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*Full Length Research Paper*

# An approach to Adaptive E-Learning Hypermedia System based on Learning Styles (AEHS-LS): Implementation and evaluation

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**This paper presents an approach to integrate learning styles into adaptive e-learning hypermedia. The main objective was to develop an adaptive e-learning system and assess the effect of adapting educational materials individualized to the student's learning style. The proposed approach utilized adaptive hypermedia technology to improve learning process by adapting course content presentation to student learning styles. The combination of Apache, MySQL and PHP were used to implement the system based on learning styles to present the appropriate subject matter, including the content, format and media type. The system was organized into 3 models; domain model, learner model and adaptation model. The 3 models interact together to perform adaptively. An experiment between 2 groups of students was conducted to evaluate the impact on learning achievement. Inferential statistics were applied to make inferences from the sample data to more general conditions. Descriptive statistics were applied simply to describe what's going on in the sample data. Results showed that students taught using learning style adaptive system performed significantly better in academic achievement (p<0.05) than students taught the same material without adaptation to learning style. The findings support the use of learning styles as guideline for adaptation into the adaptive e-learning hypermedia systems.**

**Key words:** E-learning, adaptive hypermedia, learning styles, technology based education, academic achievement.

## INTRODUCTION

The adaptive hypermedia research received more attention during the last two decades in the area of technology-based education. There are many systems developed for learning purposes, which are referred to as adaptive e-learning hypermedia. An adaptive e-learning hypermedia is an approach whose target is to personalize the learning experience for the learner (De Bra et al., 2004; Henze and Nejdl, 2004). A number of Adaptive E-Learning Hypermedia Systems have been developed to support learning style as a source for adaptation. AEC-CS (Trantafillou et al., 2002), INSPIRE (Grigoriadou et al., 2001), iWeaver (Wolf, 2003) and ILASH (Bajraktarevic et al., 2003a) are good examples. However, most of these systems lack the experimental evaluation to assess their impact on student's achievement.

Most of the attempts in this area based their adaptation to user's level of knowledge (Stash and De Bra, 2004; Popescu et al., 2007). Other learner features taken into account are background, hyperspace experience, preferences and interests (Brusilovsky, 2001; Popescu

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et al., 2007). However, less attention was paid to learning styles and their effects on learning achievement. This is despite the fact that learning styles constitute a valuable tool for improving individual learning among the user features (Paredes and Rodriguez, 2002). Statistics revealed that considering students' learning style is a significant factor that improves learning performance in web-based learning or e-learning (Manochehr, 2006). In addition, there is also the equally important issue of evaluating the effect of adaptation to learning styles on students' achievement. In their recent research Brown et al. (2009) investigated adaptive e-learning hypermedia that specially utilize learning style as their adaptation mechanism, they found that out of 10 systems, 6 systems did not seem to have published any quantitative evaluations. 2 systems; AES-CS (Triantafillou et al., 2003) and INSPIRE (Papanikolaou et al., 2003) presented some empirical data in the form of descriptive statistics and no inferential statistics testing was carried out using samples of n = 10 and n = 23, respectively. Unlike these studies Bajraktarevic et al. (2003b) and Wolf (2007) presented statistical testing and this was done practically well. The most widely used evaluation approach is to compare adaptive with non-adaptive versions of the whole system. Consequently, any difference between the two approaches might be attributed to users' features other than learning styles like adaptation to user's knowledge, goals etc. Moreover, in most evaluations of adaptive systems, the adaptive application is usually built first and then a second version is generated from the adaptive one. The two versions are then compared through user testing. This is not a fair comparison because the non-adaptive version of the application is not well designed and thus put at a disadvantaged side right from the start (De Bra, 2000).

Trantafillou et al. (2002) developed a prototype system to test the hypothesis that cognitive learning styles could benefit learning outcomes. They conducted a small scale experiment to evaluate learner's performance. Only descriptive statistics in the form of mean and standard deviation was used. In Grigoriadou et al. (2001) authors performed an empirical study to evaluate the adaptation framework and assess learners' attitudes towards the proposed instructional design. The number of students involved in the experiment was 23, which is still relatively small. They used descriptive statistics analysis in the form of bar and line charts. The author in Wolf (2003), developed an interactive web-based adaptive e-learning environment. An experiment (Wolf, 2007) was conducted to analyze whether it is more beneficial for participants to learn with a choice of media experiences, or to learn with only one media experience. Unlike the previous studies, they used descriptive and inferential statistical analysis. In another study (Bajraktarevic et al., 2003b) the authors conducted an empirical evaluation to assess the impact of incorporating learning styles within e-learning hypermedia courseware on learning outcomes. The sample involved in the experiment comprised 22 students. They used inferential statistics in the form of t tests.

In recent years, the technology of adaptive hypermedia in learning has received increased attention. Adaptive hypermedia systems can offer a richer learning experience by giving more attention to personalization to learning styles. Most approaches to adaptive e-learning hypermedia were based around acquiring and representing user's knowledge. While this is crucial for user modeling in general adaptive hypermedia, it is very limited for e-learning hypermedia because it does not address the far more fundamental problem which is "students learn in different ways and different learning styles". The integration of technology in learning needs to address this important problem. Moreover, few experimental studies were conducted to investigate the effectiveness of matching learning materials to user's learning style. Most of the analysis these studied was descriptive statistics, which basically aim to quantitatively summarize a sample data set, rather than being used to support inferential statements about the entire population that the data are thought to represent.

The proposed approach for adaptation to student learning styles in technology driven learning and assessing the effect of providing educational experiences individualized to the learning style of the students can be summarized. Adaptive hypermedia technology was utilized to improve learning process by adapting course content presentation to student learning styles. An Adaptive E-Learning Hypermedia System based on Learning Styles (AEHS-LS) was implemented and verified. The technologies and software used on the server-side are Apache, MySQL and PHP.

To achieve the main objectives, a case study for the domain of JavaScript programming course was developed. An experimental evaluation was designed to assess the feasibility and benefit of the proposed approach. The main objectives were to evaluate the new approach of matching learning materials with learning styles and their influence on student's learning achievement. Inferential statistics were used in the form of independent sample t-test to make inferences from the data to more general conditions. Descriptive statistics were used in the form of mean and standard deviation simply to describe what was going on in the data.

## MATERIALS AND METHODS

AEHS-LS was implemented to achieve the main objectives. The system is organized in the form of three basic models: The domain model is used to structure the knowledge about the domain to be learned, the student model is used to provide a complete description of the current state of the learner and the adaptation model to implement the specification of adaptation rules (the adaptive methods and techniques used for content selection,

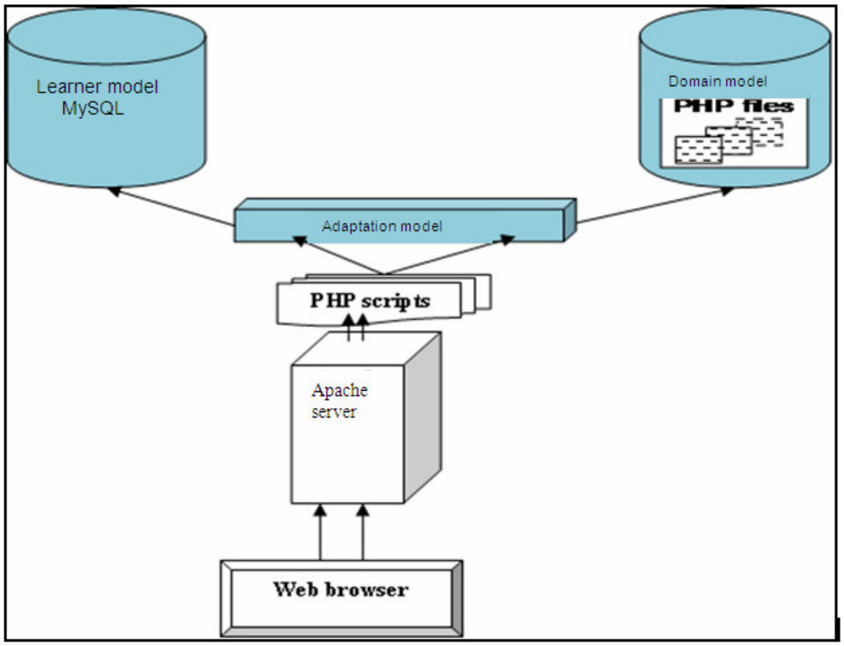


**Figure 1.** The AEHS-LS architecture.

navigation or presentation). These three components interact to adapt different aspects of the instructional process.

### System technologies and software

Apache, MySQL database and PHP language server have been used in order to develop the system. These technologies were used because of their faster reaction for dynamic web application and because the communication between them tends to be perfect. AEHS-LS utilized the following software versions:

(i) Apache 2.2.8
(ii) MySQL 5.0.51a
(iii) PHP 5.25
(iv) Windows XP/Vista

### System architecture

The main characteristic of AEHS-LS is that it can be adapted to the learning style and to the level of knowledge acquired by the student. The system was organized in the form of three basic components: The domain model, the learner model and the adaptation model. These three components interacted to adapt different aspects of the instructional process. Figure 1 illustrates the system architecture.

When first time learners enter AHES-LS, they signed up to the system by using a registration form. Once a learner registers, a learner profile will be created to store all his information and will be saved in the database, a unique identification (ID) is generated for the learner for further reference and tracking of his progress. AHES-LS used the Fleming's visual, aural, read/write and kinesthetic (VARK) learning style model (Felming, 2001) because it is one of the simplest and therefore, most widely influential model. The system classified students into four categories: Visual preference which includes the depiction of information in maps, diagrams, flow charts and all the symbolic arrows; Auditory perceptual mode that describes a preference for information that is "heard or spoken"; Read/write preference for information displayed as text and Kinesthetic modality which refers to the perceptual preference related to the use of experience and practice.

After successful registration, AHES-LS shows an introduction page to the learner, explaining the learning style categories and their general characteristics. Then it offers two choices either to answer the learning style questionnaire, or to select his suitable learning style based on the provided information. Due to copyright restrictions, permission is then obtained from VARK questionnaire author to use it. AHES-LS calculates the answers given by the user and deduces a learning style based on the VARK logic of stepping stone following Felming (2001). The learning style preference is then saved in MySQL database (learner profile) and the learner is re-directed to the lesson page. Next, the first lesson is displayed with learning materials and media presentation based on learner profile. Every lesson starts with objectives, followed by a small introduction, then lesson content with concrete examples and finally an evaluation quiz. This evaluation is used by AHES-LS to adapt the knowledge and learning preference.

Learner friendliness and navigation is an important aspect of Adaptive E-Learning Hypermedia Systems which makes it more usable. The navigation and learner friendliness attempts to know if learners are easily able to navigate in the course. The lesson contents appear in the navigation area as tree-like structure of hyperlinks, whilst in the content area the learning content is presented with the media matched for the learner preference. Figure 2 shows a snapshot of the navigation and content areas.

The navigation was implemented using a JavaScript tree menu following Heyes (2005), as depicted in Figure 2. The tree menu is similar to the Windows Explorer tree structure with expandable and collapsible submenus and content leaves.

An important part of well-designed navigation is that the learner maintains a sense of orientation; if learners get “lost in space”; it is more likely they lose their motivation (Conklin, 1987). AHES-LS offered many signs to prevent learner from getting lost. First, the learning tree shows already visited pages in a different colour (blue instead of black). Secondly, the learner typically progresses through

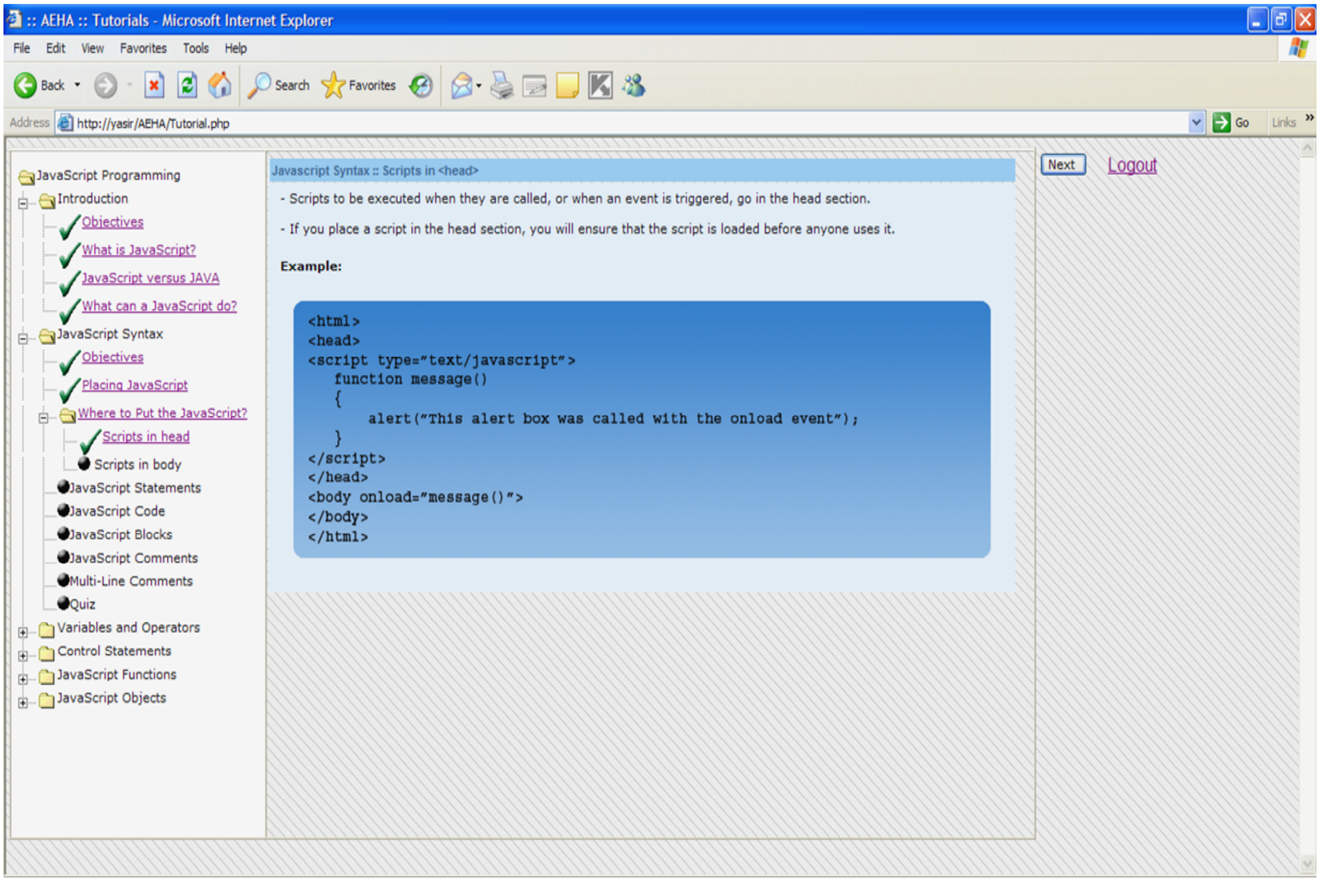


**Figure 2.** Snapshot of navigation and contents area of AHES-LS.

AHES-LS in a hierarchical manner. As the learning tree grows, new pages will be added below the last branch. The new branch expands and the first content page is displayed when the learner enters a new lesson. Finally, link annotations have been added to learning contents to show the currently viewed content pages.

## Domain model

The domain model contained the knowledge about the domain and the curriculum structure. Basically, the model was built on a conceptual network of nodes and arcs. Nodes represented the knowledge concepts while arcs represented relationships between concepts.

AEHS-LS divided the domain model into two interconnected sub-models: A knowledge item sub-model and a resources item sub-model. The knowledge item sub-model was structured into three hierarchical levels of abstraction concepts (composite, node and atomic concepts), while resources structure sub-model consisted of object concepts. The concept of the object had an attribute called "media" with values (text, audio, visual, kinetic). The media attribute was used by the system to trace media preference and to indicate how these object concepts represented atomic concepts. The purpose of establishing resources structure as a part of the domain model was to allow the design of multiple representations for a knowledge concept. This provides the student with the represent-tation that best matches the student's learning style, while simultaneously giving the additional representations to include the process of adaptive learning path selection in order to produce a personalized learning path.

Furthermore, it allows the granularity of the learning content into lots of smaller learning resources. The granularity of a resource can vary from the content of a whole chapter (composite concept) to a single picture or paragraph of text (object concept). This fine grained representation of the learning resources was needed to insure adaptation to learning styles. Figure 3 illustrates a hierarchical organization of the knowledge concepts, while Figure 4 shows a typical instance of "control statements concept.

AEHS-LS implemented concept relationships to connect knowledge concepts to other knowledge concepts or resource concepts to knowledge concepts. Figure 5 illustrates examples of concept relationships used by the system followed by their meaning. The meanings of the relationships used to connect concepts were:

(i) Consists (CC1; CC1.1) means that the composite concept (CC1) consists of the smaller composite concept (CC1.1). Through "consists" relationships sections can be part of chapters or other sections.
(ii) Contains (CC1; NC1.2) means that the composite concept (CC1) contains the node concept (NC1.2). Through "contains" relationships pages can belong to composite concepts.
(iii) Prerequisite (CC1.1; CC1.3) specifies that the composite concept (CC1.1) has to be known before the composite concept (CC1.3) is accessed. "Prerequisite" relationships between concepts represent the fact that one of the related concepts has to be learned before another.

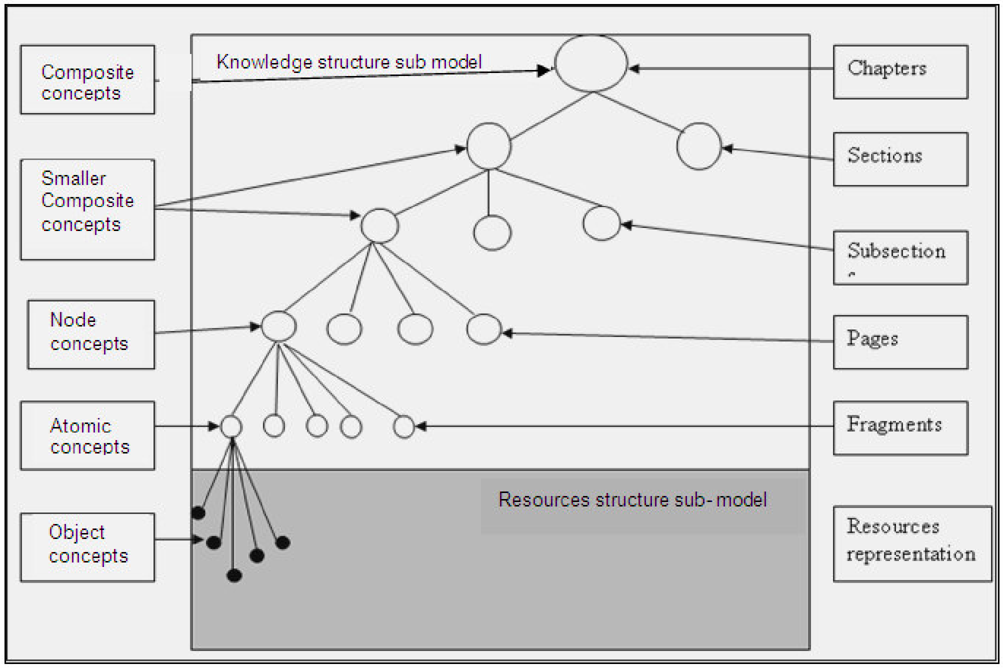


**Figure 3.** A hierarchical organization of the knowledge concepts.

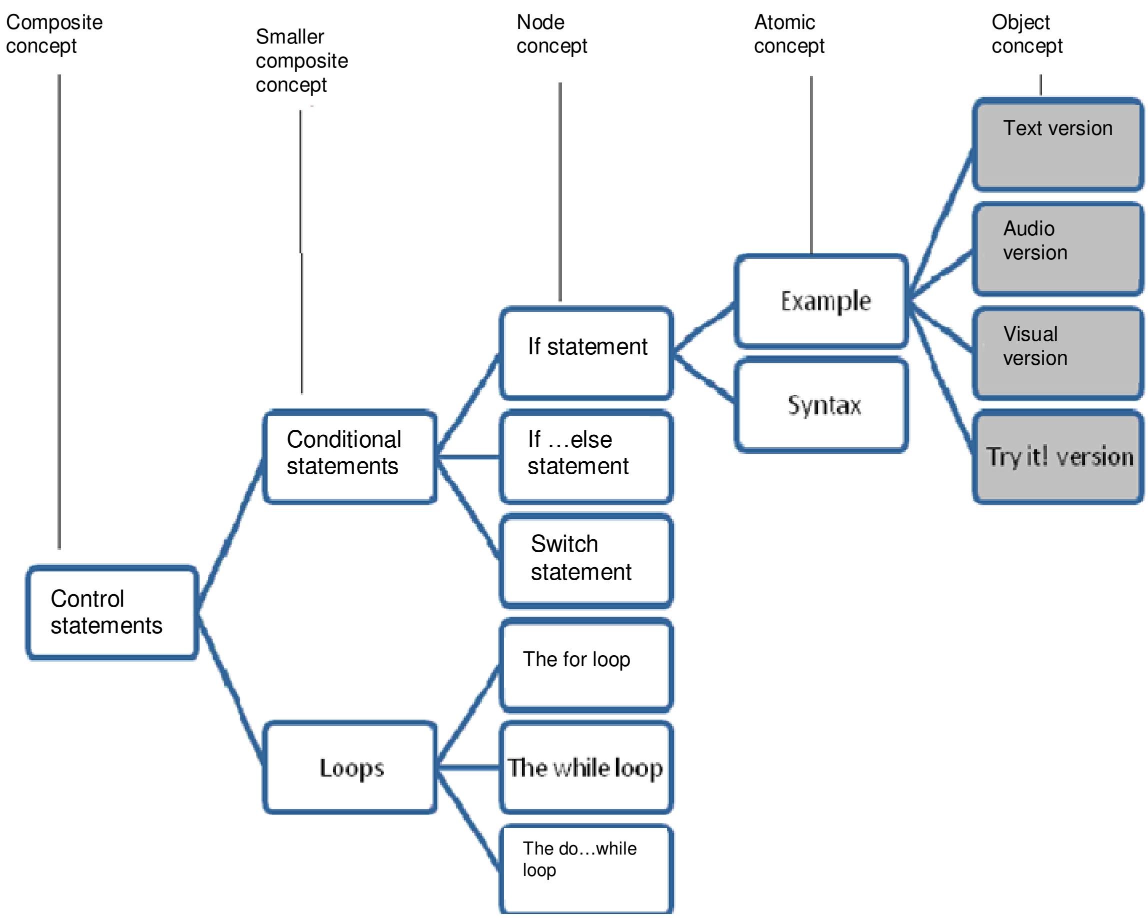


**Figure 4.** Typical instance of "control statements" hierarchical organization.

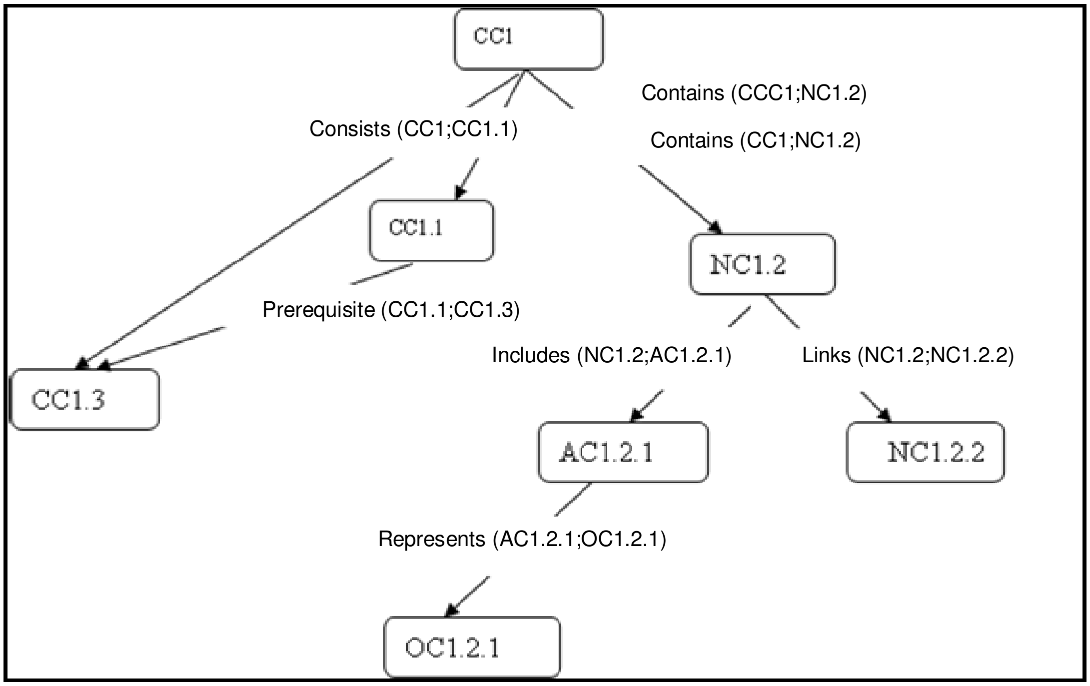


**Figure 5.** Examples of concept relationships.

(iv) Includes (NC1.2; AC1.2.1) means that the atomic concept (AC1.2.1) is included in the node concept (NC1.2). Through "includes" relationship fragments can be included in pages.
(v) Link (NC1.2; NC1.2.2) means that there is a hyperlink from the node concept (NC1.2) to the node concept (NC1.2.2).
(vi) Represents (AC1.2.1; OC1.2.1) means that the object concept (OC1.2.1) represents the atomic concept (AC1.2.1); "represent" relationship was used to represent fragments with different media format. Through "link" relationship two pages can be connected as source and destination pages. Also they were used to perform adaptation of link based on the desirability of the link destination.

## Learner model

A distinct feature of an adaptive e-learning system is the learner model it employs, that is, a representation of information about an individual learner. Learner modeling and adaptation are strongly correlated, in the sense that the amount and nature of the information represented in the learner model depend largely on the kind of adaptation effect that the system has to deliver.

The learner model in AEHS-LS was defined as three sub-models: The profile sub-model, the knowledge state overlay sub-model and the learning style preferences overlay sub-model. 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, e-mail and learning style. The knowledge level recorded by the system for student's knowledge about each domain knowledge concept; It is an overlay of the knowledge structure concepts. It associated learner's knowledge level with each concept of the domain sub-model knowledge structure. The learning style state stores values for objects concepts to match learner's learning style that is, media type. It is an overlay of the resources structure concepts. It associates a number of learner preferences with each object concept of the domain sub-model resources structures.

## Adaptation model

The adaptation model in AEHS-LS specified the way in which the learners' knowledge and learning style modify the presentation of the content. 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 was divided into two layers: Knowledge adaptation layer and learning style adaptation layer. The knowledge adaptation layer consisted of abstract concept selection rules that determine which concepts from the knowledge space sub-model to be covered based on the knowledge attribute in the learner model. The learning style adaptation layer consisted of object concept selection rules that determine which object concept from the resources space sub-model to be included in the presentation. The inclusion of appropriate object concepts is based on the learning style attribute associated with the learner model. Figure 6 shows a snapshot of a visual component of the "if ... else" statement, while Figure 7 shows a snapshot of the practice tool for Kinesthetic learner.

To support adaptivity, AEHS-LS used a combination of adaptive navigation support and adaptive presentation technique following Brusilovsky (1996) which aimed to adapt the information presented to the user according to his learning style and knowledge state.

AEHS-LS implemented adaptive presentation by classifying learners according to their current learning styles. Learners with different learning styles view different presentations of the same educational material. The system implemented various adaptive navigation support technologies, which help the user in navigating the domain space. 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).

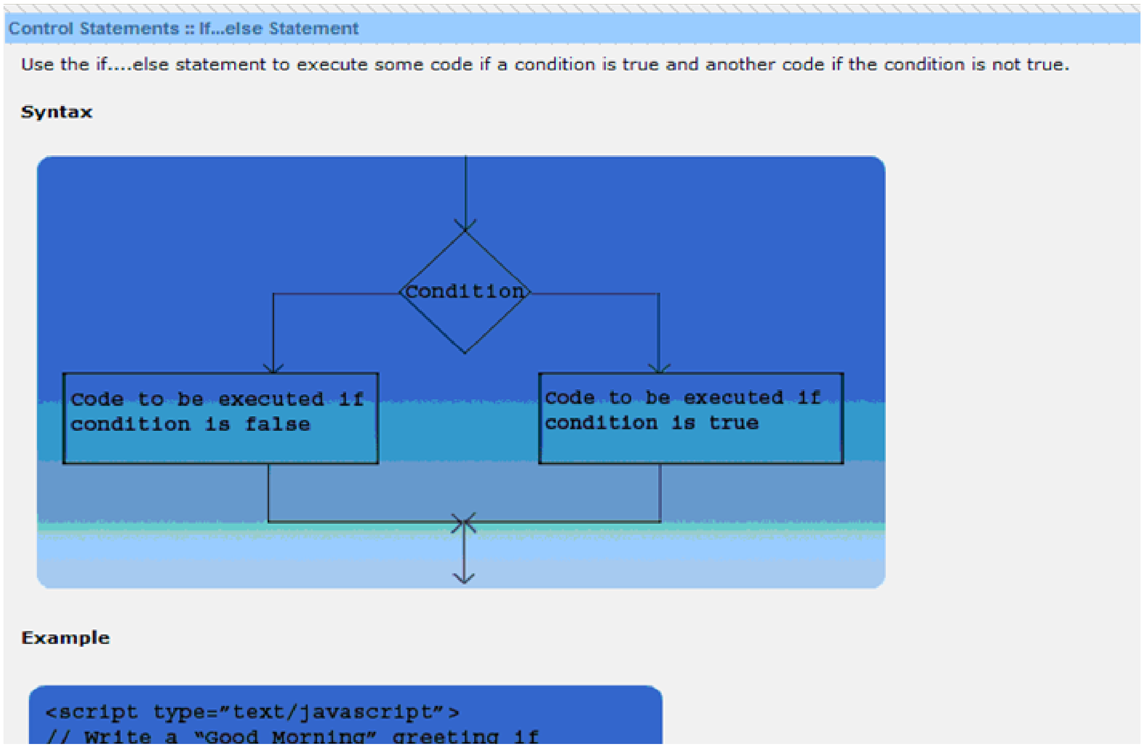


**Figure 6.** Example of a visual component of the "if ... else" statement.

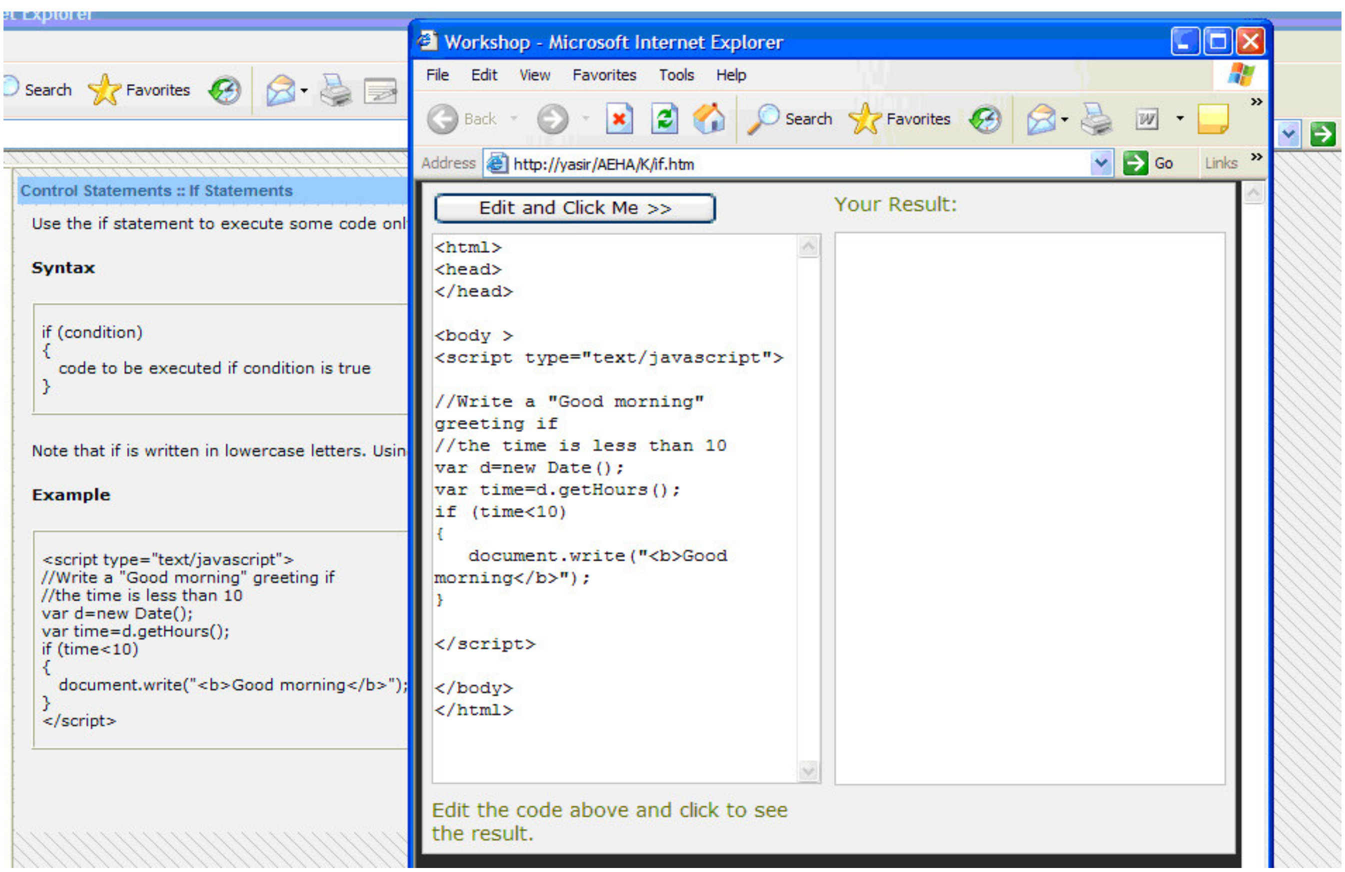


**Figure 7.** A snapshot of technical details on the practice tool to try an example.

**Table 1.** Demographic data and student's characteristics.

| Items | Choices | Control group | | Experimental group | | Total | |
|---|---|---|---|---|---|---|---|
| | | F | % | F | % | F | % |
| Sex | Male | 7 | 33.3 | 1 | 4.8 | 8 | 19 |
| | Female | 14 | 66.7 | 20 | 95.2 | 34 | 81 |
| Age | 18 years | 0 | 0 | 1 | 4.8 | 1 | 2.4 |
| | 19 years | 3 | 14.3 | 6 | 28.6 | 9 | 21.4 |
| | 20 years | 7 | 33.3 | 8 | 38.1 | 15 | 35.7 |
| | 21 years | 6 | 28.6 | 4 | 19 | 10 | 23.8 |
| | 22 years | 4 | 19 | 0 | 0 | 4 | 9.5 |
| | 23 years | 0 | 0 | 2 | 9.5 | 2 | 4.8 |
| | 24 years | 1 | 4.8 | 0 | 0 | 1 | 2.4 |
| Mean age | | M = 20.7 | | M = 20.1 | | M = 20.4 | |

F = Frequency, % = percentage.

**Experimental settings**

Using AEHS-LS, an experiment was designed to explore the effect of adaptation to different learning styles and to determine the impact on learning achievement when learning materials were matched with learning preferences. In particular it was set up to see whether there is a significant difference in learning achievement between two groups, an experimental group who studied with adaptation to learning styles and a control group who studied with another version of the system without adaptation to learning styles.

Fouty-two students were randomly selected to take part in this experiment. All were third year students at the College of Computer Sciences and Information Technology, Sudan University for Sciences and Technology. Students were randomly allocated into two groups. An experimental group that worked with a learning styles adaptive version of the system (AEHS-LS) and a control group that worked with the non adaptive version to learning styles.

Four testing instruments were used in this experiment. The first was the VARK questionnaire developed by Fleming (2006), which was used to determine the learning style of the participants. The second was a questionnaire designed to collect data about students' demographic and academic background. Part of this questionnaire was filled by college administering staff for students past records in related subjects. The third one was an immediate quiz after each lesson to assess the understanding at the end of the lesson. The fourth was an attitude and acceptance questionnaire for the experimental group that included items related to the completeness and ease of use of the system, and also items on subject's satisfaction and willingness to use the system in the future.

The experiment was conducted over a working week (5 days). It took place in the computer laboratory of the university. The procedure was completed in three phases for both experimental and control groups. In the first phase all the students were informed that they will participate in an experimental process. The students filled the first questionnaire (demographic and academic background), and received a short introduction on how to use the system and to create a user account for login purposes into the system. Then, information about learning styles categories were given to the experimental group and were asked to complete the VARK questionnaire. At the second phase, the students followed regularly the lessons up to the completion of the course; meanwhile they received a quiz at the end of each lesson. Table 1 shows the demographics and the frequency of control and experimental group's responses.

The experimental group consisted of 1 (4.8%) male and 20 (95.2%) female students. The mean age was 20.1 with a standard deviation of 1.3. The control group consisted of 7 (33.3%) male and 14 (66.7%) female students. The mean age was 20.7 with a standard deviation of 1.3.

To benchmark the academic background of each participant prior to the registration in the course in which the experiment took place, students' final grades in previous courses were accessed from the university database. Fundamentals of computing, principles of programming 1, principles of programming 2 and data structures courses were recorded because they reflect students' academic background on area of computer programming. Distributions for experimental and control groups are shown in Figures 8, 9, 10 and 11, along with the mean values and standard deviations. The figures show that the distribution is approximately a normal distribution for all the subjects recorded.

The independent sample t- test was performed first in order to determine whether the control and experimental groups had the same prior knowledge on studied domain. As can be seen in Table 2, there was no significant differences between the experiment group and the control group in their prior knowledge in all courses ($p < 0.05$). This result means that the students had the same prior knowledge about the studied subject.

## RESULTS AND DISCUSSION

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 student's academic achievement after they were enrolled in the experiment. At the end of each of the 5 lessons, a quiz was administered by the system to assess students on the concepts that were covered in this lesson. Figure 12 show the comparison of average quizzes scores in experimental and control groups. It shows that the average scores for experimental group were higher than

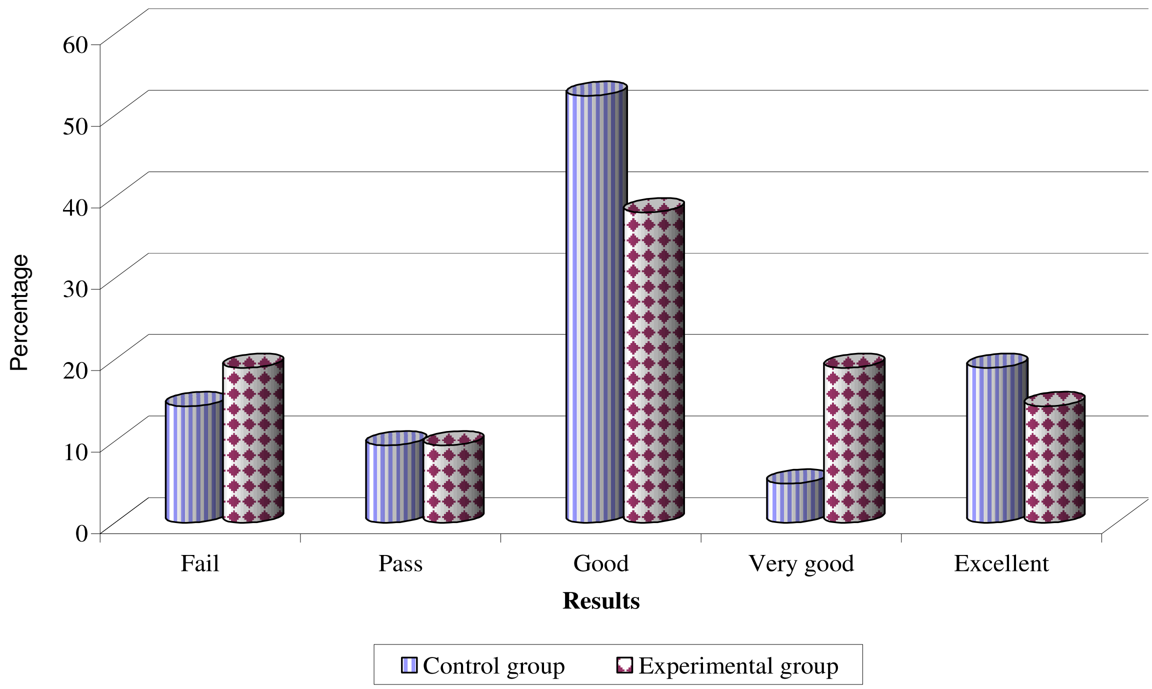


**Figure 8.** Distribution of students grades in the fundamentals of computing course by group. Experimental group: Mean = 65.80; standard deviation = 13.51. Control group: Mean = 64.76 and standard deviation = 16.12.

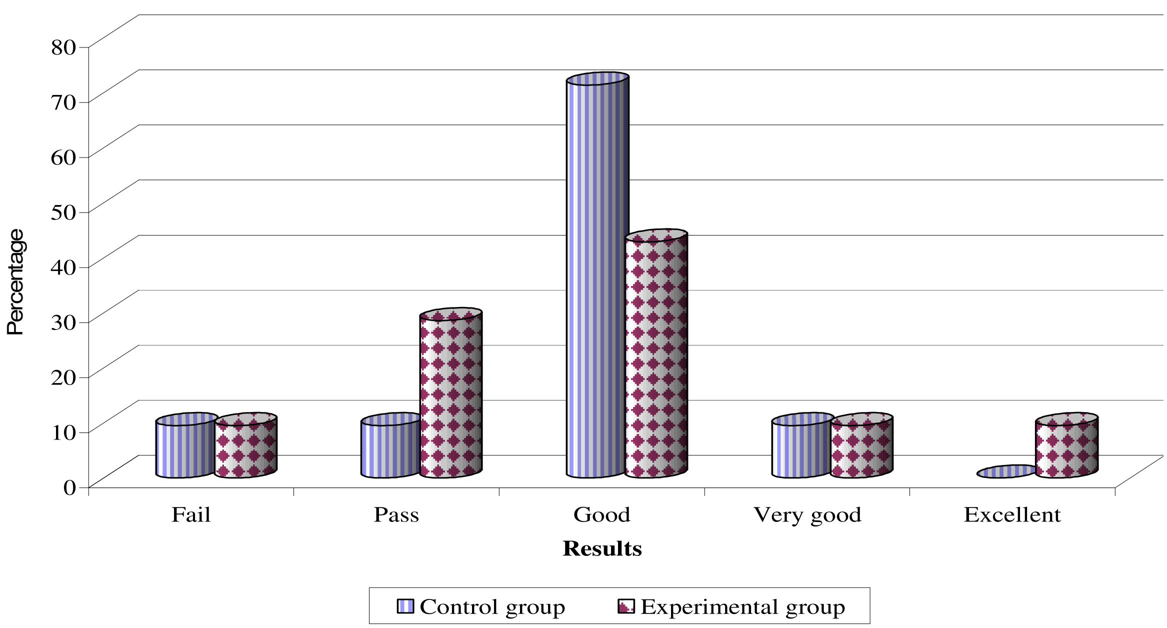


**Figure 9.** Distribution of students' grades in the principles of programming (1) course by group. Experimental group: Mean = 62.38 and standard deviation= 10.07. Control group: Mean = 60.90 and standard deviation = 6.76.

control groups in all quizzes. The independent sample t-test was performed to compare the mean scores for the two groups in each quiz. 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 the learning through learning styles adaptation given to the experimental group. Results show the experimental group performed significantly better than the control group in the second, third and fourth quizzes ($t = -2.105$, $df = 40$, $p < 0.05$), ($t = 2.098$, $df = 40$,

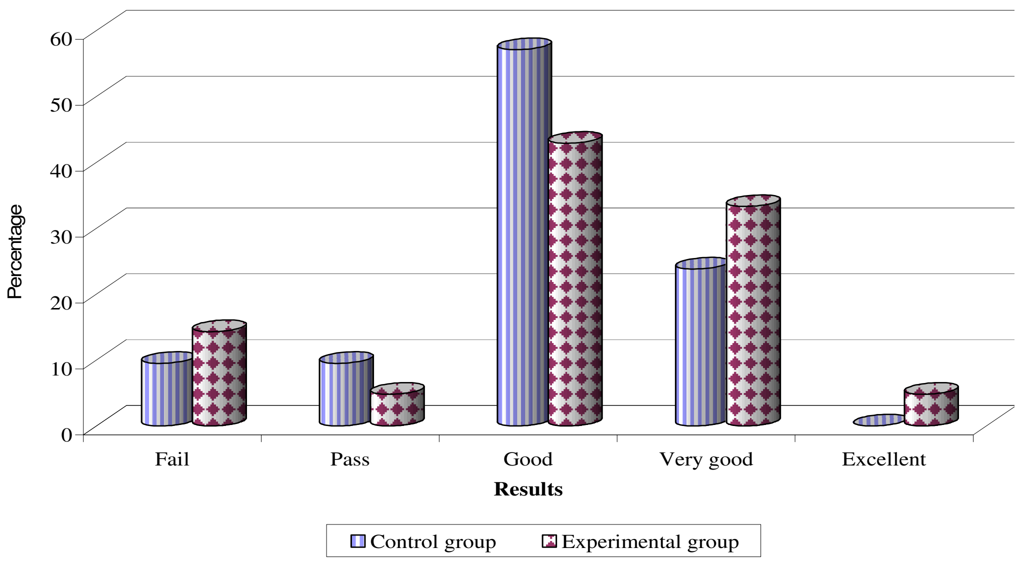


**Figure 10.** Distribution of students' grades in the principles of programming (2) course by group. Experimental group: Mean = 65.33 and standard deviation = 10.31. Control group: Mean = 63.00 and standard deviation = 7.74.

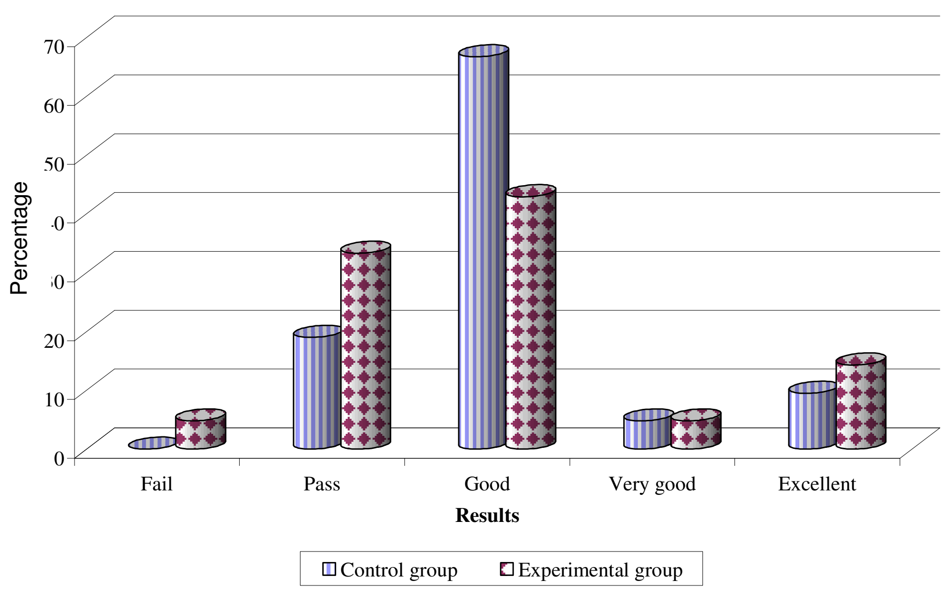


**Figure 11.** Distribution of students grades in the Data Structures course by group. Experimental group: Mean = 63.76 and standard deviation = 11.84. Control group: Mean = 66.14 and standard deviation = 8.39.

P < 0.05) and ($t = -2.322$, df = 40, $p < 0.05$), respectively. No significant difference was detected on the other two quizzes. However, these two quizzes were related to the grammatical syntax of the programming language. Hence it required sort of talent on mathematical background. Table 3 shows the comparison results.

Achievement results obtained clearly show that introducing learning styles as adaptivity in Adaptive E-learning Hypermedia System improves students' achievement and performance.

The findings agreed with previous study from Bajraktarevic et al. (2003b). Their results show that all students achieved significantly higher scores with matched materials. However, their sample size is relatively small (22 students). Wolf (2007) concluded the same results. The results also agreed to those of

**Table 2.** Comparison between control and experimental group in academic background.

| Subject | Control group | | Experimental group | | Independent t-test | | |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df | P-value |
| Fundamentals of computing | 64.76 | 16.12 | 65.80 | 13.51 | -0.228 | 40 | 0.821 |
| Principles of programming 1 | 60.90 | 6.76 | 62.38 | 10.07 | -0.557 | 40 | 0.58 |
| Principles of programming 2 | 63.00 | 7.74 | 65.33 | 10.31 | -0.829 | 40 | 0.412 |
| Data structures | 66.14 | 8.39 | 63.76 | 11.84 | 0.751 | 40 | 0.457 |

SD: standard deviation, t: t-test value, df: degrees of freedom, p-value: probability value.

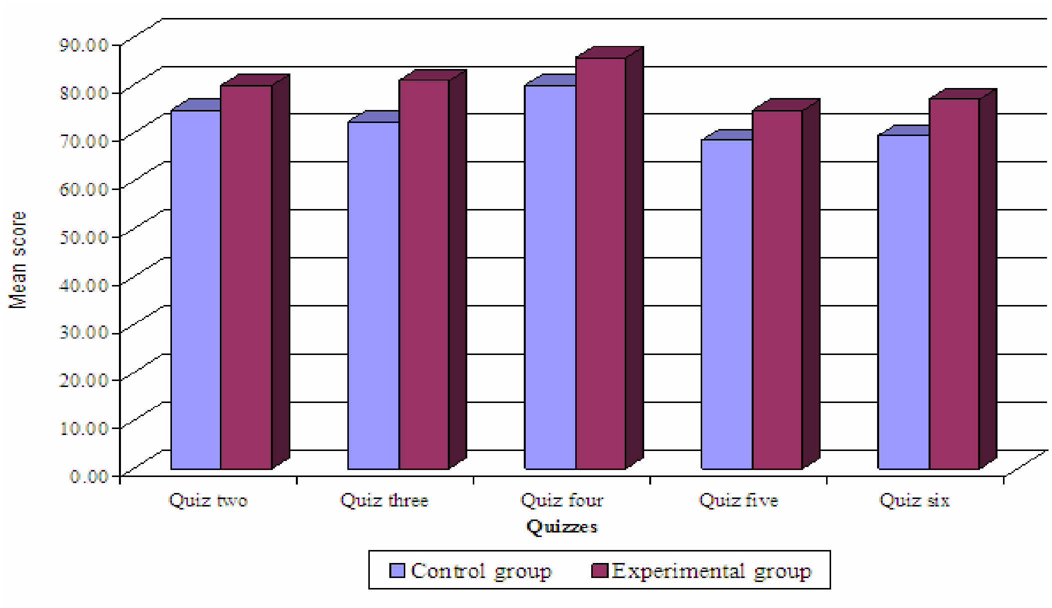


**Figure 12.** Mean score for control and experimental groups after completing the learning through the system.

**Table 3.** Comparison between control and experimental group in achievement quizzes.

| Quiz | Control group | | Experimental group | | Independent t-test | | |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df | P-value |
| Quiz 1 | 74.76 | 10.78 | 80.00 | 13.42 | -1.395 | 40 | 0.171 |
| Quiz 2 | 72.38 | 13.75 | 80.95 | 12.61 | -2.105 | 40 | 0.042* |
| Quiz 3 | 80.00 | 10.00 | 85.71 | 7.46 | -2.098 | 40 | 0.042* |
| Quiz 4 | 68.57 | 9.10 | 74.76 | 11.23 | -1.962 | 40 | 0.057 |
| Quiz 5 | 69.52 | 12.03 | 77.14 | 9.02 | -2.322 | 40 | 0.025* |

* Significant difference, SD: standard deviation, t: T-test value, df: degrees of freedom, p-value: probability value.

Trantafillou et al. (2003) and Papanikolaou et al. (2003) who use only descriptive statistics in the form of charts and frequency tables. Brown et al. (2007) reported contradictory results. They find that there is no evidence to support the theory that matching users' learning styles has any impact on making learning more effective. However, their sample was children in primary school. Consequently it was difficult to assess the learning styles of 9-11 year old children. In another study Brown et al. (2006) found that using matched or mismatched learning materials does not significantly benefit nor disadvantage the students. Their results attribute to the learning style preferences studied in their experiment which are constrained only to visual and verbal perspectives.

**Table 4.** Students' ratings about several aspects and adaptation features of the system.

| Statement | Mean | Standard deviation |
|---|---|---|
| (1) The presentation of instructional materials as components of a learning sequence for each concept (Objective, Rule, Example, Elaboration, Practice, Recall, Feedback, Quiz) in the Content Area, supported me to understand and use the concept? | 4.88 | 0.33 |
| (2) Quizzes covering each lesson increase my ability to understand and recall the meaning of presented concepts, propose and solve original problem, and apply the provided information to specific case(s) | 4.67 | 0.77 |
| (3) The presentation of the entire content into different media presentations (Visual, Audio, Textual, Kinetic media) helped in my understanding | 4.67 | 0.69 |
| (4) The learning style questionnaire is clear and easy to use | 4.41 | 1.12 |
| (5) The learning style questionnaire helped me to determine my learning style | 4.81 | 0.54 |
| (6) The option that the system provides to change the learning style in case of failing a quiz is useful | 4.33 | 0.9 |
| (7) The accommodation by text only version of the content for Read/Write learners suitable to my learning and support my understanding | 4.83 | 0.41 |
| (8) The presentation of the media in text pages with rich formatting, figures, illustrations, diagrams, flowcharts,, highlighted source code for Visual learners suitable to my learning and support my understanding | 4.40 | 0.89 |
| (9)The embed recorded materials for Aural/Auditory learners suitable to my learning and support my understanding | 3.67 | 1.15 |
| (10) The highly interactive version of the content, which supported with a practice tool with a piece of program code that address an example of the concept and the learner was encourage to modify the code, which could then be executed locally by the system and the results was displayed for Kinesthetic learners suitable to my learning and support my understanding | 4.67 | 0.71 |
| (11) The repetition of the lesson in case of failing the quiz helped me to understand the lesson | 4.76 | 0.56 |
| (12) The link adaptation through link annotation to adapt the contents according to learners level of knowledge facilitates my orientation and navigation in the lesson contents and supports my understanding | 4.78 | 0.55 |
| (13) The link adaptation through link annotation to adapt the contents according to learners level of knowledge prevents me from getting lost in hyperspace | 4.61 | 0.85 |
| (14) The link adaptation through link disabling to adapt the contents according to learners level of knowledge supports my understanding and following the course content gradually | 4.78 | 0.43 |
| (15) The implementation of the navigation area on the left hand side of the screen using collapsible tree menu structure, which grew with the progression of the learner supports my orientation and navigation and hence my understanding | 4.67 | 0.59 |
| (16) The presentation of the learning materials in Content area to the right of the Navigation area as another frame supports my understanding | 4.44 | 0.7 |

**Table 4.** Cont.

| | | |
|---|---|---|
| (17) The offering of a small navigation buttons like "next" for the content page after the current page, a "log out" button allowed the learner to exit the environment, a "submit" button appeared in each quiz to submit answers, and a drop down menu to offer choices for learners to switch between learning preference is useful and facilitates my study. | 4.56 | 0.78 |
| (18) I found the application easy to use | 5.00 | 0 |
| (19) Learning through preferred learning style is useful | 4.88 | 0.49 |
| (20) I enjoyed learning through this application | 4.94 | 0.24 |
| (21) If I found another chance, I will continue studying through this application | 4.89 | 0.32 |

## Student's feedback

The experimental group were given a chance to rate several aspects and adaptation features of the system. The rating score is from 1 low to 5 high. Table 4 shows the student's rating for each statement.

Most learners appreciated the integration of the adaptation to learning styles adopted in AEHS-LS and the support offered by the system. All of them found that the system is user-friendly. High rates were given to the media format and adaptation techniques implemented in the system. However, the auditory learners rated a less than 4 score to the recorded material. This is attributed to the fact that listening to spoken English by a non-native is difficult. The participant's opinion to use the system in the future was very high. The feedback provided valuable positive indications of participants belonging to different learning style categories towards the system.

## Conclusion

Findings showed that students taught using the system with adaptation to learning style performed significantly better in academic achievement than students taught the same material without adaptation to learning style ($p<0.05$). The findings supported the use of learning styles as guideline for adaptation into the adaptive e-learning hypermedia systems. The students were satisfied to learn with the preferred learning style and willing to use the system in the future

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