3	21.43
d	6	46.16	6	42.86
e	1	7.69	0	0.0

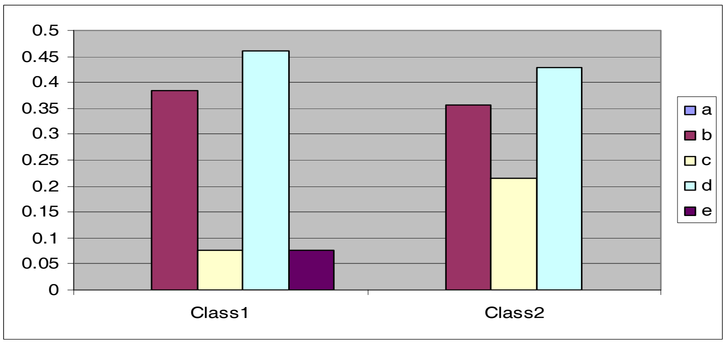

Figure K.32 Comparing course to face-to-face course.

K.2.39. Results of Q39

Q39- For each week of the course it was clear what I was supposed to learn

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	0	0.0	0	0.0
b	0	0.0	0	0.0
c	2	15.38	2	14.28
d	8	61.54	6	42.86
e	3	23.08	6	42.86

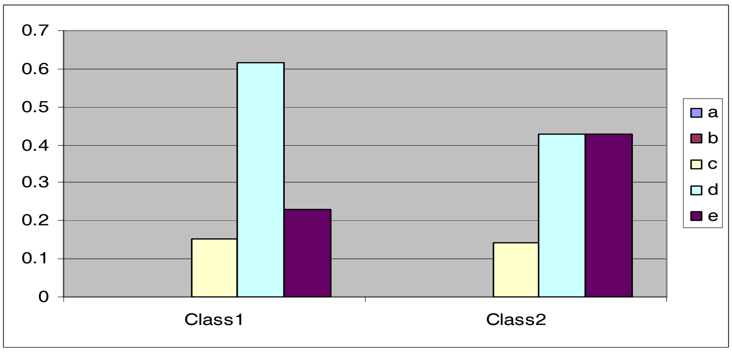

Figure K.33 The clearness of weekly duties.

K.2.40. Results of Q40

Q40- Overall, I enjoyed taking a class online

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	2	15.38	1	7.69
b	2	15.38	1	7.69
c	2	15.38	1	7.69
d	7	53.86	7	53.85
e	0	0.0	3	23.08

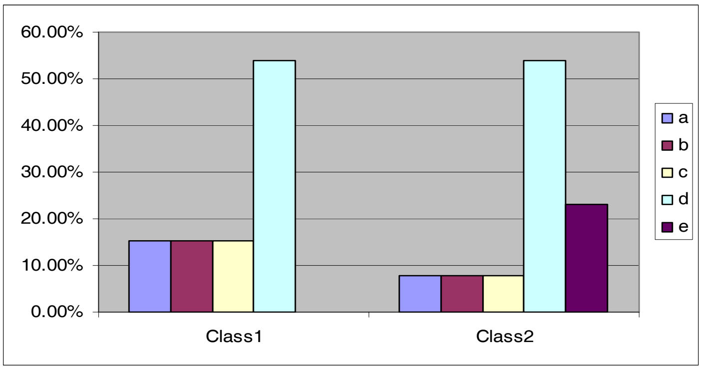

Figure K.34 Students' enjoyment levels.

K.2.41. Results of Q41

Q41- After this course, I would take another class online

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	2	15.38	1	7.14
b	3	23.08	1	7.14
c	5	38.46	3	21.43
d	3	23.08	7	50.00
e	0	0.0	2	14.29

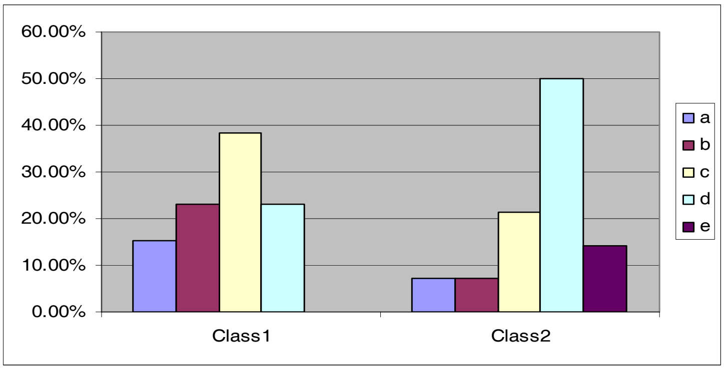

Figure K.35 The possibility of taking another online course.

K.2.42. Results of Q42

Q42- After this course, I would recommend online classes to other students

a) Strongly disagree b) Disagree c) Do not know d) Agree e) Strongly agree

Response	CLASS-1		CLASS-2	
	Number	%	Number	%
a	1	8.33	1	7.14
b	3	25.00	1	7.14
c	3	25.00	2	14.29
d	5	41.67	9	64.29
e	0	0.0	1	7.14

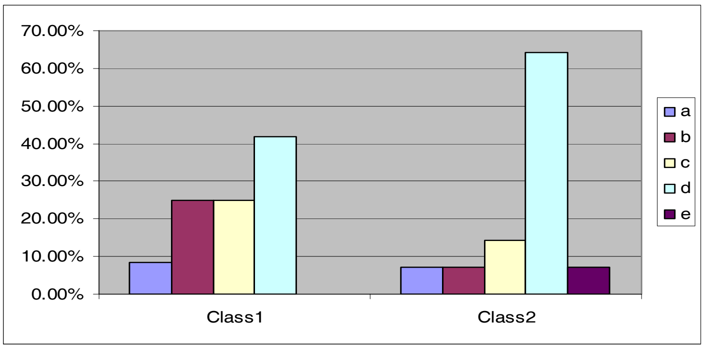

Figure K.36 Recommending online courses to other students.

K.2.43. Results of Q43

Q43- How can this course be improved for you?

Class-1

"Further coordination with face-to-face lectures and improved multimedia interactions"
"Use recorded lectures"
"Teacher should exist on line with the students (On line chatting)"
"On line chatting"
"By using material different than on the text book"

Class-2

"Online Chatting between students"
"Use multimedia to present course material"
"The use of multimedia features"
"It is good to use such system for just solving the assessment, but explaining lessons should be face to face because some students are not good in English"
"Use online course for the whole term and chat online with the teacher"

Appendix L

Samples of Advice Generated to the Facilitators and Feedback to the Students

In this Appendix, samples of the advice generated to the facilitators and corresponding recommended feedback to the students are presented. For the sake of not enlarging the Appendix, it is decided to present a portion of the generated advice. The Appendix includes the following tables:

- Table L.1 presents a sample of the advice generated about Student21 (Excellent)
- Table L.2 presents a sample of the advice generated about Student34 (Weak)
- Table L.3 presents a sample of the advice generated about Group1 on the advice generation sessions dated 18/12/2003.
- Table L.4 presents a sample of the advice generated about Class2 on the advice generation sessions dated 18/12/2003.
- Tables L.5, L.6, and L.7 show the advice rated by the facilitators or the students as "Not Appropriate" advice for Type-1, Type-2, and Type-3 advice respectively.
- Tables L.8, L.9, and L.10 show samples of the advice composed by the facilitators and sent to students, groups, and class respectively.

Following are the meanings of the symbols used in the tables:

- I column: Advice Importance (VI: Very important, I: Important, LI: Less Important)
- S column: Send status (Y: Sent, N: did not sent)
- FR column: Facilitator's Rating (A: Appropriate, D: Do not know, N: Not appropriate)
- SR column: Student's Rating (A: Appropriate, D: Do not know, N: Not appropriate)
- *** means that the subsequent message is not automatically generated by advice generator and instead it is composed by the facilitator.

Table L.1 Sample of the advice generated about student21 (Excellent).

Date	Advice to the facilitator	I	S	FR	Feedback to the student	SR
2/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Well done Ahmed, try to help your peers.	D
5/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
8/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
	Student Ahmed H Abd El lATIF should be encouraged to participate effectively in the communication activities related to 116_Composition_of_One_to_One_Function	I	Y	A	We note that you did not participate effectively in the 116_Composition_of_One_to_One_Function discussion forum. It might be useful if you visit it and read what is there or ask your peers	A
11/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Well done Ahmed, try to help your peers.	A
	Concept 212_Transitive_Closure is unlearned by student Ahmed H Abd El lATIF, TADV is unable to find the reason. It might be useful to talk directly with the student and discuss the problem	VI	N	D		
	Student Ahmed H Abd El lATIF should be encouraged to participate effectively in the communication activities related to 213_Equivalence_Relation	I	Y	A	We note that you did not participate effectively in the 213_Equivalence_Relation discussion forum. It may be useful if you visit it and read what is there or ask your peers	A
13/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
15/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Well done Ahmed, try to complete the course	A
18/12/03	Student Ahmed H Abd El lATIF is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going, Try to follow the calendar	A
	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Ahmed, you are excellent student, there are some concepts that you still need to know (214, 215, 216, and 217). We prefer if you increase your communication with other students in the class.	A

Table L.2 Sample of the advice generated about student34 (Weak).

Date	Advice to the facilitator	I	S	FR	Feedback to the student	SR
2/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
5/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
8/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
11/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
13/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
15/12/03	Student Mina R Fahmi has not started course yet	VI	Y	A	You have not started the course yet. You should start the course as soon as possible	
18/12/03	Student Mina R Fahmi is delayed in studying many concepts	VI	Y	A	You are delayed in studying many concepts. Time is going ,Try to follow the calendar	A
	Student Mina R Fahmi is evaluated by TADV as Weak and uncommunicative	VI	Y	A	*** You need to work hard with this course; we are about to stop the course. There are many concepts still need you work with. Communication with your peers may help you.	A
	Student Mina R Fahmi should be advised to study 204_Arrow_Diagramv	VI	Y	A	In order for you to master 205_Inverse_Relarion , it is highly recommended to study 204_Arrow_Diagramv first	D
	Student Mina R Fahmi should be encouraged to participate effectively in the communication activities related to 114_Composition_and_Identity. Students { Ahmed H Abd El lATIF , , } are communicative and have already mastered concept 114_Composition_and_Identity	VI	Y	A	We note that you did not participate effectively in the 114_Composition_and_Identity discussion forum. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact Ahmed H Abd El lATIF , or to discuss 114_Composition_and_Identity	A
	Student Mina R Fahmi should be encouraged to participate effectively in the communication activities related to 101_Function. Students { Marawan A Khalil , , } are communicative and have already mastered concept 101_Function	VI	Y	A	We note that you did not participate effectively in the 101_Function discussion forum. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact Marawan A Khalil , or to discuss 101_Function	A
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Table L.3 Sample of the advice generated about Group1 on 18/12/2003.

Advice to the facilitator	I	S	FR	Feedback to the students	SR		
					A	D	N
Group Group1 is evaluated by TADV as Weak and highly communicative group	VI	Y	A	*** To all members of Group1: You should work hard with the course; course is about its end. Members still need to study many concepts and solve the given assessments. Every member should try to communicate with other members and with other peers in the class.	3	0	0
Group1 members should be advised to study 202_Binary_Relation	VI	N	A	203_Function_and_Relation appears to be a common problem for students in Group1. For those students who do not master 202_Binary_Relation, it is highly recommended to study the perquisite 202_Binary_Relation first	0	0	0
Group1 members should be advised to work more with concept 209_Reflexsive_Property	VI	N	A	213_Equivalence_Relation appears to be a common problem for students in Group1. It is preferred to work more with 209_Reflexsive_Property	0	0	0
Group1 members should be advised to work more with concept 211_Transitive_Property	VI	N	A	213_Equivalence_Relation appears to be a common problem for students in Group1. It is preferred to work more with 211_Transitive_Property	0	0	0
Group1 members should be advised to work more with concept 210_Symmetric_Property	VI	N	A	213_Equivalence_Relation appears to be a common problem for students in Group1. It is preferred to work more with 210_Symmetric_Property	0	0	0
Group1 members should be advised to study 213_Equivalence_Relation	VI	N	A	215_Equivalence_Class appears to be a common problem for students in Group1. For those students who do not master 213_Equivalence_Relation, it is highly recommended to study the perquisite 213_Equivalence_Relation first	0	0	0
Group1 members should be advised to work more with concept 216_Anti-symmetric	VI	N	A	217_Partial_Order_Relation appears to be a common problem for students in Group1. It is preferred to work more with 216_Anti-symmetric	0	0	0
Group1 members should be advised to study 206_Binary_Relation_on_a_Set	VI	N	A	207_Directed_Graph appears to be a common problem for students in Group1. For those students who do not master 206_Binary_Relation_on_a_Set, it is highly recommended to study the perquisite 206_Binary_Relation_on_a_Set first	0	0	0
Group1 members should be advised to study 204_Arrow_Diagramv	VI	N	A	205_Inverse_Relarion appears to be a common problem for students in Group1. For those students who do not master 204_Arrow_Diagramv, it is highly recommended to study the perquisite 204_Arrow_Diagramv first	0	0	0
It might be useful to advise Group1 members to study concept 203_Function_and_Relation	I	N	A	206_Binary_Relation_on_a_Set appears to be a common problem for students in Group1. For those students who do not master 203_Function_and_Relation, it might be useful to study the perquisite 203_Function_and_Relation first	0	0	0
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Table L.4 Sample of the advice generated about Class2 on 18/12/2003.

Advice to the facilitator	I	S	FR	Feedback to the students	SR		
					A	D	N
Students Shady A Nossier, Ahmed H Abd El lATIF, and Fadi G Micheal are the most Excellent students relative to the whole class, while Students Mohamed A Abd El Aziz, Hager O Ahmed, and Sief A Al Sawaf are the weakest students	VI	Y	A	*** I would like to thank students Shady A Nossier, Ahmed H Abd El lATIF, and Fadi G Micheal for their excellent work with this course.	7	3	0
Relative to the whole class, students Ahmed H Abd El lATIF, Marawan A Khalil, and are the top highly communicative students while Students Abd El Rahman M Gabr , , and Mohamed A Abd El Aziz are the most uncommunicative students	VI	N	A		0	0	0
Students Ahmed H Abd El lATIF, Mostafa Y El Shami, and Shady A Nossier are the most Active students relative to the whole class, while Students Shimaa M Ahmed, Asim I Gammoor, and Hager O Ahmed are the most inactive students	VI	N	A		0	0	0
206_Binary_Relation_on_a_Set appears to be a common problem for students in Class2. The perquisite 203_Function_and_Relation is not mastered by the class members. It may be useful to advise class members to study 203_Function_and_Relation	VI	Y	A	*** Many students still need to work more effectively with the course, solve the given assessments and communicate with other students especially, Shady A Nossier, Ahmed H Abd El lATIF, and Fadi G Micheal. Those students are excellent and they are willing to help everybody. Please try to contact them through e-mail or discussion forums.	5	5	0
206_Binary_Relation_on_a_Set appears to be a common problem for students in Class2. TADV notes that class members are not participated effectively in the 206_Binary_Relation_on_a_Set discussion forum. Class2 members should be encouraged to participate effectively in the communication activities related to 206_Binary_Relation_on_a_Set	VI	N	A		0	0	0
203_Function_and_Relation appears to be a common problem for students in Class2. The perquisite 202_Binary_Relation is not mastered by the class members. It is highly recommended to advise class members to study 202_Binary_Relation	VI	N	A		0	0	0
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Table L.5 Type-1 "Not Appropriate Advice".

Student	Advice to the facilitator	I	S	FR	Feedback to the student	SR
Student 23 18/12/03	Student Mostafa Y El Shami should be advised to study 211_Transitive_Property	VI	N	N	In order for you to master 213_Equivalence_Relation, it is highly recommended to study 211_Transitive_Property first	
	Student Mostafa Y El Shami should be advised to study 210_Symmetric_Property	VI	N	N	In order for you to master 213_Equivalence_Relation, it is highly recommended to study 210_Symmetric_Property first	
Student 35 18/12/03	Student Amr M Ismail should be advised to work more with concept 211_Transitive_Property	VI	N	N	In order for you to master 213_Equivalence_Relation , it is preferred to work more with 211_Transitive_Property	
	Student Amr M Ismail should be advised to work more with concept 210_Symmetric_Property	VI	N	N	In order for you to master 213_Equivalence_Relation , it is preferred to work more with 210_Symmetric_Property	
Student 37 15/12/03	Student Wael H Yousef should be advised to work with the available learning objects and assessment quizzes related to 103_Function_Machine	VI	Y	A	In order for you to understand 103_Function_Machine we suggest you refer to its available learning objects and solve related assessment quizzes	N
	Student Wael H Yousef should be encouraged to participate effectively in the communication activities related to 103_Function_Machine. Students { Ahmed H Abd El lATIF , , } are communicative and have already mastered concept 103_Function_Machine	VI	Y	A	We note that you did not participate effectively in the 103_Function_Machine discussion forum. It may be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact Ahmed H Abd El lATIF , or to discuss 103_Function_Machine	N
Student 37 18/12/03	Student Wael H Yousef should be encouraged to participate effectively in the communication activities related to 107_One_To_One_Function. Students { Ahmed H Abd El lATIF , , } are communicative and have already mastered concept 107_One_To_One_Function	I	Y	A	We note that you did not participate effectively in the 107_One_To_One_Function discussion forum. It might be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact { Ahmed H Abd El lATIF , or } to discuss 107_One_To_One_Function	N
	Student Wael H Yousef should be encouraged to participate effectively in the communication activities related to 102_Arrow_Diagram	I	Y	A	We note that you did not participate effectively in the 102_Arrow_Diagram discussion forum. It might be useful if you visit it and read what is there or ask your peers	N
Student 40 18/12/03	Student Abd El Rahman M Gabr should be encouraged to participate effectively in the communication activities related to 107_One_To_One_Function. Students { Ahmed H Abd El lATIF , , } are communicative and have already mastered concept 107_One_To_One_Function	I	Y	A	We note that you did not participate effectively in the 107_One_To_One_Function discussion forum. It might be useful if you visit it and read what is there or ask your peers. Otherwise, you could try to contact { Ahmed H Abd El lATIF , or } to discuss 107_One_To_One_Function	N

	Student Abd El Rahman M Gabr should be encouraged to participate effectively in the communication activities related to 102_Arrow_Diagram	I	Y	A	We note that you did not participate effectively in the 102_Arrow_Diagram discussion forum. It might be useful if you visit it and read what is there or ask your peers	N

Table L.6 Type-2 "Not Appropriate Advice".

Advice to the facilitator	I	S	FR	Feedback to the student	SR		
					A	D	N
TADV can not evaluate group Group1 because most of its members have not started course yet	VI	Y	A	*** For the group members who did not start the course, time is going, please start the course as soon as possible.	0	0	1
Group2 members should be advised to study 213_Equivalence_Relation	VI	Y	A	215_Equivalence_Class appears to be a common problem for students in Group2. For those students who do not master 213_Equivalence_Relation, it is highly recommended to study the perquisite 213_Equivalence_Relation first	1	0	1
Group2 members should be advised to study 216_Anti-symmetric	VI	Y	A	217_Partial_Order_Relation appears to be a common problem for students in Group2. For those students who do not master 216_Anti-symmetric, it is highly recommended to study the perquisite 216_Anti-symmetric first	1	0	1
Group2 members should be advised to work more with concept 206_Binary_Relation_on_a_Set	VI	Y	A	207_Directed_Graph appears to be a common problem for students in Group2. It is preferred to work more with 206_Binary_Relation_on_a_Set	0	1	1

Table L.7 Type-3 "Not Appropriate Advice".

Advice to the facilitator	I	S	FR	Feedback to the student	SR		
					A	D	N
Students Ahmed H Abd El lATIF, Ahmed K Othman, and Ahmed I El Shwadfy are the most Active students relative to the whole class, while Students Ahmed I El Shwadfy, Ahmed K Othman, and Ahmed H Abd El lATIF are the most inactive students	VI	N	N		0	0	0
TADV can not evaluate class Class2 because most of its students have not started course yet	VI	Y	A	*** For the class members who did not start the course, time is going, please start the course as soon as possible.	0	2	2

Table L.8 Sample of the advice composed by facilitators and sent to the students.

Date	Advice to the facilitator	I	S	FR	Feedback to the student	SR
Student 20 12/11/03	Student Sief A Al Sawaf is evaluated by TADV as Weak and uncommunicative	VI	Y	A	*** You should work hard with the course. Try to read the material and solve the given assessments.	A
Student 21 12/2/03	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Well done Ahmed, try to help your peers.	D
Student 21 12/18/03	Student Ahmed H Abd El lATIF is evaluated by TADV as Excellent and uncommunicative	VI	Y	A	*** Ahmed, you are excellent student, there are some concepts that you still need to know (214, 215, 216, and 217). We prefer if you increase your communication with other students in the class.	A
Student 23 12/15/03	Student Mostafa Y El Shami is evaluated by TADV as Weak and uncommunicative	VI	Y	A	*** You should work hard with the course. Try to solve the given assessments. You should also communicate with your peers through the discussion forums prepared for each concept.	A
Student 34 12/18/03	Student Mina R Fahmi is evaluated by TADV as Weak and uncommunicative	VI	Y	A	*** You need to work hard with this course; we are about to stop the course. There are many concepts still need you work with. Communication with your peers may help you.	A

Table L.9 Sample of the advice composed by facilitators and sent to groups.

Advice to the facilitator	I	S	FR	Feedback to the student	SR		
					A	D	N
TADV can not evaluate group Group1 because most of its members have not started course yet	VI	Y	A	*** For the group members who did not start the course, time is going, please start the course as soon as possible.	0	1	0
Group Group1 is evaluated by TADV as Weak and highly communicative group	VI	Y	A	*** To all members of Group1: You should work hard with the course; course is about its end. Members still need to study many concepts and solve the given assessments. Every member should try to communicate with other members and with other peers in the class.	3	0	0
Group Group2 is evaluated by TADV as Weak and uncommunicative group	VI	Y	A	*** To all members of the group2: You should work more effectively with the course. Try to solve the given assessments. You should also communicate with your peers in the group through the discussion forums prepared for each concept and through mail.	2	0	0

Table L.10 Sample of the advice composed by facilitators and sent to Class2.

Advice to the facilitator	I	S	FR	Feedback to the student	SR		
					A	D	N
TADV can not evaluate class Class2 because most of its students have not started course yet	VI	Y	A	*** For the class members who did not start the course, time is going, please start the course as soon as possible.	3	2	0
Students Shady A Nossier, Ahmed H Abd El lATIF, and are the most Excellent students relative to the whole class, while Students Amr M Ismail, Abd El Rahman M Gabr, and Mohamed A Abd El Aziz are the weakest students	VI	Y	A	*** To all class members: There many students who do not start working with the course; this makes class evaluated by the system as Weak. Please, those students should start the course as soon as possible. Most students should work hard with the course, solve the given assessments, and communicate with other students through the discussion forums prepared for each concept. Students who face problems can communicate with Shady A Nossier and Ahmed H Abd El lATIF; they are excellent.	7	4	0