Automated Adaptive Mobile Learning System using Shortest Path Algorithm and Learning Style

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Abstract—A directed graph represents an accurate picture of course descriptions for online courses through computer-based implementation of various educational systems. E-learning and m-learning systems are modeled as a weighted, directed graph where each node represents a course unit. The Learning Path Graph (LPG) represents and describes the structure of domain knowledge, including the learning goals, and all other available learning paths. In this paper, we propose a system prototype that implements a propose adaptive learning path algorithms that uses the student's information from their profile and their learning style in order to improve the students' learning performances through an m-learning system that provides a suitable course content sequence in a personalized manner.

Keywords—Adaptive Learning, m-learning, Learning style, Shortest Path, Algorithm.

1 Introduction

E-LEARNING researchers explore and develop adaptive techniques that provide a better educational experience for students. Researchers offer accurate and personalized content to students in an intelligent way [1], that may allow for adjustments in course content based on students most recent performances. This technique allows the student to skip unnecessary learning activities by providing automated and personalized support for the student [2]. Students with different educational backgrounds are the main challenge of the e-learning and m-learning systems. These systems provide personalized course units that meet different students' educational needs.

2   Related Work

Adaptive learning makes the learning process easier, faster, and more effective by personalizing the course content for the students based on students' profile. Since adaptive learning systems are still being developed, many issues about adaptive learning have concerned computer science and education researchers. Many techniques and approaches are being introduced. Eventually, these techniques will greatly improve the future of adaptive learning systems. They will adjust more rapidly to the students' goals and preferences. Many different techniques were proposed to generate the adaptive learning paths. These approaches are categorized based on the techniques used to generate an effective learning path.

The current challenge in designing adaptive systems is to provide personalized courses to different students with different learning strategies that are practical to use and more efficient [3][4]. Based on the variety of adaptive learning techniques, they posses' different capabilities in manipulating the learning systems, however, none of these techniques are suitable for all tasks and situations. The Learning Path Graph Technique represents and describes the structure of domain knowledge, the learning goals, and all available learning paths [5][6]. Based on the student's learning paths and learning goals, the student's attributes such as the level of knowledge, the learning style and preferences are used to select a personalized learning path from the Learning Path Graph.

The Concept Map Technique represents the entire course structure and the knowledge of the course domain. The role of Ontology is to describe the learning materials that are composed together in order to create a course [7][8][9]. The Extended Ant Colony Technique combines the previous user's learning profile and an ant colony system approach in order to generate an adaptive learning path [10]. The Ant Colony Optimization (ACO) Technique predicts the best path based on the student's profile and the previous learning paths that have been followed by previous students.

The students are grouped by using the clustering technique based on their learning styles. The technique using Bayesian networks to generate an adaptive learning path is based on learning styles, level of expertise, etc. Based on Bayesian Probability Theory, a node probability table is created. This table has the node probability based on candidate learning paths that consist of different consequent nodes and could be traversed from the current node. Then, the Bayesian network is constructed to calculate the probability value which represents each knowledge unit in the learning path. To create candidate learning paths, the shortest path is selected to provide the appropriate learning path for students [11].

Based on the above referenced works, it is evident that further research is necessary to improve the efficiency of learning systems. Accordingly, our research focuses on discovering the effective learning path. In addition, we need to emphasize on additional adaptation features, smart techniques that can be used to identify the learning style, different educational experiences, skills, learning and learning preferences based on student's interactions and different types of learning mode that lead to better learning abilities.

3 Methodology

A directed graph represents an accurate picture of course descriptions for online courses through computer-based implementation of various educational systems [12]. E-learning and m-learning systems are modeled as a weighted directed graph where each node represents a course unit [13]. The Learning Path Graph (LPG) represents and describes the structure of domain knowledge, including the learning goals, and all other available learning paths. This paper proposes adaptive learning path algorithms that use the student's information from their profile in order to improve students' learning performance through e-learning and m-learning systems that provide suitable course content sequence in a dynamic form for each learner.

3.1 Learning Path Graph (LPG)

In general, the LPG illustrates the structure of domain knowledge and the learning goals and all available learning paths [14] [15].

In order to create and generate a Domain Concept Module (DCM), a two-step procedure is implemented [15].

The first part consists of a designing Learning Goals Hierarchy (LGH) and Concepts Hierarchy (CH) of the Domain Concept Module. Concepts Path Graph (CPG) is a directed acyclic graph which represents the structure of the Domain Concept Module (DCM) which is generated from the connection between the Learning Goals Hierarchy (LGH) and the Domain Concept (DC). The learning path graph is a directed acyclic graph which represents all possible learning paths that match the targeted learning goal. In order to build the Learning Path Graph (LPG), within each concept of the Concept Path Graph (CPG), associated learning resources are selected from media space database. Media space database describes the educational characteristics of the learning resources.

The second part of Domain Concept Module (DCM) includes a personalized learning path. A personalized learning path is selected from the graph that contains all the available learning paths according to the characteristics of the Student Module (SM). The Student Module (SM) identifies a level of student expertise (student knowledge space), learning style (cognitive characteristics) and preferences. The suitability function is applied in order to find the weight of each connection of the Learning Path Graph (LPG) to provide a suitability factor for learning resources.

By applying the adaptive shortest path algorithms to the weighted graph, the system will generate the optimal learning path for a specific student.

3.2 Student Profile

The main challenge of the e-learning and m-learning systems is to create an appropriate adaptive course sequence to provide different students with different educational backgrounds. One of the most important aspects of these systems which has not been completely thoroughly examined, is the capability of the learning system to adapt to the students' profile [16]. An adaptive learning path algorithm uses the stu-

dent's information from their profile to improve the e-learning and m-learning systems and to provide suitable course content sequence in a dynamic form for each student [17].

3.3 Using graphs to represents course units

Graphs are considered as an efficient representation of online courses where have been used in the implementation of e-learning and m-learning systems. The course content is divided into portions called learning atoms that could be implemented at all levels and learning modes [18]. Each course unit could be represented as a graph that includes the learning objectives located on the nodes and after the partition of the nodes. The graph will contain course concepts (Slide, Text, Examples, and Video etc.) [18].

4 Adaptive Shortest Path Algorithm

Most of the styles are intuitive. However, we invite the reader to read carefully the brief description below.

4.1 Document title and meta-data

Fig. 1, below, represents course units that consist of n units whereas G is a graph with n vertices where n >= 0. Let V(G) = { v1, v2,.....,vn }. W is a two dimensional n x n matrix such as:

$$W(i,j) = \begin{cases} w_{ij} \ if\left(v_i, v_j\right) is\ an\ edge\ in\ G\ and \\ w_{ij}\ is\ the\ weight\ of\ the\ edge\left(v_i, v_j\right) \\ \infty\ if\ there\ is\ no\ edge\ from\ v_i\ to\ v_j \end{cases}$$
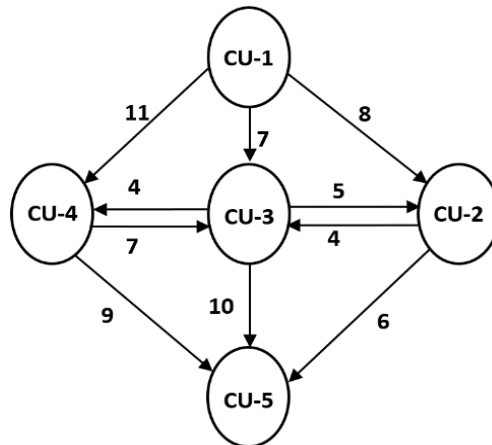

Fig. 1. Weighted graph represents the course units (CUs) structure.

The adaptive shortest path consists of two stages: In stage 1 the algorithm-1 identifies the minimum cost matrix between each pair of course/learning units (CUs). In stage 2 the algorithm-2 constructs an optimal learning path for each student. The shortest learning path designs an adaptive environment for individual students based on the minimum cost between each pair of course learning units and their relevant personal information.

In stage 1, in order to locate the minimum cost matrix between each pair of course/learning units, we applied algorithm-1. Algorithm-1 was implemented through the following steps:

Algorithm-1.

Step 1: Input matrix W which represents the weighted graph course units' structure;

Step 2: For X=1 to X<N repeat step3tostep 7where N is equal to number of CUs;

Step 3: For I= 1 and I<= N repeat step 4;

Step 4: For J= 2 and J<= N repeat step 5, step 6 and step 7;

Step 5: Compare If $W_{IJ} > (W_{IX} + W_{XJ})$, if true then [19]

$$\{$$
$$W_{IJ} = (W_{IX} + W_{XJ});$$

Compare If $P_{IX}=0$, if true then
$$P_{IJ}=X+1;$$
$$\text{Else}$$

$$P_{IJ} = P_{IX};$$
$$\}$$

Step 6: Compare If $W_{IJ} < (W_{IX} + W_{XJ})$. if true then
No change;

Step 7: Compare If $W_{IJ} = (W_{IX} + W_{XJ})$, if true then
$$\{$$
$$W_{IJ} = (W_{IX} + W_{XJ});$$
Compare If $P_{IX}=0$ if true then
$$P_{IJ} = X+1;$$
Else
$$P_{IJ} = P_{IX};$$
Create new PcmID+1 (I, J) =CU (Alternative path for IJ);
Create new W+1 (I, J) =CU (Alternative minimum cost for IJ) where New $W_{IJ} +1 = W_{IJ}$;
$$\}$$

Step 8: End.

We assumed that there is no path between the same node, so for each I=J then WIJ = ∞ and where each $W_{IJ}=\infty$ then $P_{IJ}=\infty$ was modified.

In stage 2; in order to identify the shortest path movement between each pair of course/learning units we, applied Algorithm-2.

Algorithm-2. Algorithm-2 represents the shortest path movement between CUI and CUJ. We followed the steps listed below:

Step 1: CU_I start node and CU_J end node (Target node);
Step 2: if $PI_J = \infty$ then no path between CU_I and CU_J go to *Step 7*;
Step 3: If $PI_J = 0$, if true then
       {
     PI_J is end node (Target node in shortest path);
        Go to *Step 7;*
       }
Step 4: Repeat *Step 5*, *Step 6* and *Step 3*;
Step 5: PI_J is next node in shortest path;
Step 6: $I = PI_J$;
Step 7: End.

5 Mathematical View

To explain how algorithms work, First, we created an initial weighted matrix W=W, where WIJ is the arrowhead weight from CUI to CUJ. Then, we initialized the weighted matrix W from graph in Fig. 1 as shown in Table 1 as follow:
- If no arrowhead exists between the two CUs, then the WIJ = ∞.
- For each I=J, then WIJ = ∞.

Table 1. Graph from Fig. 1 Represented by W(N,N) Matrix, Where N is the number of Course Units= 5.

W(5,5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	∞	8	7	11	∞
CU-2	∞	∞	4	∞	6
CU-3	∞	5	∞	4	10
CU-4	∞	∞	7	∞	9
CU-5	∞	∞	∞	∞	∞

Then, we created Table 2, where P is path matrix: P is a two dimensional n x n matrix such that for each P(I, J) = { p11 = p12 = p13 …. pnn = 0}:

Table 2. Initialized Shortest Path Traveling Matrix by 0 Between Any CUs: P (I, J)=0.

P(5,5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	0	0	0	0	0
CU-2	0	0	0	0	0
CU-3	0	0	0	0	0
CU-4	0	0	0	0	0
CU-5	0	0	0	0	0

After applying Algorithm 1, in stage 1, we generated Table 3 and Table 4:

Table 3. Shortest Path Traveling Cost Matrix W (I, J) between any CUs

W(5, 5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	∞	8	7	11	14
CU-2	∞	9	4	8	6
CU-3	∞	5	9	4	10
CU-4	∞	12	7	11	9
CU-5	∞	∞	∞	∞	∞

Table 4. Shortest Path Traveling Matrix P(I, J) for CUs

P(5,5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	0	0	0	3	2
CU-2	0	3	0	3	0
CU-3	**0**	0	2	0	0
CU-4	0	3	0	3	0
CU-5	∞	∞	∞	∞	∞

After applying to each I=J for cost matrix, then W(I,J)= ∞ as shown in Table 5:

Table 5. W(I,J) is the Shortest Path Traveling Cost, for Each I=j Cost Matrix W(I,J)= ∞.

W(5,5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	∞	8	7	11	14
CU-2	∞	∞	4	8	6
CU-3	∞	5	∞	4	10
CU-4	∞	12	7	∞	9
CU-5	∞	∞	∞	∞	∞

After applying to each, W(I,J)=∞ then P(I,J)=∞ as shown in Table 6:

Table 6. Shortest Path Traveling Matrix P for Each W(I, J) =∞, Then P(I,J)=∞.

P(5,5)	CU-1	CU-2	CU-3	CU-4	CU-5
CU-1	∞	0	0	3	2
CU-2	∞	∞	0	3	0
CU-3	∞	0	∞	0	0
CU-4	∞	3	0	∞	0
CU-5	∞	∞	∞	∞	∞

In stage 2, Algorithm-2 was applied in order to find the shortest path movement between the learning CUs according to the results shown in Table 6.

Now we need to find the shortest path cost CU1→CU5. The solution is reflected in Table 5 where W(1,5)=14. And then, determine the path movement between CU1 and CU5. In order to complete this task, we use Table 6 to locate the path movement between CU1 and CU5 as follows:

From Table 6 the path beginning with CU1→CU5=2, then CU2→CU5=0 (end nod), then the path is CU1→CU2→CU5

6   Adaptation of the Shortest Path Algorithm to the Relevant Personal Student Information

In our first scenario, assume the student is at the initial stage and logs into the system, the student begins the coursework with the CU1. After student successfully finishes and wants to continue onto CU2, the system will direct the student towards the shortest path CU1➔CU2 which is equal to 8.

In second scenario, assume the student has completed the coursework in CU1 and CU2 and has logged out of the system. The student, then, decides to log back into the system to complete CU3, the system automatically direct the student from CU1➔CU3 which is equal to 7. The system does not take CU2 into consideration and ultimately affect the student learning path based on student's personal information.

To make the Algorithm3.2 more adaptive to student's profile the flow of Algorithm3.2 must be accordingly:

Once the student completes a new CU, the system will update the student's personal profile with the new information. Therefore, if the student decides to learn the new a CU, the system will identify the shortest path between each CU in the student's profile as well as any new CUs that the student plans to study.

A.   Algorithm-3

Step 1: For each CU learned in the student's profile complete Step 2;

Step 2: Find the shortest path between CUs in the student's profile and new target CU by using the result from Table 5;

Step 3: Find the minimum cost from all of the shortest paths to the new target CU between CUs in the student's profile and the new CU target;

Step 4: Then determine the shortest path according to the student's profile that reflect the Cui (min cost) to the new target CU;

Step 5: Use Algorithm 2 and Table 6 to find the shortest path movement between learning CUi (min cost) and new target CU;

Step 6: If student complete the newly targeted CU, then the student's personal profile will automatically be updated by the system;

Step 7: End.

Once Algorithm-2 has been modified, then in following scenario assumes the student is at the initial stage and logs into the system, the student completes CU1. After once CU1 is completed, the student moves onto CU2 and the system will direct the student to the shortest path CU1➔CU2 which is equal to 8. This information is stored in the student's profile.

However, the next time the student logs onto the system to study CU3, by applying Algorithm 3 according to the student's profile, the system will compare CU1➔CU3=7 with CU2➔CU3=4 and then, the system will direct the student to the path CU2➔CU3 which is equal to 4.

The personalization of a student's learning path is the core feature of the e-learning and m-learning systems processes. Our current algorithms will construct an adaptive m-learning prototype for Computer Science courses.
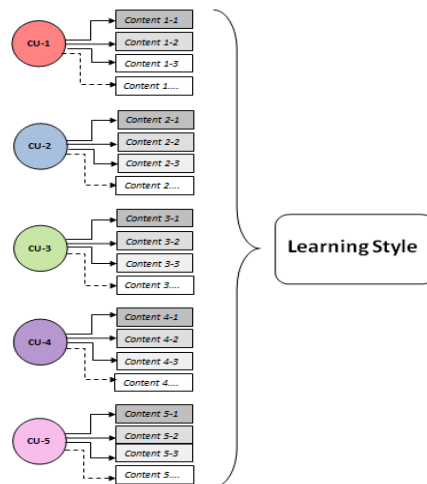
7 Automatic Detection of Learning Style

Fig. 2. AML System Contents According to Learning Style

Our AML learning system presents course instruction for students by using the shortest path algorithm in order to find the most efficient learning path between the learning course units (CUs), according to students' profiles. In order to discover the most effective path, we need to implement and use learning style methods in the designing stage of course content.

According to a student's learning style, we can introduce the same course content through different presentation methods as shown in Fig 2. In our AML system design, we used the Data Driven Method based on the Index of learning style questionnaires created by Felder and Soloman [20]. In addition, we used the Literature Based Method [21] that uses the students' behavior in order to determine a student's learning style. Both the Data Driven Method and the Literature Based Method were used as base tools for analyzing students' learning styles.

The Index of Learning Styles is used for identifying learning style preferences in the Felder and Soloman model. The Index of Learning Styles has 44 questions. The Felder and Soloman model has four dimensions where each dimension defines two differing learning styles. Each dimension has 11 questions containing two options). Also, each dimension uses scaling values between -11 to +11.

The student's results indicate which learning style the student like better, for example if a student's scaling result is between -3 to +3, then the student prefer the two

learning styles of the dimension equally. Otherwise, the student prefers one learning style more than the other of the dimension [22].

The reason for the Index of Learning Style questionnaire is that it provides us with important information to determine the type of content necessary for the students according to their learning styles. The Index of Learning Style questionnaire can be easily implemented to analyze the students' learning styles [23].

According to the model introduced by Felder and Soloman and [24] [25] [26], the learning contents in our AML system are categorized as shown in Table 7.

Table 7. Four Dimensions of Learning Style

	Processing		Perception		Input		Understanding	
	Active	*Reflective*	*Sensing*	*Intuitive*	*Visual*	*Verbal*	*Sequential*	*Global*
Outlines		✔						✔
Definitions				✔				
Step by Step Problem Solving							✔	
Text						✔		
Facts			✔					
Practical Content			✔					
Examples		✔	✔					
Exercises	✔						✔	
Self Assessment	✔							
Images					✔			
Audio						✔		
Graphics					✔			
Charts					✔			
Animations					✔			
Videos					✔			
Summaries		✔						✔

Our AML system can select appropriate learning styles with attention to the behavior and appropriate needs of the student. The AML system adapts to the student's learning style by implementing a learning style assessment and the Literature Based Method. Both were used in our AML system to identify the student's learning style.

According to the Student Learning Style Module, this process can be completed in the following ways:

a) *Initial Learning Style Adaptation:* If the student decides not to take the learning style assessment based on the Felder and Soloman Index of Learning Styles, by default, the students learning styles are categorized as active, sensing, sequential, and visual. The AML system will provide students with the appropriate learning content according to the Initial Learning Style [27] [28].

b) *Student Learning Style Adaptation:* At the beginning of the course, the AML system provides the student with the learning style assessment. If the student decides to take the learning style assessment, then the AML system will analyze the learning style assessment results and provide students with the right learning content according to the student's learning style [29].

c) *Literature Based Method Adaptation:* The Literature Based Method is used in our AML system to automatically identify students learning styles based on the features of Learning Style Module that describe students' behaviors. The features and the behavior patterns in our Learning Style Module refer to the Felder and Soloman model that have been used in our system's design. In our system, we adapt the following behavior patterns:

1) *Active Learning Style:* Can be identified by the number of exercises that a student completed, the number of questions that a student answered, and the number of questions that a student fails to answer twice or more.
2) *Reflective Learning Style:* Can be identified by the number of reviewed learning materials, and the time spent on this learning material.
3) *Sensing Learning Style:* Can be identified by the number of correct answers about facts, the number of correct answers after reviewing the examples, and the number of correct answers after seeing practical material.
4) *Intuitive Learning Style:* Can be identified by the number of correct answers given after a theoretical explanation, the number of correctly answers about concepts, the number of correct answers about creating new solutions.
5) *Visual Learning Style:* Can be identified by the number of correct answers given after seeing graphs, charts, images and video, and time spent watching videos.
6) *Verbal Learning Style:* Can be identified by the number of correct answers given after reading text, and the number of correct answers given after listening to audio.
7) *Sequential Learning Style:* Can be identified by the number of times the student prefers to the step by step problem solving, and the number of correct answers about details.
8) *Global Learning Style:* Can be identified by the number of times the student decides to solve a problem directly, the number of reviewed outlines, and the time spent on outlines.

According to [30], the behavior patterns as described above and the students' information based on these behaviors are used to obtain the hints in order to calculate the student's learning style. Hints are described as (hdim, i), where hints are collected for every dimension (dim) and every pattern(i) that includes related information for this dimension.

After we determine the relevant features (patterns) of students' behavior, based on Felder and Soloman learning style model, we need to use a threshold value to classify the occurrence of behavioral patterns. The threshold value identifies the presence of behavioral patterns and categorized them based on the hint of 0 to 3, where, 0 = no information about students' learning style, 1 = low (e.g., reflective), 2 = moderate does not provide a specific hint, and 3 = high (e.g., active). To find the student's learning style, we apply the following [30]:

1. Sum up all hints and divide them by the number of patterns that include available information (P_{dim}).
2. Use formula 1 to measure the individual learning style (ls_{dim}).
3. Use formula 2 to find (nls_{dim}), by normalizing the measure result from formula 1 on a range from 0 to 1.

$$nls\text{dim} = \sum_{i=1}^{P\text{dim}} h\text{dim}, i \qquad (1)$$

$$nls\text{dim} = \frac{ls\text{dim}-1}{2} \qquad (2)$$

Where 1 indicates a strong positive preference and 0 indicates a strong negative preference for the respective learning style. If no pattern includes existing information, no information about the learning style can be found.

The AML system will update the Learning Style Module with new information. Once a Learning Style Module is updated, the AML system will deliver only the learning content that is suitable to the student's learning style.

8   Adaptive Learning System Prototype

The main characteristic of our AML (Adaptive Mobile Learning) system is that it can predict the student's optimal learning process based on the student's relevant background information, prior knowledge, learning preferences and student's learning style. Through the implantation of our algorithms, the AML system identifies a student's optimal shortest learning path.

 This AML system was designed using System Interface, an Adaptive Engine Module, a Student Profile Module, a Learning Style Module, a Course Content Module, a Student Assessment Module, a Domain Concepts Module, and a Learning Path Generation Module. Fig. 3 illustrates our AML systems architecture.
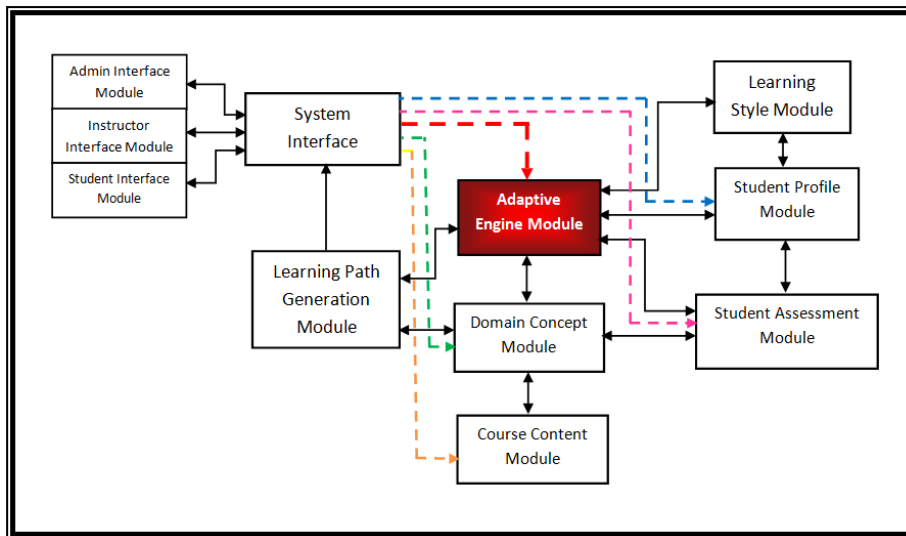

Fig. 3. Adaptive M-learning System Architecture

8.1   System interface (SI).

System Interface includes Admin Interface Module (AIM), Instructor Interface Module (IIM) and Student Interface Module (SIM).

Admin Interface Module (AIM). The Admin Interface Module enables the system administrator to access the Course Content Module, Student Profile Module,

Learning Style Module, Course Content Module, Student Assessment Module, and the Domain Concepts Module.

AIM provides the services for the system administrator to define access control rules, access privileges [31] [32], maintain student enrollments, user profiles course schedules, student examination, create course concept units, course material and archives. AIM, also, provides the services for the system administrator to monitor the learning progress [33] [34].

The system administrator can also perform a number of system maintenance operations through various modules. In the Student Profile Module, the system can create, edit and delete a student profile [34] [35]. The system administrator can create, edit delete of course material. In Student Assessment Module the administrator manages exams [36].

Instructor Interface Module (IIM). The Instructor o Interface Module allows instructors to manage and control course subject pages [37], create and modify course material, manage and control online learning activities, and monitor students' performance based on all types of exams and grading.

Through the Instructor Interface Module an instructor controls the active period that a student can access each lesson's or exam. This Module prevents students from advancing to new lesson contents. A student must finish any test or exercises related to the student current course content [38].

Student Interface Module (SIM). The Student Interface Module presents the educational material to the student in the most effective way. Through the SIM, students enter their personal information that is then will be saved to their profile database. As a first time user, SIM prompts the student to take pre-test. This pre-test evaluates the student's knowledge, and the results are stored in the student's profile.

The system will invoke the Adaptive Engine Module which creates and provide personalized learning paths, according to Student Profile Module and Learning Style Module.

The student has option to attend one of the available course units or search for a specific unit in order to that the system will provide one or more optimal learning path. The student selects one of these learning paths and attends his course.

8.2   Student Profile Module (SPM)

A Student Profile Module is the key resource for facilitating our AML system process that represents essential information about each student.

The Student Profile Module quantify the student's relevant background, prior knowledge, learning preferences, learning style linked to Learning Style Module and student's personal information. Each student has his own profile which enables the system to deliver personalized course learning path with customized course materials, on the basis of the student's learning style [39].

8.3 Learning Style Module (LSM)

It is observable that different students have different preferences, needs and different ways to learn [40]. According to these differences learning style indicates how a student learns and likes to learn [41] or the perception that individuals differ in regard to what type of instruction or study is the most effective for them [42].

Our Learning Style Module predict the learner's behavior uses Felder and Silverman for engineering student's module to classifies students according to where they fit on a number of scales belonging to the ways in which they receive and process information, the dimensions of the learning styles in this module, namely perception, input, processing, and understanding [43] [44].

When students are registered in the system, their learning styles need to be tested. The student needs to answer a short assessment that is used to determine student's preferred learning style [45]. This style indicates a preference for some media type over others. The assessment results are stored in the Learning Style Module, which will be used for the initial adaptation in our system.

8.4 Domain Concept Module (DCM).

The Domain Concept Module is divided into two interconnected sub Modules:

— **Concept sub-Module.** Concept sub Module contains the information about the domain and the course structure. Our Domain Concept Module was built based on a weighted directed graph, where each node represents a course unit while arcs represented relationships between course units as introduced in Section I Learning Path Graph.
— **Media Resources sub-Module (MRM).** The system used media Resources sub-Module to trace media preference where each concept in Concept sub Module composite with different media types such as audio, video, text, pdf etc. in this way we provide the students with the best media that represent the course units according the students learning style [46].

8.5 Course Content Module (CCM)

All the course units' materials are stored in databases contained in the Course Content Module. In this module is easy to extend the database by adding new topics to any course unit.

The idea behind the separation the Domain Concept Module and Course Content Module is to make it possible to reuse part or all of the course unit's material if we need to use these materials to build a new course with same related materials.

8.6 Learning Path Generation Module (LPM)

The graph in the Domain Concept Module containing all possible learning paths, the Learning Path Generation Module has all the available personalized learning paths

generated from Adaptive Engine Module according to student profile and his learning style.

8.7 Student Assessment Module (SAM)

In our adaptive mobile learning system prototype the Student Assessment Module is used to adapt the needs and traits of the students [47], according to student performance assessment we can dynamically generate suitable learning content fit the student needs.

An online Assessment can be designed to begin with a pre-test, which is an assessment of student pre knowledge of each learning unit before taking the course. Based on the pre-test results the system only presents to the student the cores unite that he needs to study according to the learning objectives of the course. Also, there is post-test for each unit that the student must pass in order to receive credit for each unit.

8.8 Engine Module (AEM)

The Adaptive Engine Module is algorithms that integrate information from the preceding modules in order to select appropriate learning path to present the course to the students [48].

An Adaptive Engine Module incorporates the adaptive algorithms of an adaptive M-Learning system by combining all Modules in order to select appropriate learning path to present the course to the students. The process of adaptive module starts with selecting representative nodes by analyzing the student needs from the Student Profile Module, Learning Style Module and Student Assessment Module [49].

The Adaptive Engine Module performs two tasks, the first task is find all the personal learning paths using adaptive algorithm detailed in section II incorporates with the Student Profile Module and Student Assessment Module, so the student selects one of the optimal paths and attends his course. Second task is retrieves the related teaching material according to student learning style.

9 Experiment and Results

In order to verify the analytical research results, experimental results are introduced in this section. For this experiment, we have used the Network Security course CPEG 561. CPEG 561 is a graduate course offered as an elective course for Computer Science and Computer Engineering students.

This work proposes that our AML system improves the student's performance more than control system. This section summarizes the statistical power analysis performed with the aim to test of the alternative hypothesis.

Let M_x denote the mean for the AML group and M_y denote the mean for the Control group.

The statistical Hypotheses for this work are as follows:

$H_0: Mx - My = 0$
$H_a: Mx - My > 0$

The difference significance is determined by the used Level of Significance (α), Significance level: $\alpha = 0.05$.

9.1   T-test

The Student's t-test is used to assesses whether the mean (average) of two groups are statistically different from each other [50] [51].

Pre-test. The Pre-test was designed to ensure that both the Control group and the Experimental group had the equivalent computer knowledge required for taking the Network Security course. The examination questions of the Pre-test included 25 multiple choice questions and true-false questions covering the content of tested units of Network Security course.

Question: *What was the average Pre-test score for the two groups: AML experimental group and Control group?*

As shown in Fig. 4, we have examined the Pre-test results of the AML experimental group (N=15) and the Control group (N=15). For the AML experimental group, the average score was 57.87. For Control group the average score was 67.20.
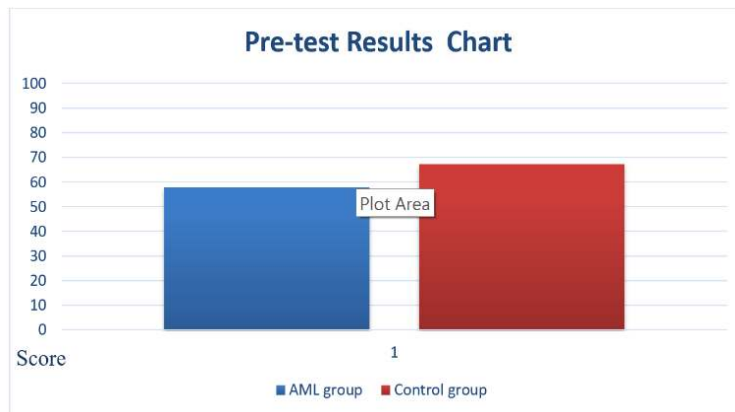

Fig. 4. Experimental Group and Control Group Pre-test Comparison Graph.

Question: *When comparing the Pre-test results of the two groups, was there a significant difference in scores (either positive or negative)?*

Table 8 and Fig. 5 present the t-test results of the Pre-test for both groups. As shown in Table 8, the mean of the Pre-test was 57.8667 and the standard deviation was 11.8916 for the AML experimental group. Whereas, the mean was 67.20 and the standard deviation was 13.8729 for the Control group. The p-value result indicates that the two groups do not significantly differ from each other at $p < 0.05$. Clearly, it is evident that the two groups of students have statistically equivalent abilities in learning of the Network Security course.

Table 8. T-test Results of Pre-test.

	AML group	Control group
Mean	57.8667	67.20
Variance	141.4095	192.4571
Stand. Dev.	11.8916	13.8729
N	15	15
T	-1.9783	
degrees of freedom	28	
critical value	2.048	

AML experimental group   Mean = 57.867 ± 6.585

51.281   64.452

Control group   Mean = 67.2 ± 7.683

59.517   74.883

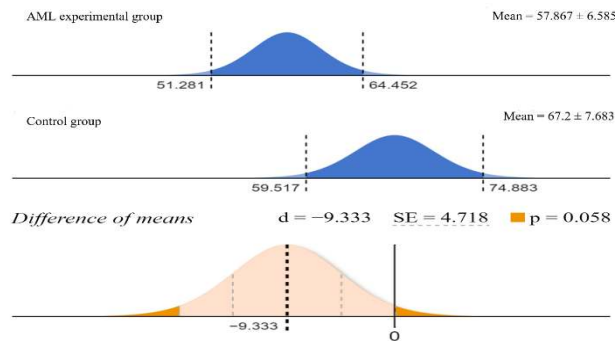*Difference of means*   d = −9.333   SE = 4.718   p = 0.058

−9.333   0

Fig. 5. Pre-test Confidence Intervals and Estimated Difference.

Post-test. The Post-test was proposed to compare the learning achievements of two groups of students after taking the Network Security course. The Post-test contained three essays and 90 multiple choice/ true-false questions that covered all of the units of the Network Security course.

Question: *What was the average Post-test student's score for AML experimental group and Control group?*

We examined the Post-test of the AML experimental group (N=15) and the Control group (N=15). As shown in Table 9, the average score was 66.56 for the AML experimental group. The average score was 45.97 for Control group.

Question: *When comparing post-test student's scores was there a significant difference in scores (either positive or negative)?*

We compared the Post-test student's scores for AML experimental group and Control group (N=30), based on 15 students per group. The average Post-test was 66.558 for AML experimental group, and the average Post-test was 45.9707 for the Control group, yielding a difference of +20.5873 as shown in Fig. 6. While this difference is positive, it was also found to be statistically significant. When a correlation was performed, the post-tests for both groups were significantly correlated at the 0.05 level (p=.05) as shown in Table 9, meaning that the tests measure the same units for both groups. Further, the results of a t-test yield significance at the .05 level (p<0.05), meaning that for the whole groups the difference between the post-tests average score for both groups was statistically significant. In order to obtain the magnitude of the

difference between the means of the two groups, we need to calculate Cohen's d. as shown in Table 10. The Cohen's d is approximately 1.60. These results show that the magnitude of the difference between the groups is called a very large effective size, besides being not only statistically significant with a difference at $p < 0.05$.

Table 9. T-test Results of Post-test.

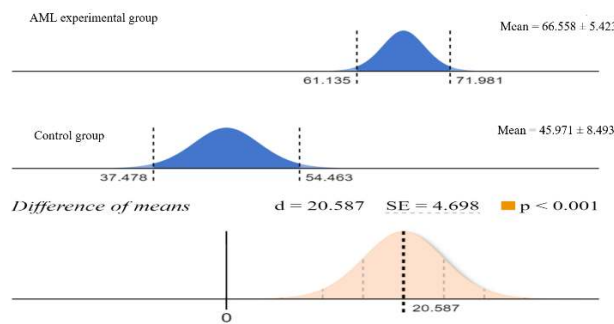|	**AML Group**	**Control group**
Mean	66.558	45.9707
Variance	95.8901	235.1811
Stand. Dev.	9.7923	15.3356
N	15	15
T	**4.3821**	
degrees of freedom	**28**	
critical value	**2.048**	

Fig. 6. Post-test Confidence Intervals and Estimated Difference.

To make the decision: t value and Critical values are used. If t value is greater than Critical t (Probability Ho is True is Low), Reject Ho. In this test, the critical value for t with degrees of freedom = 28 and α=0.05 is 2.0548, the calculated t exceeds the critical value (4.3821>2.048), so the means of AML experiment group and control group are significantly different at $p < 0.05$. This means Reject Ho and Accept Ha that our AML system improves the student's performance more than control systems. It is evident that the difference is positive, and that our AML prototype improves the student' performance of AML experimental group more than the Control group.

9.2 One-way ANOVA.

The one-way analysis of variance (ANOVA) is used to determine whether there are any significant differences between the means of two or more independent groups.

We use the one-way (ANOVA) to compare the means between the AML experimental group and the Control group to determine whether these means are significantly different from each other [52] [53]. Here, we will test the null hypothesis:

H0: $M_x - M_y = 0$.

Table 10.   Cohen's D and the Effect-size Correlation, R_{Y_λ}

Cohen's d	effect-size r
1.60	0.6247254

Table 11.   One-way ANVOA Test Results of the Post-test.

	SS	df	MS	F	P
Between	3178.776909675	1	3178.776909675	19.203	0.000150
Within	4634.9968	28	165.5356		
Total	7813.773709675	29			

The F ratio is the ratio of two mean square values. Where F (1,28) = 19.203 as shown in Table 11. Since the F ratio is greater than 1, the results show the means of the AML experiment group and the control group are significantly different at p < 0.05. Based on the hypothesises of Reject Ho and Accept Ha, our AML system improves the student's performance more than control systems.

10   Conclusion and Future Work

The purpose of developing an online learning system is to discover the most effective learning path for any university student enrolled in computer science and engineering courses. We accomplished this task through our design of the AML system prototype. Our AML system prototype identifies the best learning path through the implementation of the shortest path algorithm and the designed methods of a student's learning style. By performing various Statistical Power Analysis tests, such as t-test, and one way (ANOVA), we determined that students' performances from the AML experimental group had a higher improvement rate than control group. In addition, our system identified the student' learning styles and provided the students with different presentations of the learning materials.

Through our experimental results, our proposed AML system prototype positively enhances the student's learning process

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