Developing Adaptive Intelligent Tutoring System based on Item Response Theory and Metrics

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Abstract

To design an adaptive intelligent tutoring system which can manage both different disciplinary domains and a guide for the learner is difficult. The specialization of the analysis treatments is responsible for the loss of reusability in other disciplinary domains. The analysis is didactic and thus strongly connected to the domain concerned. It results that an intelligent tutoring system is consequently, specialized in a type of taught knowledge and not easily transposable to other domains. To propose a model transposable to different domains of learning, the former has to take into account this diversity and to situate the learning activity. In this paper, we will show how to produce a guide model parameterized by the learning domain. Our objective was to develop an adaptive intelligent tutoring system based on item response theory and metrics, adapted for letting the learners work in several disciplinary fields in the University of Annaba. In this context, our constraint is threefold: to represent knowledge relative to several disciplinary domains, to propose interactive activities to the learners and finally, to be able to support student guidance in her/his course by proposing her/him relevant support activities when he meets difficulties.

Keywords: *Hypermedia, Learner model, Strategy guide, Trace, Intelligent tutoring system, Item Response Theory*

1. Introduction

Nowadays, learning systems take various forms: micro-worlds, intelligent tutoring systems (ITS), adaptive hypermedia (AH), learning games, etc. The conception of a learning system is a multidisciplinary task based on theoretical models inspired by pedagogy, by didactic and by psychology. The direct application of such models is not always easy, or even possible, and in general requires major adaptations. Intelligent Tutoring Systems (ITS) are designed to assist learners in the acquisition of skills rather than the complete mastery of a domain. Intelligent tutoring systems are primarily used as instruction during the tutorial section of a lecture course, or in conjunction with an alternate instruction method [2, 6, 19, 26]. Conversely, Adaptive Hypermedia (AH) are primarily designed to impart the concepts of a domain that a student must know in order to utilize these skills [22, 16, 11]. While some adaptive hypermedia systems do provide instruction in skills, it is generally less advanced than comparable ITS instruction. For a system to provide a standalone solution comparable to a lecture course it must provide instruction in both concepts and skills. A general instruction system requires both of these instruction methods to provide a full learning system [23, 15, 8, 18]. This paper describes a generic model for guiding learners in Adaptive Intelligent

Tutoring System AITS based on item response theory and metrics, composed of two components: adaptive hypermedia and intelligent tutoring system.

2. Background and Related

First of all, let us begin by giving a state of the art on Item response theory (IRT). Then, we will give a state of the art on adaptive hypermedia system. Finally, we will give a state of the art on intelligent tutoring system that use traces.

2.1. Item Response Theory (IRT)

Item response theory (IRT) was first introduced to provide a formal approach to adaptive testing [30]. The main purpose of IRT is to estimate an examinee's ability (θ) or proficiency [31] according to his/her dichotomous responses (true/false) to test items. Based on the IRT model, the relationship between examinee's responses and test items can be explained by so-called item characteristic curve (ICC) [32]. In the case of a typical test item, this curve is S-shaped; the horizontal axis is ability scale and the vertical axis is the probability that an examinee with certain ability will give a correct answer to the item. The item characteristic curve is the basic building block of item response theory; all the other constructs of the theory depend upon this curve [33]. Several nice features of IRT include the examinee group invariance of item parameters and item invariance of an examinee's ability estimate [32]. Under item response theory, the standard mathematical model for the item characteristic curve is the cumulative form of the logistic function. It was first used as a model for the item characteristic curve in the late 1950s and, because of its simplicity, has become the preferred model [33].

Based on the number of parameters in logistic function there are three common models for ICC; one parameter logistic model (1PL) or Rasch model, two parameter logistic model (2PL) and three parameter (3PL) [32, 33]. In the 1PL model, each item i is characterized by only one parameter, the item difficulty b_i , in a logistic formation as shown

$$P_i(\theta) = \frac{1}{1 + exp(-D(\theta - b_i))}, \qquad (1)$$

Where D is a constant and equals to 1.7 and θ is ability scale. In the 2PL model, another parameter, called discrimination degree a_i , is added into the item characteristic function, as shown

$$P_i(\theta) = \frac{1}{1 + exp(-a_i D(\theta - b_i))}. \qquad (2)$$

The last 3PL model adds a guess degree c_i to the 2PL model, as shown in Eq. (3), modeling the potential guess behavior of examinees (Wang, 2006).

$$P_i(\theta) = c_i + \ frac1 - c_i 1 + exp(-a_i D(\theta - b_i)). \qquad (3)$$

Several assumptions must be met before reasonable and precise interpretations based on IRT can be made. The first is the assumption of unidimensionality, which assumes there is only one factor affecting the test performance. The second assumption is the local independence of items, which assumes test items are independent to each other. This assumption enables an estimation method called maximum likelihood estimator (MLE) to effectively estimate item parameters and examinee's abilities [32].

$$L(\theta|u_1, u_2, \ldots, u_n) = \prod_{i=1}^{n} P_i(\theta)^{u_i} Q_i(\theta)^{1-u_i}, \qquad (4)$$

Where Qi(θ)=1-Pi(θ). Pi(θ) denotes the probability that learner can answer the I th item correctly, Qi(θ) represents the probability that learner cannot answer the I th item correctly, and u_i is 1 for correct answer to item i and 0 for incorrect answer to item i [31].

Since Pi(θ) and Qi(θ) are functions of learner ability θ and item parameters, the likelihood function is also a function of these parameters. Learner ability θ can be estimated by computing the maximum value of likelihood function. Restated, learner ability equals the θ value with maximum value of likelihood function [34].

Item information function (IIF) in IRT plays an important role in constructing tests for examinees and evaluation of items in a test.

Any item in a test provides some information about the ability of the examinee, but the amount of this information depends on how closely the difficulty of the item matches the ability of the person. The amount of information, based upon a single item, can be computed at any ability level and is denoted by Ii(θ), where i is the number of the items. Because only a single item is involved, the amount of information at any point on the ability scale is going to be rather small [33]. Item information function is defined:

$$I_i(\theta) = \frac{P_i'^2(\theta)}{P_i(\theta) Q_i(\theta)}, \qquad (5)$$

Where P'(θ) is the first derivative of Pi(θ) and Qi(θ)=1-Pi(θ). A test is a set of items; therefore, the test information at a given ability level is simply the sum of the item information at that level. Consequently, the test information function (TIF) is defined as:

$$I(\theta) = \sum_{i=1}^{N} I_i(\theta), \qquad (6)$$

Where Ii(θ) is the amount of information for item i at ability level θ and N is the number of items in the test. The general level of the test information function will be much higher than that for a single item information function. Thus, a test measures ability more precisely than does a single item. An important feature of the definition of test information given in Eq. (6) is that the more items in the test, the greater the amount of information. Thus, in general, longer tests will measure an examinee’s ability with greater precision than will shorter tests [33].

Item response theory usually is applied in the computerized adaptive test (CAT) domain to select the most appropriate items for examinees based on individual ability. The CAT not only can efficiently shorten the testing time and the number of testing items but also can allow finer diagnosis at a higher level of resolution.

Presently, the concept of CAT has been successfully applied to replace traditional measurement instruments (which are typically fixed-length, fixed-content and paper–pencil tests) in several real-world applications, such as GMAT, GRE, and TOEFL [35].

2.2. Adaptive Hypermedia

Hypermedia systems are becoming increasingly popular as tools for user-driven access to information. They typically offer users a lot of freedom to navigate through a large hyperspace. Adaptive Hypermedia (AH) combines hypermedia with user modeling [4]. The content presented by the system is adapted to the user's knowledge, goals and preferences by maintaining a user model. In the educational hypermedia context, the topics suggested to the learner for subsequent study would be determined by the learner's existing knowledge. AH aim at overcoming these problems by providing adaptive navigation support and adaptive content [12]. The adaptation is based on a user model that represents relevant aspects of the user such as preferences [4], knowledge and interests. The system gathers information about the user by observing the use of the application, and in particular by observing the browsing user's behavior. Adaptive hypermedia build a model of the goals, preferences and knowledge of each individual user, and use this model throughout the interaction with the user, in order to adapt the hypertext to the needs of that particular user [5]. For example, a learner in an adaptive hypermedia system will be given a presentation which is adapted specifically to his or her knowledge of the subject and a suggested set of most relevant links to precede further [21]. An adaptive electronic encyclopedia will personalize the content of an article to increase the user's existing knowledge and interests [17]. A virtual museum will adapt the presentation of every visited object to the user's individual path through the museum [20].

2.3. Intelligent Tutoring System

The necessary components of an ITS are the domain model, the learner model, the diagnostic module, the tutorial module and the user-interface module. The domain model in an ITS consists of domain knowledge that the system intends to teach the learner. The domain model provides the necessary skill to the tutor in order to help him solve problems posed by the learner as well as determining correct answers for the questions asked by learners. The learner model is that part of an ITS which represents the current knowledge state of the learner. This information helps the tutor to adapt the instruction in accordance with competence, abilities and needs.

The tutor can accordingly choose a suitable level and method of presentation of the subject based on the learner's learning abilities and other factors such as those represented in the learner model. The main objective of the diagnostic module is to maintain the learner model and performing the learner evaluation before, during and after the tutorial process. The information provided by the diagnostic module is to be used by the tutorial module to decide about what to teach and how to teach. The tutorial module contains instructional strategies like choosing an effective presentation method, determining what to present next and when to interrupt the instruction process. The instructional strategies are based on the information provided by the diagnostic and the learner modules, whereas the user-interface module provides communication between the learner and the tutor. For example, we can cite intelligent tutoring systems developed for teaching on E-learning system: COLER [9, 10, 26], Prolog-Tutor [27], ZosMat [14].

2.4. Toward and Adaptive Intelligent Tutoring System (AITS)

From the study of this a state of the art, we can conclude by stating the disadvantages of these systems:

- The majority of these systems are dedicated to a specific domain, allowing them to offer accurate models of the domain and the learner. The analysis produced from traces left by the users is didactically very precise and specific to the domain in question. It allows one to guide the learner in case of difficulty and to offer her/him some support.
- An intelligent tutoring system is very limited in its level of expertise, long to develop, rigid and difficult to change, whereas hypermedia is theoretically unlimited in its expertise, developed rapidly and easily updated;
- item A hypermedia system, given its freedom and flexibility, is deemed by both problems of disorientation and cognitive overload, which deprive the learner's initial target, while an intelligent tutoring system is deemed by the fact that it effectively guides the user towards his goal.

To overcome these limitations, we will try to combine the benefits of both paradigms (AH and ITS) in order to adapt the course to the needs and intellectual abilities of each learner.

3. AITS based on IRT and Metrics

Figure 1 gives home page of AITS based on IRT and Metrics. It consists of tree main interfaces, which are associated with each of the following human actors: learner, teacher and administrator. In addition, it contains an adaptive intelligent tutoring which is made up of two components: adaptive hypermedia (domain model, learner model and adaptation model) [13, 7] and intelligent tutoring system (domain model, learner model, Instructional Model) [3, 24, 1, 25].

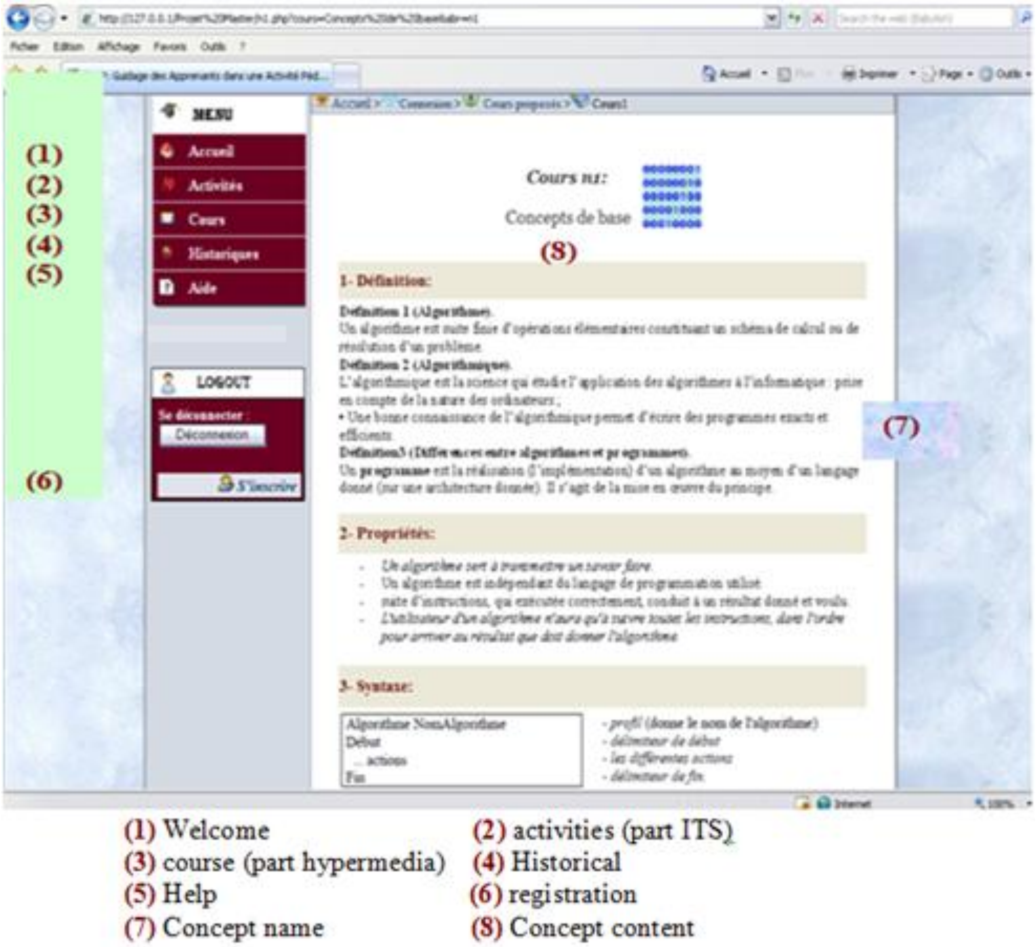

Figure 1. Home Page of AITS based on IRT and Metrics

3.1. Models and Knowledge Representation

We present in the following sections the available features in AITS.

3.1.1. Domain model: The domain model is based on the concepts notion that the learner can select and study. These concepts are interconnected by relations: relations of sufficiency and precedence relations.

- ***Relationship of precedence***: A concept N1 is precedence relation with a concept N2 if the control (or partial control) of N2 is necessary for learning to N1. This relationship has an attribute: S is the minimum threshold of N2 control to allow the start of learning N1.

- ***Relationship of Sufficiency:*** A concept N1 is linked with a concept of sufficiency N2 if the control of N2 (or partial control) results control of N1. This relationship with two attributes: S is the minimum threshold of N2 control to activate the requisite relationship. A is the contribution (in percentage) of control N2 to N1.

In addition, the teacher organizes the learning according to pedagogical activities. Linked to our domain model, we have defined a corpus of interactive activities. These activities have to be organized in a progressive manner by possibly using serious games, interactive exercises, simulation and artifacts that support the construction of the knowledge.

3.1.2. Learner's Model: Learner modeling and adaptation are strongly correlated, in the sense that the amount and nature of information represented in the learner model depend largely on the kind of adaptation effect that the system has to deliver. The learner model in AITS was defined as three sub-models: The profile, the knowledge level and the trace. The learner profile was implemented as a set of attributes which store learner's static personal characteristics, for example username, password, unique ID, age, e-mail. The knowledge level recorded by the system for learner's knowledge about each domain knowledge concept; It is an overlay of the domain model. It associated learner's knowledge level with each concept of the domain model. We want to continually assess the skill level of the learner to develop a map of his state of knowledge. The learner model is enriched at the end of each activity after analysis of the traces produced.

3.1.3. Adaptation Model: The adaptation model in AITS specified the way in which the learners' knowledge modifies the content presentation. It was implemented as a set of the classical structure: If condition, then action type rules. These rules form the connection between the domain model and learner model to update the learner model and provide appropriate learning materials. The adaptation model consists of abstract concept selection rules that determine which concepts from the domain model to be covered, based on the knowledge in the learner model.

To support adaptivity, AITS used a combination of adaptive navigation support and adaptive presentation technique. AITS implemented adaptive presentation by classifying learners according to their current knowledge state. Learners with different knowledge state view different presentations of the same educational material. The system implemented various adaptive navigation support technologies, which help the user in navigating the domain model. It offered linear navigation (direct guidance, next and previous units) hierarchical navigation (through the tree-like structure of contents) and relational navigation (link insertion and link disabling through prerequisite concepts relationship).

3.1.4. Instructional Model: Instructional model contains knowledge for making decisions about instructional tactics. It relies on the diagnostic processes of the learner model for making decisions about what, when and how to present activity to a learner. Following an activity, the model offers guidance in learning other activities. For that purpose it takes into account completions, context and proficiency levels, by analyzing the rest of the activities already carried out. The analysis is based on a set of metrics [29].

a) Metrics. To construct the learner model we define a few indicators [29]:

- Achievement (σ)

$A_i = (N_i, \sigma, M)$ defines the learning gain σ concerning a notion N_i with a maximum M. An achievement (N, 0.1, 0.2) signifies that the skill concerning the notion N may increase by 10% to a maximum of 20% of the skill level. For a learner with a skill level of 5% concerning this notion, such an achievement will increase her/his skill level to 15%. Naturally, if her/his skill level is 12% at the beginning then it will reach 20% and not 22%.

- Skill level (α)

It is a couple, (Ni, α), the real number α corresponds to the skill level of the notion Ni; 0 notion not acquired, 1 fully acquired. In the learner model, it defines her/his skill concerning a notion. In the pedagogical activities, it deals with the lowest skill level required in order to access a specific activity.

To compute a learner's progression we need to sum skill level and achievement:

$$Li + Ai = (Ni, max(\alpha, min(\alpha + \sigma, M))). \quad (7)$$

Such a sum is the skill level; the goal of this operation is to re-evaluate the skill level of a learner after her/his activity.

For this, we distinguish three cases:

- A skill level and achievement are on the same concept; in this case we are their sum.

- There is no achievement on a concept of a skill level; in this case the skill level remains unchanged.

- There is no skill level on a concept of an achievement in this case we add a skill level with an initial value gain of achievement.

- Gap control

The gap control is defined as the difference between the skill level after the achievement of the activity and the initial skill level of a given concept.

$$GCi = \alpha i' - \alpha i. \quad (8)$$

- Potential control

For a given concept, the potential control is the maximum skill level that the learner can achieve by performing an activity correctly.

$$PC = max(\alpha; min(\alpha + \sigma; M)). \quad (9)$$

- Learning Success Rate

For a given concept, the success rate of learning quantifies the magnitude of what was learned while taking into account the learning potential of the learner in this activity. For an activity with potential for learning near the skill level of the learner, it is the success rate and thus overcomes the activity.

$$SRLi = 100 * (GCi/(PCi - \alpha i)) \ For \ PCi > \alpha i \quad (10)$$

$$SRLi = 100 * (\sigma i'/\sigma i) \ For \ PCi = \alpha i$$

b) Item Response Theory

The Item Response Theory - IRT- is used to ensure a proper balancing test and give their description in the form of a characteristic curve [28]. The theory assumes that a learner's response to a test item can be approximated using a probabilistic function. We propose this method to assess the probability for a student to correctly answer an assessment activity. This method is used as an additional discriminating criterion in our guide. It would occur at the end of selection, to choose an activity of several possible after the computation using the metric (figure 2).

For this study, Item difficulty can be determined by using IRT approach with one parameter which uses the formula: ID = MSCA/SCAE.

Where, ID = item difficulty, MSCA = Minimum Sum of Correct Answers, SCAE = Sum of Correct Answers of Each Question.

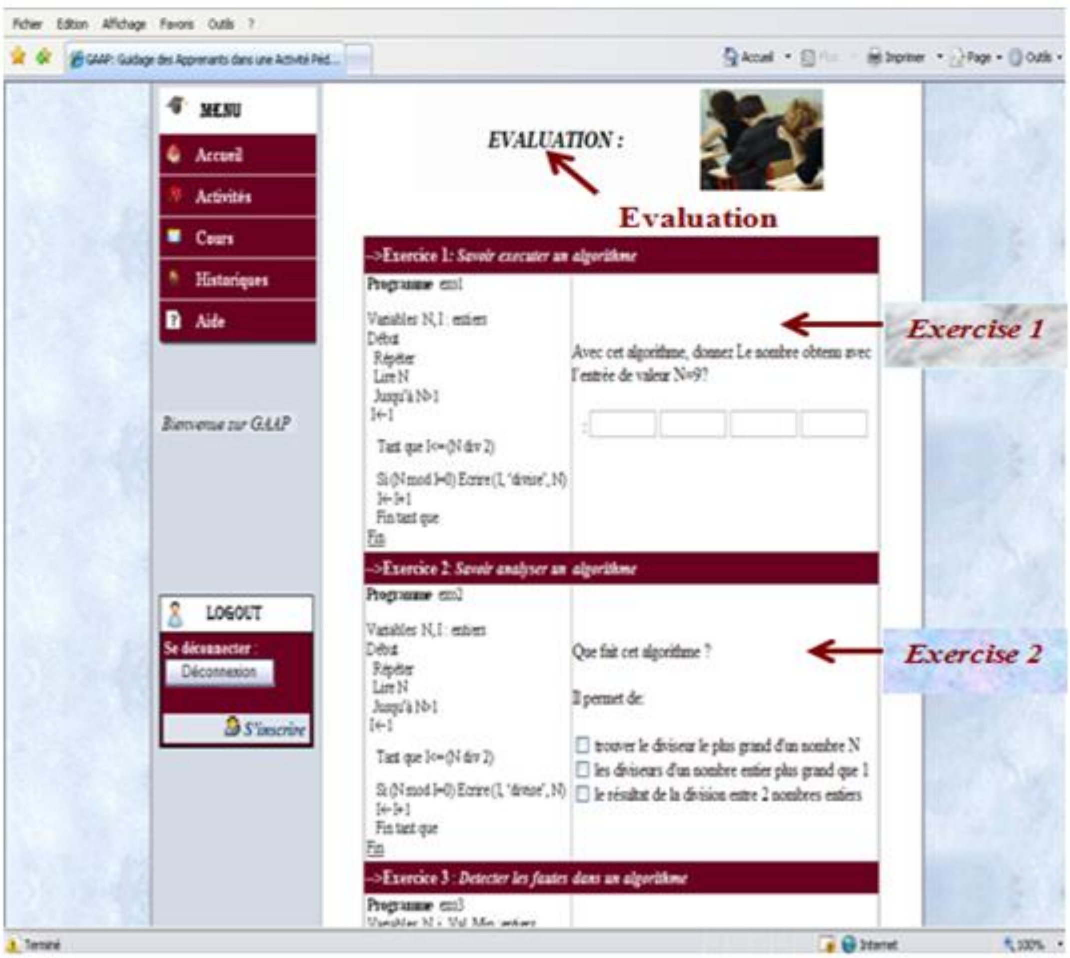

Figure 2. An Assessment Activity based on IRT

4. Experiment

In this section, we present a description of an experiment that was conducted at the University of Annaba. First of all, we will begin by giving an overview of the subject to be studied and the participants. Then, we present the adopted methodology. At the end of the experiment, a questionnaire was submitted to the participants. The results are presented and discussed in the next sub-section. Finally, we will present some problems faced by learners.

4.1. Overview

An experimental study was conducted within Annaba University (Algeria) with 1st year licence students where the subject was "algorithmic". This subject is studied by several students in the licence degree. In fact, students from MI (Mathematics and Informatics), ST (Science and Technology), Economics and Sciences of Nature must take a subject termed "initiation into informatics and algorithmic". Students can use the system from any computer connected to the university intranet network. We took into account, in this experiment, only students from the MI (Mathematics and Informatics) specialty.

4.2. Methodology

We conducted an experiment in computer science department at Annaba University (Algeria), with 40 students from 1st year bachelor degree, where the major subject is: "algorithmic". The participants are divided into two groups (at random). The first group (control group) follows a system prototype without the model for guiding learners in adaptive hypermedia, while the second (experimental group) uses AITS system with all its features.

Our hypothesis is that the model for guiding increases the cognitive level of learners.

4.3. Results and Discussion

To verify our hypothesis, the experiment data was compared using the independent sample t-test through the Statistical Package for the Social Sciences (SPSS) software. Quizzes were the methods used to evaluate learners after they were enrolled in the experiment.

After tree months of experimentation, a quiz was administered by the system to assess learners on the concepts that were covered in the course (see table 1).

Table 1. t-test Statistics: Comparison of Average Quizzes Scores

N	Mean of control group	Mean of experimental group	T_{score}	Degree of freedom	P_{value}
40	69.52	77.14	- 2.322	40	0.025

Table 1 show the comparison of average quizzes scores in experimental and control groups. It shows that the average scores for experimental group were higher than control groups in quizzes (Control Group: Mean=69.52, Standard Deviation=12.03), (Experimental Group: Mean=77.14, Standard Deviation=9.02). The independent sample t-test was performed to compare the mean scores for the two groups. The t-test determined that the differences measured between the means of the control and experimental group were significantly different and could be attributed to learning through AITS given to the experimental group. Results show that the experimental group performed significantly better than the control group (T-test Value=-2.322, Degrees of Freedom=40, Probability Value=0.025<0.05). The achievement results obtained, show clearly, that introducing intelligent tutoring in adaptive hypermedia improves learners' achievement and performance.

4.4. Learner's Feedback

To extract problems encountered as well as the global opinion of the learners, we prepared a questionnaire addressed to learners after using the system. The questions where divided into three categories:

- General opinion about the interface of the system and the main available features.

-The quality of the interface as well as its options.

-The quality of the content of courses.

We present in what follows (Table 2) some responses of the learners about the main questions of the questionnaire.

Table 2. Responses of Learners after the Experiment

Questions	Answers			
Do you think that the use of this system is	Very easy 3	Easy 15	Difficult 2	Very Difficult
Do you prefer the learning done by an adaptive hypermedia or an intelligent tutor system?	Hypermedia 4	Its 6	Both 10	
How do you see the organization of the concepts ?	Very good 2	Good 14	Average 4	Weak 0
How do you see the assessment activities?	Very easy 2	Easy 13	Difficult 5	Very Difficult 0
The content of activity guide is	Very clear 5	Clear 12	Quite Clear 3	Not Clear 0
Are you satisfied with the learner space?	Yes	Slightly	No	

Most learners appreciated the integration of the intelligent tutoring system to adaptive hypermedia adopted in AITS and the support offered by the system. All of them found that the system is user-friendly. The participant's opinion to use the system in the future was very high. According to them, the concepts were organized in a good manner. The content of activity guide is clear for the majority of students.

Concerning the faced problems, the learners cited:

- Lack of tools for the graphical representation of traces,
- Knowledge assessment tool is less efficient,
- Same activities without adaptation to learning style,
- Lack of tools to communicate with teacher.

5. Conclusion and Future Work

Adaptive Hypermedia and Intelligent Tutoring Systems are both effective methods of computer-based learning. However, adaptive hypermedia is better suited for the instruction of concepts whereas intelligent tutoring system generally assists in the use of these concepts to solve problems. This paper was dedicated to the combination of these systems. The aim of adaptive intelligent tutoring system (AITS) has been to propose a non domain-dependent model to represent teaching activity. For each teaching domain, a domain model has been used to organize the learning process.

Metrics have been elaborated to associate the exercises of an activity corpus to the domain model mentioned previously. As we have explained, it is thus possible to elaborate and update dynamically a learner model and even to propose remediation activities as a function of context trace observation. Importance was also given to the use of several types of activity and many types of resources. With the spread of the LMD (Licence-Master-Doctorate) educational system in Algeria, we took into account the licence (bachelor) degree, making our system useful for the university community. The application focused on teachers who are not specialized in ICT (Information and Communication Technology) and who possess only basic knowledge in ICT. At present, AITS is used only in French but we plan to take into account other languages. As an answer to the questions cited of this paper, we can say that merging adaptive hypermedia and intelligent tutoring system has good impact on the cognitive profiles of learners. Teachers and learners of various departments can use the system from any computer connected to the intranet of the university. The first results of this experiment were very encouraging. Most of the teachers and the learners appreciated the use of the system. As a result, we drew several conclusions and several research tracks were opened. In the future we would like to include many more teaching subjects (mathematics, languages, science, etc.).

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