Development of an adaptive and intelligent tutoring system by expert system

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Abstract: Learners usually meet cognitive overload and disorientation problems when using e-learning systems. At present, most of the studies on e-learning either concentrate on technological aspects or focus on adapting learners’ interests or browsing behaviours, while, learners’ skill level and learners’ multiple intelligences are usually neglected. In this paper, an Adaptive and Intelligent Tutoring System (AITS) by expert system based not only on the difficulty level of activities, but also the changing learning performance of the individual learner during the learning process is proposed. Therefore, considering learners’ skill level and learners’ multiple intelligences can promote personalised learning performance. Learners’ skill level is obtained from pre-test result analysis, while learners’ multiple intelligences are obtained from questionnaire analysis. After computing learning success rate, the system then modifies the difficulty level or the presentation of corresponding activity to update courseware material sequencing.

Keywords: intelligent tutoring system; e-learning; cognitive overload; disorientation; trace; multiple intelligences; learner’s feedback.


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1 Introduction

Many researchers focused on developing Adaptive and Intelligent Tutoring Systems (AITS) with personalised learning mechanisms to assist online learning and adaptively provide learning paths (Chen et al., 2005; Hwang, 2003; Lee et al., 2009; Papanikolaou and Grigoriadou, 2002; Andharini, 2012; Wang et al., 2012).

In order to aid more efficient learning, many powerful personalised and adaptive guidance mechanisms (i.e., adaptive presentation, adaptive guidance path support, curriculum sequencing and artificial intelligence analysis of learner’s solutions) have been proposed to improve learners’ learning performance.

Curriculum sequencing is an important research issue for AITS because no fixed learning paths will be appropriate for all learners.

Therefore, personalised systems consider learner preferences, interests and browsing behaviours in providing personalised curriculum sequencing (Dabbagh, 2007; Huang et al., 2007; Bai and Chen, 2008; Chen, 2008; Bhaskar et al., 2010; Chu et al., 2011). However, these systems neglect the importance of a learner’s multiple intelligences, feedback and skill level when implementing personalised mechanisms.

Generally, inappropriate courseware leads to learner cognitive overload or disorientation during learning processes, thus reducing learning performance (Cobos et al.,
2.1 Adaptive and intelligent tutoring systems

This subsection provides a brief review of current research on AITS. Currently, all adaptation technologies applied in AITS are adopted from either the intelligent tutoring system area (curriculum sequencing, intelligent analysis of student’s solutions, interactive problem solving support and example-based problem solving support) or the adaptive hypermedia area (adaptive presentation and adaptive navigation support) (Canales et al., 2007; Milićević et al., 2011; Aggarwal and Kumar, 2011).

The goal of the curriculum sequencing technology is to help the student find an ‘optimal path’ through the learning material. The classic examples of AITS are ELM-ART, CALAT, InterBook, AST, MANIC, Medtec and DCG (Brusilovsky and Peylo, 2003).

The intelligent analysis of solutions is a very suitable technology in the context of slow networks. It needs only one interaction between browser and server for a complete solution. It can provide intelligent feedback and perform student modelling when more interactive techniques will be hardly useful. The classic examples of AITS are ELM-ART and WITS (Brusilovsky and Peylo, 2003).

The goal of interactive problem solving support is to provide the student with intelligent help on each step of problem solving – from giving a hint to executing the next step for the student.

The classic examples of AITS are the LISP-TUTOR, ACT Programming Tutor, GRACE, PAT-Online, Belvedere and ADIS (Brusilovsky and Peylo, 2003).

In an example-based problem solving context, students solve new problems using as help examples from their earlier experience. Examples of AITS are ELM-PE and ELM-ART (Brusilovsky and Peylo, 2003).

The goal of the adaptive presentation technology is to adapt the content of a hypermedia page to the user’s goals, knowledge and other information stored in the user model. In a system with adaptive presentation, the pages are not static, but adaptively generated or assembled from pieces for each user. Only two AITS implement full-fledged adaptive presentation: C-Book and De Bra’s adaptive course on Hypertext (Brusilovsky and Peylo, 2003). Both these systems apply the conditional text technique. Some other systems use adaptive presentation is special contexts. Medtec is able to generate adaptive summary of book chapters. ELM-ART, AST and InterBook use adaptive presentation to provide adaptive warnings about the educational status of a page.

The goal of the adaptive navigation support technology is to support the student in hyperspace orientation and navigation by changing the appearance of visible links. Adaptive navigation support can be considered as an extension of curriculum sequencing technology into a hypermedia context. It shares the same goal – to help students to find an ‘optimal path’ through the learning material. At the same time, adaptive navigation support guides students implicitly and leaves the choice of the next knowledge item to be learned and next problem to be solved to them. Examples of AITS are ISIS-Tutor which uses adaptive hiding and adaptive annotation and Hypadapter which uses adaptive hiding and adaptive sorting, ELM-ART, InterBook, WEST-KBNS and AST (Brusilovsky and Peylo, 2003). Table 1 summarises the proposed system and some available ones in terms of different properties. It is clear in this table that available systems do not have all of these useful properties while proposed system has been designed to cover them all.

2.2 Multiple intelligences

The study of individual differences is central to understand how some students perform better than others (Serce et al., 2011; Shirakawa and Kurahashi, 2013; Zang et al., 2013). Two main categories of individual traits in learning that are consistent over the long term can be identified: intelligences and style. Comparing intelligences to style, individual differences in intelligence refer to the ability with which one can do something, whereas styles refer to preferences in the use of abilities.

Many researchers have studied the integration of learning styles in the design of adaptive educational systems. However, it has been difficult to demonstrate conclusively how the concept of learning style can be supported and how it can improve learning outcomes. Some reasons for this include:

- the lack of a unifying framework or organising theory to understand different styles in relation to each other
- difficulty in developing valid methods for objectively assessing dimensions of style
• arbitrary classification of individuals into categories, theories classify people but people are flexible and do not fit neatly in predefined types
• questions around the construct validity of style with statistical analyses providing mixed support.

In contrast, there is much evidence to support the concept of intelligence as a predictor of learning performance (Sonboli and Noruzi, 2012; Hajhashemi et al., 2012). Instead with intelligence, the debate about how intelligence can be measured and on the concept of a single general intelligence level where all abilities are remains. Critics argue that good or poor performance in one area in no way guarantees similar performance in another and that the full range of intelligent behaviour is not completely captured by any single general ability (Sternberg, 1996).

Table 1 Adaptation technologies in AITS

<table>
<thead>
<tr>
<th>System</th>
<th>Hypertext component</th>
<th>Adaptive sequencing</th>
<th>Problem solving support</th>
<th>Intelligent solution analysis</th>
<th>Adaptive presentation</th>
<th>Learner’s feedback</th>
<th>Adaptive test</th>
</tr>
</thead>
<tbody>
<tr>
<td>AST</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td>Some</td>
<td></td>
</tr>
<tr>
<td>InterBook</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td>Some</td>
<td></td>
</tr>
<tr>
<td>PAT-InterBook</td>
<td>Y</td>
<td>Y</td>
<td>Server</td>
<td>Y</td>
<td></td>
<td>Some</td>
<td></td>
</tr>
<tr>
<td>PAT</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DCG</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WITS</td>
<td>N</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C-Book</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manic</td>
<td>Y</td>
<td>Some</td>
<td>Server</td>
<td>Y</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed system</td>
<td>Y</td>
<td>Y</td>
<td>Server</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

In particular, Gardner (2000) proposes the concept of Multiple Intelligences, a theory which describes how different intelligences are used to solve problems and fashion products (Maftoon and Sarem, 2012). In the past 20 years since the theory of Multiple Intelligences was introduced, it has been found to be a useful construct in many settings such as education and training, career guidance and development, counselling and personal development. In particular, research has suggested that the impact of the Multiple Intelligence theory in the classroom has been significant (Hajhashemi et al., 2012; Hernández et al., 2010). It should be noted however that the theory of Multiple Intelligence has many critics who state that intelligences should be described as special talents and that there is no empirical basis for the different intelligences.

Despite critics, the theory of Multiple Intelligence has remains very popular. One reason for this is that the different intelligences are not abstract concepts, but are easily recognisable through experience. Intuitively, it is possible to understand the differences between musical and linguistic, or spatial and mathematical intelligences. As a consequence, it offers a rich structure and language in which to develop content and model the student. Currently, the application of Multiple Intelligence to adaptive educational systems is still very limited and in the early stages of research (Hernández et al., 2010). Hence, this research proposes that the use of the Multiple Intelligence framework of individual differences in the design of AITS offers an unexplored dimension that may enhance learning.

3 The proposed Adaptive and Intelligent Tutoring System by expert system

Figure 1 gives an overview of the overall architecture of the system. It consists of two main interfaces, which are associated with each of the following human actors: learner and teacher, respectively. In addition, it is made up of four components: domain model, learner model, pedagogical model and expert system.

We present in the following sub-sections the available features in each human interface.

3.1 Model and knowledge representation
3.1.1 Domain model

The domain model is based on the concepts that the learner can select and study.

The skill level is a couple, \( (N_i, \alpha) \) where, the real number \( \alpha \) corresponds to the skill level of the concept \( N_i \); 0 concept not acquired, 1 fully acquired.

These concepts are interconnected by two relations: relations of sufficiency and precedence relations (Hafidi et al., 2011).

- **Relationship of precedence**: A concept \( N_1 \) is in relation of precedence with a concept \( N_2 \) if control (or partial control) of \( N_2 \) is necessary for learning \( N_1 \).

The precedence relation \( P = (N_1; N_2; \zeta) \) is defined as \( N_1, N_2 \) are two concepts and \( 0 \leq \zeta \leq 1 \) with \( \zeta \) the minimum threshold of \( N_2 \) control to allow the start of learning to \( N_1 \).
• **Relationship of sufficiency:** A concept $N_1$ is in relation of sufficiency with a concept $N_2$ if control of $N_2$ (or partial control) results control of $N_1$.

The sufficiency $S = (N_1; N_2; \zeta; \pi)$ is defined as $N_1$, $N_2$ are two concepts and $0 \leq \pi \leq 1$ and $0 \leq \zeta \leq 1$ with $\zeta$ the minimum threshold of $N_2$ control to activate the requisite relationship and $\pi$ the contribution (in percentage) of control $N_2$ to $N_1$.

In addition, the teacher organises the learning according to pedagogical activities. Linked to our domain model, we have defined a corpus of interactive activities. These activities have to be organised in a progressive manner by possibly using serious games, interactive exercises, simulation and artefacts that support the construction of the knowledge. These activities have been developed using the principles of Multiple Intelligences. Each activity uses dominantly one intelligence (Logical/mathematical, Linguistic, Visual-Spatial, Musical-Rhythmic, Kinesthetic, Intrapersonal, Interpersonal and Naturalist) and is used to explain or introduce several concepts in a different way. Here in the following example of an architecture domain model in our approach.

**Figure 1** Overview of the adaptive and intelligent tutoring by expert system (see online version for colours)

3.1.2 Learner model

Learner modelling and adaptation are strongly correlated, in the sense that the amount and nature of the represented information 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 four sub-models: the profile, the knowledge level, the learning style and the trace. The learner profile was implemented as a set of attributes which store static personal characteristics about the learner, for example username, password, unique ID, age and 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.
Multiple intelligences inspire the learner model in AITS. Gardner identifies eight intelligences (Sadeghi and Farzizadeh, 2012; Altan, 2012) which are summarised in Table 2.

- **Logical/mathematical**: reasoning and calculating. They think conceptually, abstractly and are able to see and explore patterns and relationships. They like to experiment, solve puzzles and ask cosmic questions. They can be taught through logic games, investigations and mysteries. They need to learn and form concepts before they can deal with details.

- **Linguistic**: using words effectively. They have highly developed auditory skills and often think in words. They like reading, playing word games, making up poetry or stories. They can be taught by encouraging them to say and see words or to read books together. Tools include computers, games, multimedia, books, tape recorders and lecture.

- **Visual-Spatial**: think in terms of physical space, as do architects and sailors. They are very aware of their environment. They like to draw, do jigsaw puzzles, read maps and daydream. They can be taught through drawings, verbal and physical imagery. Tools include models, graphics, charts, photographs, drawings, 3D modelling, video, videoconferencing, television, multimedia and texts with pictures/charts/graphs.

- **Musical-Rhythmic**: sensitive to rhythm and sound. They love music, but they are also sensitive to sounds. They may study better with music in the background. They can be taught by turning lessons into lyrics, speaking rhythmically and tapping out time. Tools include musical instruments, music, radio, stereo, CD-ROM and multimedia.

- **Kinesthetic**: use the body effectively, like a dancer or a surgeon. They like movement, making things and touching. They communicate well through body language and can be taught through physical activity, hands-on learning and role playing. Tools include equipment and real objects.

- **Intrapersonal**: understanding one’s own interests and goals. They tend to shy away from others. They are in tune with their inner feelings: they have wisdom, intuition and motivation, as well as a strong will, confidence and opinions. They can be taught through independent study and introspection. Tools include books, creative materials, diaries, privacy and time. They are the most independent learners.

- **Interpersonal**: understanding and interacting with others. They learn through interaction. They have many friends, empathy for others, street smarts. They can be taught through group activities, seminars and dialogues. Tools include the telephone, audio conferencing, time and attention from the instructor, video conferencing, writing, computer conferencing and e-mail.

- **Naturalist**: demonstrates expertise in the recognition and classification of species of the environment. Value is placed on these individuals who can recognise members of a species that are especially valuable or notably dangerous and can appropriately categorise new and unfamiliar organisms.

### Table 2 Summarisation of multiple intelligences model

<table>
<thead>
<tr>
<th></th>
<th>Simulation</th>
<th>Game</th>
<th>E-mail</th>
<th>Video-conf</th>
<th>Audio-conf</th>
<th>Chat</th>
<th>Video</th>
<th>Audio</th>
<th>Slides</th>
<th>Group-work</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual-spatial</td>
<td>☒</td>
<td>☒</td>
<td></td>
<td></td>
<td></td>
<td>☐</td>
<td></td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Bodily-kinesthetic</td>
<td>☒</td>
<td>☒</td>
<td></td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Musical-rhythmic</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Intrapersonal</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Linguistic</td>
<td>☐</td>
<td>☐</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Logical/mathematic</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Naturalist</td>
<td>☒</td>
<td>☒</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>

#### 3.1.3 Expert system

An expert system consists of the fact base, the rule base and the inference engine. The fact base contains facts, which are created from the problem data, whereas the rule base contains the rules used by the inference engine to solve problems (Jiang et al., 2008) (see Figure 2).

The pre-test, evaluation and post-test includes of some questions planned by an expert system. Question selection should satisfy some rules. Firstly, none of them should be repetitious even if a learner would be trained one concept several times. Secondly, the question must be planned for all sections of a concept entirely. And finally, expert system plans questions in all levels. Sum of scores is calculated and learner level is determined after answering the questions (Ghadirli and Rastgarpour, 2013).

Now, let us see the way expert system helps in the computation of skill level for a given concept N. Initially, the data collected from the student’s answers to the test is converted to corresponding facts. The expert system
processes those facts via the rules, according to the inference engine instructions, and deduces the skill level values of the student for the concepts involved in the delivered test. Rules represent the way a tutor evaluates the answers of a student.

For example, Table 3 depicts that way for the case that the test includes two questions for a concept. There are similar tables for the cases that the test includes many questions related to a concept.

**Figure 2** The structure of an expert system (see online version for colours)

<table>
<thead>
<tr>
<th>Question 1</th>
<th>Answer 1</th>
<th>Question 2</th>
<th>Answer 2</th>
<th>Skill level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy</td>
<td>0</td>
<td>Medium</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Easy</td>
<td>1</td>
<td>Medium</td>
<td>0</td>
<td>0.33</td>
</tr>
<tr>
<td>Easy</td>
<td>0</td>
<td>Medium</td>
<td>1</td>
<td>0.66</td>
</tr>
<tr>
<td>Easy</td>
<td>1</td>
<td>Medium</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Easy</td>
<td>0</td>
<td>Difficult</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Easy</td>
<td>1</td>
<td>Difficult</td>
<td>0</td>
<td>0.25</td>
</tr>
<tr>
<td>Easy</td>
<td>0</td>
<td>Difficult</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>Easy</td>
<td>1</td>
<td>Difficult</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Medium</td>
<td>0</td>
<td>Difficult</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>1</td>
<td>Difficult</td>
<td>0</td>
<td>0.2</td>
</tr>
<tr>
<td>Medium</td>
<td>0</td>
<td>Difficult</td>
<td>1</td>
<td>0.6</td>
</tr>
<tr>
<td>Medium</td>
<td>1</td>
<td>Difficult</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 3** Rules for test include two questions for a concept

3.1.4 Pedagogical module

First, the proposed AITS determines learning style and characteristics of learner by a questionnaire and then make his model. After that learners should take pre-test so that the system acknowledges learners’ initial skill level. Then, the proposed AITS will analyse the test result and store the learners score into a database. Afterwards, the learner should learn about recommended concepts which are generated by the system. When learners can answer is wrong, the system will set the corresponding course as recommended activity. For obtain remediation activity, we define a few indicators (Hafidi et al., 2012):

**Definition 1**: Have called $Ai$ an achievement on the concept $Ni$, the triple $(Ni, \sigma, M)$ such that $0 \leq \sigma \leq 1$ and $0 \leq m \leq 1$, where $\sigma$ is the learning gain concerning a concept $Ni$. If $\sigma = 0$ the learning gain concerning a concept $Ni$ is zero. $M$ represents the maximum skill level.

**Definition 2**: To compute a learner’s progression ($\alpha'$) we need to sum skill ($\alpha$) level and achievement ($\sigma$):

$$\alpha' = (Ni, \max(\alpha, \min(\alpha + \sigma, M)).$$  

**Definition 3**: 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.

$$GCi = \alpha' - \alpha_i.$$  

**Definition 4**: For a given concept, the potential control is the maximum skill level that the learner can achieve by performing an activity correctly.

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

**Definition 5**: For a given concept, the learning success rate quantifies the magnitude of what was learned while taking into account the learning potential of the learner in this activity.

$$LSR = 100 \times (GCi / (PCi - \alpha_i)).$$  

The example of these indicators will illustrate in Table 4.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial skill level</td>
<td>(Concept X, 0.15)</td>
</tr>
<tr>
<td>Achievement</td>
<td>(Concept X, 0.04, 0.2)</td>
</tr>
<tr>
<td>Skill level after the achievement of the activity</td>
<td>$\alpha' = 0.19$</td>
</tr>
<tr>
<td>Gap control</td>
<td>0.04</td>
</tr>
<tr>
<td>Potential control</td>
<td>0.2</td>
</tr>
<tr>
<td>Learning success rate</td>
<td>80%</td>
</tr>
</tbody>
</table>

The procedure of determining the new activity is presented as follows:
3.1.5 System operation procedures

Based on the above-mentioned system architecture, the system operation procedures are briefly described as follows:

- **Step 1:** The test questions, the structure of concepts and activities were constructed by teachers and stored in the domain model. Next, the skill level for each concept was created according to each teacher.

- **Step 2:** Interface learner is responsible for selecting learners and their learning mode:

  **Ordinary Adaptive and Intelligent Tutoring System (O-AITS):** the learners just received skill level when they finished their pre-test process.

  **Proposed Adaptive and Intelligent Tutoring System (P-AITS):** the learner was received skill level, learning style and personalised remedial learning path after they finished their pre-test process.

- **Step 3:** For both learning modes (O-AITS or P-AITS), learners should take pre-test so that the system acknowledges learners’ initial skill level.

- **Step 4:** For learning mode P-AITS, the system determines learning style and characteristics of learner by MI-test and then makes his model.

- **Step 5:** Expert system will analyse the test result and stores the learners score into learner model.

- **Step 6:** There is a different path for O-AITS and P-AITS. In O-AITS, the learner may take any activities after doing pre-test. Nevertheless, in P-AITS, the learner should learn about recommended activities which are generated by pedagogical model. When learners can answer correctly the corresponding test questions of some activities, this indicates that the learners have acquired the concepts. Otherwise, if the learners’ answer is wrong, the system will set the corresponding course materials as a recommended activity.

- **Step 7:** New skill level of an activity as defined by the metrics. These metrics have been implemented to determine the activities to provide a response to difficulty of the learner.

- **Step 8:** After the learners give feedback, the system will modify the difficulty level and the presentation of the corresponding activity in course using collaborative voting.

- **Step 9:** Interface teacher is also responsible to manage the course material of concept, the exercises, pre-test and post-test. Test contains four types of question, namely: true/false question, completion question, multiple choice and further exercise. While the type of questions in pre-test and post-test is only multiple choice.

- **Step 10:** Once the learners have learned a recommended activity, they have to take a test and satisfy the minimum score (success rate) before continuing to learn the next concepts. The learners may continue to start the next concepts if their test score (success rate) over 50% of correct answer. This step then should be repeated again until the learners pass the entire recommended concepts.

- **Step 11:** The learners may take post-test to acknowledge their new skill level.

- **Step 12:** The learners were provided with the survey to express their opinions to the use of the O-AITS or the P-AITS.

4 Application of an algorithmic module

The learner interface of free browsing in O-AITS is represented in Figure 3. This learning content consists of 30 concepts and a number of QCM. Each concept has its own difficulty. Teacher may input the course material and set the difficulty level each material at the beginning.
As presented in Figure 1, the first step of our proposed work is the system determines learning style and characteristics of learner by MI-test and then makes his model. This test is shown in Figure 4.

The next step is the learner takes a pre-test. Afterward, the system analyses the test result and makes a list of a concept that should be studied by the learners. This list of recommended concept, called learning path is shown in Figure 5.

When learners have learned a recommended activity, they, then, have to take assessment exercises as displayed in Figure 6 and satisfy the minimum success rate before continuing to learn the next concepts. Learners may continue to start the next concepts if their success rate after assessment exercises more than 50%. This step then should be repeated again until the learners pass the entire recommended concepts. Finally, the learners may take post-test to acknowledge their new ability.

The next step is the learner takes a pre-test. Afterward, the system analyses the test result and makes a list of a concept that should be studied by the learners. This list of recommended concept, called learning path is shown in Figure 5.

An experimental study was focused on the bachelor degree program that is offered in all Algerian public universities, where the studied subject was ‘algorithmic’. This subject
is studied by several Bachelor degrees. Learners can use the system from any computer connected to the intranet of the university.

Table 5 shows distribution of learners in this study by gender. There were 35 (43.75%) male learners and 45 (56.25%) female learners as respondents for this study.

Table 6 shows distribution of learners in this study by domain. Thirty (37.5%) learners were in Mathematics and Informatics, 50 (62.5%) learners were in Economics.

Among 80 university learners, 40 learners were served as the control group to perform the O-AITS, while the rest, 40 learners, were served as the experimental group to perform the P-AITS.

5.2 Pre-tests and post-tests

Pre- and post-tests were written to assess the learners’ skill level of the concepts both before and after using the systems. The pre-test gave an objective assessment of the learners’ prior knowledge of the subject domain. Each test contained 25 multiple choice questions covering content of the course. The questions were matched on the pre- and post-tests so that each question on the pre-test had a corresponding similar (but not the same) question on the post-test. Creating similar questions was achieved by either re-writing the question or changing the answer options to true/false and ‘do not know’. The questions in the post-test were also shuffled so that the number sequence was different from the pre-test.

Overall, the reliabilities of the pre-test and post-test scores were acceptable. The alpha coefficient of the pre-test scores was 0.76 while the alpha coefficient for post-test scores was 0.89.

5.3 Experimental procedures

In order to determine whether or not the P-AITS was better than the O-AITS, a between concepts was used. In other words, each learner used either of the systems once but not both. The same content was used for both systems. Furthermore, each learner went through the same procedures in order to minimise bias. The following procedures were followed:

The learners were initially briefed about the functionality of the system and the available tools that can be utilised to aid learning.

Learners were automatically provided with the questionnaire to determine learning style and characteristics of learner. Subsequently, the right version of the P-AITS was presented based on the results of the questionnaire. On the other hand, the O-AITS provided the same interface for each style after the questionnaire.

Learners were then asked to, carefully, go through a pre-test to measure their initial levels of knowledge. To draw learners’ attention to details, answers could not be changed once they have been given.

When learners studied the learning units, they then followed a link to do the post-test. Finally, learners were provided with the survey to express their opinions to the use of the P-AITS or the O-AITS.

5.4 Experimental procedures

This study aims to compare the differences between the P-AITS and the O-AITS based on the learners’ learning performance.

Learners’ post-test scores were used to determine the differences in their learning performances.

The differences between the P-AITS and the O-AITS were analysed by using Matlab software.

The testing of statistical significance for the differences between the P-AITS and the O-AITS was done by independent t-tests because they are suitable to compare the means of two independent samples. A significance level of 0.05 was adopted for the study.

5.5 Results and discussion

The independent sample t-test was performed first in order to determine whether those that used the O-AITS and the P-AITS had the same prior knowledge on studied domain. As can be seen in Table 7, there were no significant differences between those that used the O-AITS (Mean = 60.90) and the P-AITS (Mean = 62.38) in their prior knowledge in course (p > 0.05). This result means that learners have the same prior knowledge about the studied subject.

5.6 Learners’ multiple intelligences

This study adopted a descriptive survey method where a set of questionnaire was used for the purpose of data collection.

The questionnaire consists of two parts: Part A of the questionnaire is made up of items to obtain demographic
information of respondents and Part B of the questionnaire determines the Intelligence profile of the respondents. All items are assessed using the 5-point Likert-scale ranging from

1. Strongly not agree
2. Not agree
3. Less agree
4. Agree
5. Strongly agree.

Table 8 shows the analysis of learners’ multiple intelligences by gender. The table shows that the male learners had the highest intelligence in interpersonal (Mean = 3.79, Standard Deviation = 0.61), followed by intrapersonal (Mean = 3.66, Standard Deviation = 0.63) and musical (Mean = 3.65, Standard Deviation = 0.86). For female learners, they had the highest intelligence in interpersonal (Mean = 3.80, Standard Deviation = 0.59), followed by musical (Mean = 3.79, Standard Deviation = 0.80) and intrapersonal (Mean = 3.75, Standard Deviation = 0.61).

An independent-samples t-test was conducted to compare learners’ multiple intelligences according to their gender. As shown in Table 8, between male learners and female learners, there are significant differences in learners’ visual spatial intelligence ($t$-test = 2.74, $p$-value = 0.00), linguistic intelligence ($t$-test = –5.64, $p$-value = 0.00), intrapersonal intelligence ($t$-test = –2.40, $p$-value = 0.02), musical intelligence ($t$-test = –2.80, $p$-value = 0.00) and kinesthetic intelligence ($t$-test = 5.79, $p$-value = 0.00).

Table 9 shows learners’ multiple intelligences by domain. The table shows that learners from Mathematics and Informatics domain had the highest intelligence in musical (Mean = 3.76, Standard Deviation = 0.83), followed by interpersonal (Mean = 3.76, Standard Deviation = 0.58) and intrapersonal (Mean = 3.66, Standard Deviation = 0.58). Meanwhile, learners from Economics domain had the highest intelligence in interpersonal (Mean = 3.82, Standard Deviation = 0.61), followed by intrapersonal (Mean = 3.74, Standard Deviation = 0.65) and musical (Mean = 3.71, Standard Deviation = 0.83).

An independent-samples t-test was conducted to compare learners’ multiple intelligences according to domain. As shown in Table 9, between Mathematics and Informatics domain learners and Economics domain learners, there are significant differences in learners’ visual partial intelligence ($t$-test = 4.16, $p$-value = 0.00), linguistic intelligence ($t$-test = 2.73, $p$-value = 0.01), logical-math intelligence ($t$-test = 7.20, $p$-value = 0.00) and intrapersonal intelligence ($t$-test = –2.09, $p$-value = 0.04).

### Table 8 Comparation of learners’ multiple intelligence by gender

<table>
<thead>
<tr>
<th>Intelligences</th>
<th>Male</th>
<th>Female</th>
<th>t-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard deviation</td>
<td>Mean</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>Visual spatial</td>
<td>2.52</td>
<td>0.72</td>
<td>2.40</td>
<td>0.68</td>
</tr>
<tr>
<td>Linguistic</td>
<td>2.67</td>
<td>0.70</td>
<td>2.90</td>
<td>0.62</td>
</tr>
<tr>
<td>Naturalistic</td>
<td>3.07</td>
<td>0.79</td>
<td>3.14</td>
<td>0.78</td>
</tr>
<tr>
<td>Logical-math</td>
<td>3.18</td>
<td>0.72</td>
<td>3.22</td>
<td>0.70</td>
</tr>
<tr>
<td>Intrapersonal</td>
<td>3.66</td>
<td>0.63</td>
<td>3.75</td>
<td>0.61</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>3.79</td>
<td>0.61</td>
<td>3.80</td>
<td>0.59</td>
</tr>
<tr>
<td>Musical</td>
<td>3.65</td>
<td>0.86</td>
<td>3.79</td>
<td>0.80</td>
</tr>
<tr>
<td>Kinesthetic</td>
<td>3.09</td>
<td>0.74</td>
<td>2.83</td>
<td>0.69</td>
</tr>
</tbody>
</table>

### Table 9 Comparation of learners’ multiple intelligence by domain

<table>
<thead>
<tr>
<th>Intelligences</th>
<th>Mathematics and informatics</th>
<th>Economics</th>
<th>t-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard deviation</td>
<td>Mean</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>Visual spatial</td>
<td>2.55</td>
<td>0.70</td>
<td>2.37</td>
<td>0.68</td>
</tr>
<tr>
<td>Linguistic</td>
<td>2.87</td>
<td>0.67</td>
<td>2.75</td>
<td>0.67</td>
</tr>
<tr>
<td>Naturalistic</td>
<td>3.17</td>
<td>0.80</td>
<td>3.08</td>
<td>0.77</td>
</tr>
<tr>
<td>Logical-math</td>
<td>3.38</td>
<td>0.66</td>
<td>3.07</td>
<td>0.71</td>
</tr>
<tr>
<td>Intrapersonal</td>
<td>3.66</td>
<td>0.58</td>
<td>3.74</td>
<td>0.65</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>3.76</td>
<td>0.58</td>
<td>3.82</td>
<td>0.61</td>
</tr>
<tr>
<td>Musical</td>
<td>3.76</td>
<td>0.83</td>
<td>3.71</td>
<td>0.83</td>
</tr>
<tr>
<td>Kinesthetic</td>
<td>2.98</td>
<td>0.70</td>
<td>2.91</td>
<td>0.74</td>
</tr>
</tbody>
</table>
An independent-samples t-test was conducted to compare learners’ multiple intelligences according to domain. As shown in Table 9, between Mathematics and Informatics domain learners and Economics domain learners, there are significant differences in learners’ visual partial intelligence (\(t\)-test = 4.16, \(p\)-value = 0.00), linguistic intelligence (\(t\)-test = 2.73, \(p\)-value = 0.01), logical-math intelligence (\(t\)-test = 7.20, \(p\)-value = 0.00) and intrapersonal intelligence (\(t\)-test = 2.09, \(p\)-value = 0.04).

Multiple intelligence theory insists that every person has at least one dominant intelligence domain and it is necessary to find the strong intelligence domains and consistently develop them. Besides, the dominant domains serve to complement weaker domains, it is also important to develop the weaker intelligences in order to facilitate overall achievement (Jung and Kim, 2005). Research findings showed that learners from both gender possessed high intelligence in common domains, namely interpersonal (Mean = 3.79, Standard Deviation = 0.61), followed by intrapersonal (Mean = 3.66, Standard Deviation = 0.63) and musical (Mean = 3.65, Standard Deviation = 0.86). This research finding is very much similar with the findings obtained by Chan (2001) where learners were reported to have higher ratings on items related to interpersonal and intrapersonal intelligences, and lower ratings in items related to kinesthetic and visual spatial intelligences.

Based on the findings, between male learners and female learners, there are significant differences in learners’ visual spatial intelligence (\(t\)-test = 2.74, \(p\)-value = 0.01), linguistic intelligence (\(t\)-test = −5.64, \(p\)-value = 0.00), intrapersonal intelligence (\(t\)-test = −2.40, \(p\)-value = 0.02), musical intelligence (\(t\)-test = −2.80, \(p\)-value = 0.00) and kinesthetic intelligence (\(t\)-test = 5.79, \(p\)-value = 0.00). This indicates that there is a significant difference between the ‘talents’ of learners according to gender which is similar with the idea proposed by Chan (2001) and Loori (2005), however, the differences in domains may be different in the studies conducted.

5.7 Learning performance

Analysis of learning performance was measured by the post-test scores for learners using the O-AITS and the P-AITS.

The group means of the post-test are shown in Table 10. The group means of post-test for the P-AITS are higher than those who used the O-AITS.

<table>
<thead>
<tr>
<th>Questionnaire</th>
<th>O-AITS</th>
<th>P-AITS</th>
<th>t-test</th>
<th>p-value</th>
<th>Effect size</th>
</tr>
</thead>
<tbody>
<tr>
<td>How do you think the use of this system?</td>
<td>2.55</td>
<td>2.37</td>
<td>4.16</td>
<td>0.000</td>
<td>0.260</td>
</tr>
<tr>
<td>How do you evaluate the structure of this course?</td>
<td>2.87</td>
<td>2.75</td>
<td>2.73</td>
<td>0.008</td>
<td>0.179</td>
</tr>
<tr>
<td>How do you evaluate the sequence of learning units?</td>
<td>3.38</td>
<td>3.07</td>
<td>7.20</td>
<td>0.0</td>
<td>0.452</td>
</tr>
<tr>
<td>How do you find a route for a specific learning unit in this course?</td>
<td>3.66</td>
<td>3.74</td>
<td>−2.09</td>
<td>0.039</td>
<td>0.129</td>
</tr>
</tbody>
</table>
6 Conclusion and future work

This study proposes a personalised learning path generation scheme for individual learners to support personalised intelligent tutoring system (P-AITS). The aim of P-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 organise the learning. 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. The proposed scheme can simultaneously consider learner’s multiple intelligence, learner’s feedback, courseware difficulty level and the concept continuity of successive courseware according to the incorrect testing responses in a pre-test while implementing personalised courseware sequencing during learning processes. An important advantage is that the learning mode of curriculum sequencing recommendation customises learning for those learners who have very specific needs and not much time or patience to complete the topics they have to be learned.

Our work focused on the bachelor degree program that is offered in all Algerian public universities. 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. As a result, we drew several conclusions and several research tracks were opened.

Further work will be devoted to extending the personalised mechanism to handle more complex individual characteristics and behaviours of the learners. We will also research how to help learners to learn.

References


