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Personalized E-Learning Based on Ant Colony Optimization

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With the advancement in technology, the approach to learning has also been modified. "Standardization" and "One-size-fits-all" has become an outdated concept. To adjust to the changing learning approaches, e-learning came into being, but this was not as per the knowledge and intelligence of users. This created a hurdle in the achievement of better learning and acquisition of skills. This calls for the provision of personalization in e-learning. Successful implementation of personalized e-learning in the present education system will lead to better and faster learning by adapting as per the preferences and knowledge of students. The core idea behind this research is to make an application using Android, which provides a personalized and adaptable route of e-learning using Ant Colony Optimization and recommendations from similar peers. This research will cater to the needs of many students, and it will help in decreasing the time taken to complete any subject or course. It will also help in attaining better and efficient learning as the learning route is determined as per the user. Also, the collection of records of every user will help in improving efficiency and accuracy in the determination of the learning path. The developed app aiming for adaptative e-learning can act as a promising solution during the Covid-19 scenario.

Keywords: Personalized e-learning; learning aim; ant colony optimization; learning preferences; forward learning path.

1. Introduction

With the advancement of technology, the needs and wants of people have also expanded. Learning is an essential part of the grooming of every individual, and mode of learning plays a vital role in determining how we develop as an individual. Earlier classroom education was considered as the best and only mode of education, but it was based on the One-size-fits-all approach. It doesn't take into consideration the learning[1] ability and

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learning style of different students. So, with the advancement of technology, there emerged the concept of e-learning where education is provided online reducing the efforts needed to go to remote places for acquiring knowledge. But still, the problem of "one-size-fits-all" persisted. So, further enhancement in technology[5,6] paved the way for personalized e-learning.

Personalized e-learning is the all-new approach and vision towards the learning process. Personalized e-learning involves customization as per the user's needs.

Some of the terms related to the current research are described below:

1.1. *Perspective aim contribution table*

Each concept in a course can be learned through various perspectives depending on the purpose of learning. This table is used to determine the contribution of different perspectives at a particular level towards different learning aims.

Learning Object Priority Table

Whatever the perspective, a concept can be explained through various types of learning objects (for example, pdf files, ppts, videos, etc.). This table is used to determine the contribution of a particular learning object towards different learning aims.

Question Relevance Table

This table contains the relevance of questions in determining the learning ability of the student at each level after the quiz for different learning aims, i.e., depending upon the learning aim, the contribution made by each question in assessing the capability of the student varies at each level.

Dynamic Learning Ability

The learning ability of a user is not static; rather, it changes as the user learns and gains more knowledge. After each level, an examination is conducted to determine the new learning ability of the user. This is done by calculating the marks of users by determining the contribution of the questions towards a particular learning aim using the Question Relevance Table.

User Attribute Database

It is a database that is used to store various attributes of previous users and current users.

2. Problem Statement

This research provides personalization in e-learning of various subjects and courses and doing away with "one-size-fits-all" approach by creating a free and open-source application that stores the data of users in a database[14,15] and provides the learning path to the user as per his/her learning aim, learning ability, and preferences. Thus, we can conclude that this research is solving the following problems:

Lack of free and open-source application
There are many applications providing e-learning[2,3] courses, but most of them are paid and not personalized. This research intends to provide a solution to this problem.

Lack of personalization in learning route
Although many service providers provide a variety of e-learning courses most of them provide a static route of learning irrespective of the background and learning aim of the student due to which the learning ability of every student doesn't increase similarly. Some students tend to produce better results while some experience deterioration in their learning ability due to the static learning route.

Lack of proper storage of data of each user
Although many efforts have been done in this direction still proper storage and consequently adequate usage of data in recommending better learning paths, learning objectives and perspectives have yet not been done.

Although many tools and technologies exist in the market to handle these problems individually still an approach to solving all of these problems in a wholesome way is lacking, and we intend to work in providing a solution to all the above-mentioned problems.

2.1. *Approach to problem*

As per the information given in Table 1, it is evident that the given approach to the problems will provide a free and open-source application that ensures that the most optimal learning path is provided to the student and various attributes of students are being stored to provide a better path to the future students through recommendation.

2.2. *Significance of the problem*

This research provides a free and open-source application having an environment of e-learning through personalization and recommendation of the most optimal learning path and thus ultimately helps in reducing the time and efforts needed for learning any course. Therefore, this research will help in achieving the following:

(i) Better results of students as they will learn as per their knowledge and learning ability.
(ii) Increases efficiency of students
(iii) Well management of various attributes of students
(iv) It allows students to think, learn, and innovate in a sheltered and safe environment.
(v) This allows learners to become reliable, accountable, and independent.
(vi) It is one of the best solutions for rural students where there is lack of proper education facilities, educators, study material, etc
(vii) It provides a mobile learning environment i.e. it can be used anytime and anywhere.

Table 1. Approach to problems.

Challenge	Approach
Lack of free and open-source application	Using Firebase and SQLite in Android to store various learning objects needed for various learning aims and provide them to the users as per his/her needs.
Lack of personalization in learning route	Using Ant Colony Optimization technique, which is based on personalized and continuous learning, i.e., continuous adjustment. In this technique, artificial ants, which are a set of software agents, are used to search for an excellent solution to an optimization problem.
Lack of proper storage of data of each user	Data of each user is stored in the User Attribute Database using Firebase, which will be used for recommending the most optimal path.

3. Related Work

The insights of the work done till today in the field of personalized[12] e-learning and the tools and technologies which exist in the market presently are provided in this section. Table 2 gives a detailed description of all the technologies which are present in the market and provides an e-learning platform. Though these technologies offer an e-learning platform they are based on subscription and provide a partial solution to the problems stated above. Table 3 describes various approaches that have been used previously in the field of personalization of learning experience and the research gaps which were encountered while using those approaches. Some of these approaches have also been used for a better learning experience and prediction of the forward learning path in the project.

Table 2. Comparison of existing tools and technologies.

Organization	Service Provided	Description
Coursera	E-learning	It provides mobile learning for the app through Android and iOS. It provides a feedback mechanism for technical and academic issues. It provides a static course, though.
Internshala	Online training and internships	It offers various training programs to the user. Though these programs are static, they provide a wide variety of learning objects and quizzes which help in assessing the learning ability and attaining new skills.
Udemy	E-learning	It provides a variety of courses in 65+ languages and hence connects instructors and students across the globe. Though it gives solutions to a few problems, it is paid and static.
UpscPathshala	E-learning	Students are trained for the preparation of civil services using it. Various types of study materials are provided, and a mentor is assigned to each student to assess his/her performance. A timely quiz is also taken to check their learning ability. But this is a paid app and helps in achieving personalization to a small extent.

Table 3. Insights gained and research gaps in the literature.

Research Paper	Publishing details	Content incorporated	Research gaps
Personalized E-learning based on intelligent agent.[22]	D. Sun and Y. Zhou, *Physics Procedia* **24** (2012) 1899–1902, doi:10.1016/j.phpro.2012.02.279.	Building Unit of Learning (UoL) which includes a course, a module, or a lesson using a learning model. Monitor and analyze the continuous progress in real-time.	Efficiency was not as expected. Improper feedback mechanism.
A personalized E-learning based on Recommender System.	O. Bourkoukou, E. El Bachari, and M. El Adnani, *Int. J. Learning and Teaching* **2**(2) December 2016).	It is based on three models: Learner model, domain model, and recommendation model.	Recommendation factor gives more importance to peers associated with the learner reducing the efficiency.
Adaptive framework for recommender based learning management system.[4]	M. Maravanyika and N. Dlodlo, *2018 Open Innovations Conference* (*OI*), Johannesburg, 2018, pp. 203–212.	It provides a framework for differentiated teaching and learning, i.e., Learning Information System. Automatically identifies a learner's needs through the interface of their needs from the interaction with content. Clusters were formed according to student interest, and an effective interface was provided to the user.	One-Size-Fit-All approach to learning has serious limitations.
Review of personalized learning approaches and methods in E-learning environment[9]	A. S. M. Ghazali, S. F. Mat Noor, S. Saad (*The 5th International Conference on Electrical Engineering and Informatics*, August 10–11, 2015, Bali, Indonesia)	It uses the Felder and Silverman learning style model based on an automatic approach to identify the learning style of the user. Based on a questionnaire, users are divided into four categories depending on their learning style.	It lacks adaptation in the learning path as the learn-ing progresses.
Research on personalized E-learning based on decision tree and RETE algorithm.[10]	T. F. Zhou, Y. Q. Pan, L. R. Huang, *Int. Conference on Computer Systems, Electronics and Control* (*ICCSEC*) (2017).	It prescribes using decision trees to classify the learners. RETE algorithm is used to provide a production rule engine which further helps in diagnosing and helping learners.	It gives more weightage to the behavior and learning experience of other users compared to the learner himself.
Personalized E-learning system by using intelligent algorithm.[11]	M. Gong, Workshop on Knowledge Discovery and Data Mining (2008).	The new intelligent algorithm uses association rules mining and collaborative filtering to mine a variety of categories of interesting teaching resources and recommends few teaching resources respectively	It lacks adaptation in the learning path. The solution recommends only teaching resources and hence is incomplete as it lacks recommendation and adaptation in the learning path.
Personalized E-learning model: A systematic literature review.[12]	International Conf. of Information Management and Technology (ICIMTech, 2017).	The interaction of students globally is introduced. Best techniques and learning algorithms were obtained based on previous research data.	It does not include many factors of personalized E-learning such as feeling, cultural background, student environment, etc.
Personalized E-learning with adaptive recommender system.[13]	M.-H. Hsu, A personalized English learning recommender system for ESL students, *Expert Systems and Applications* **34** (2008) 683–688.	It uses Ant Colony Optimization to provide a personalized E-learning path. It focuses on the pheromone deposition along a particular	Involving the heuristic factor can yield a better result.

		path, which further helps in determining the most optimum path.	
Optimizing dynamic multi-agent performance in E-learning environment.[21]	M. M. Al-Tarabily, R. F. Abdel-Kader, G. A. Azeem and M. I. Marie, in *IEEE Access* **6** (2018) 35631–35645, doi:10.1109/ACCESS.2018.2847334.	It focuses on building an e-learning environment based on multiple agents using Particle Swarm Optimization. It uses five agents to provide a different learning path to different users based on their knowledge and preferences.	It does not consider the social profile of the user for a better learning experience.
Integration of data mining clustering approach in personalized E-learning.[20]	S. Kausar, X. Huahu, I. Hussain, Z. Wenhao and M. Zahid, in *IEEE Access* **6** (2018) 72724-72734, doi:10.1109/ACCESS.2018.2882240.	It proposes to use a clustering algorithm to partition students into groups based on their learning patterns. It also suggests various modules to different groups based on their learning ability.	CFSFDP can form clusters more spontaneously. The social profile of the user is not considered.
An adaptable and personalized E-learning system applied to computer science programmes design.[17]	E. Aeiad and F. Meziane, *Educ. Inf. Technol.* **24** (2019) 1485–1509 (2019), https://doi.org/10.1007/s10639-018-9836-x.	Various learning sources are extracted based on the learner's model having background, learning style, and needs of the user. The natural language processing technique is then used to utilize these extracted resources for path generation.	Predictive evaluation lacks accuracy. Multimedia sources are not taken into account in this for learning.
A personalized group-based recommengation approach for web search in E-learning.[18]	M. M. Rahman and N. A. Abdullah, in *IEEE Access* **6** (2018) 34166–34178.	Augmentation of web search is done with a personalized recommendation of web search based on the learning style and behavior of students. It improves performance as well as the satisfaction of students.	Social identities of students are not taken into account. Just 100 queries are allowed per day, which is quite low.

In a recent research,[23] an integrated multi-objective optimization has been implemented to minimize the energy consumption of IoT based smart classroom by considering ant colony optimization and crossover operator.

A fuzzy inference system model has been used which processes the realization parameters (e.g., satisfied, depressed) using a fuzzy rule base to generate crisp measurements of the learner's cognitive states in terms of belief, behavior, and attitude.[24] Fuzzy logic can deal with a lot of uncertainty and imprecision when it comes to learning contexts and learner characteristics.[25] Bradac and Walek use an expert system to assess a student's level of understanding to determine the need to learn specific test categories.[26] MapReduce-based Ant Colony Optimization algorithm[16,17] has been used in generating adaptive learning path in the case of Big Data.[27] The Multi-layer Adaptive[7,9] Neuro-Fuzzy Inference System is proposed in a current study for predicting student performance in online higher education environments.[28] Authors in their previous work recommend and build a goal-oriented adaptive E-learning method that effectively capitalizes on the advantages of continuous learner improvement.[29]

4. Methodology Used

4.1. *Description of the research*

The research focuses on providing a personalized and adaptable path for learning on online platforms. It does so by forming a learner's profile based on an initial quiz, as is done in previous researches as well. Later on, Ant Colony Optimization is used to suggest the most optimal forward learning path based on the learner's profile of the user. Based on the changing learning ability of the user, the path adapts itself and a forward learning path is suggested based on the recommendation from similar peers. Thus, it proposes a new approach that uses ACO and recommendation altogether to suggest the forward learning path to the user. The research has been explained in detail in Fig. 1. The research is divided into three modules, namely, ACO Optimization, Recommendation, and Personalized Examination System. These three modules are connected through User Attribute Database with each other in which ACO Optimization provides the most optimum forward learning path through updating of pheromone by artificial ants. Recommendation module is used to recommend a best forward path to the student based on the attributes of the student, and common characteristics that he/she shares with similar performing peers, and Personalized Examination System is used to determine the learning ability of the student after each level through a quiz and to update it accordingly.

Initially, the learning ability (y_c) and learning aim (LA) of the user (S_x) is determined based on an initial quiz taken up by the user, and the result is stored in the User Attribute Database (UAD). Ant colony optimization (ACO) is applied to these value and the best optimum forward-path ($\tilde{P}_c$) is generated. A test is taken after the completion of each module, and the learning ability of the user is updated in UAD according to the marks of the test. Based on the values stored in UAD and the recommendation factor by peers (RF_{peers}), ACO is implemented and $\tilde{P}_c$ is updated accordingly.

4.2. *Module-wise implementation*

Module 1: Personalized Examination Subsystem
Figure 2 shows the Personalized Examination Module, which takes information about the student such as learning aim, initial learning ability, etc., and marks obtained in the quiz as input and gives the updated value of learning ability as output.

4.3. *Working of personalized examination module*

When the course is started by a new user, he/she is registered through email id and password. This email id and password are stored in a database using Firebase using which the user can login any number of times. Then, the learning aim of the user is determined. Learning aim can be teacher, student, or researcher depending on the end goal for which the course is being taken. After successful registration of the user, a preliminary test is conducted to calculate the initial learning ability (y_0) of the user as follows.

$$y_0 = \frac{(\sum_{i=1}^{nQ} QRT_j[LA(x)][i] * M_j[i](x))}{(\sum_{i=1}^{nQ} QRT_j[LA(x)][i])} \tag{1}$$

Where, $QRT_j[LA(x)][i]$ shows the relevance of question i towards a particular learning aim LA of student x, $M_j[i](x)$ shows the marks of question i of student x.

Initial learning ability shows the knowledge of the user before the course. Using the initial learning ability of the user, we calculate the Dynamic Learning Success (DLS) as follows:

$$DLS_{j,k}(x) = MLS_j(1 - e^{-y_j(x)t_{j,k}(x)}) \tag{2}$$

where, MLS shows the Maximum Learning Success gained after each level and $t_{j,k}(x)$ represents the time taken by student x at each level.

Now, the Coverage Factor (CF) is calculated, which depicts how broad knowledge has been acquired by the user as follows:

$$CF = [DLS_{j,k}]_{y_c} * PACT[LA(x)][j][k] \tag{3}$$

Then, Total Coverage Factor (TCF) is calculated:

$$TCF = CF1 + CF2 + CF3 + CF4 \tag{4}$$

Where, CF1, CF2, CF3, and CF4 represent the coverage factor at level 1, level 2, level 3, and level 4, respectively.

Now, the Depth Factor (DF) is determined, which shows the depth of knowledge acquired by the user in terms of total perspectives covered at each level.

$$DF_j(\overline{P_c}, x) = {(\sum_{k\in\overline{P_c}}[\sum_{k\in\overline{P_c}} DLS_{j,k}(x)]_{y_c} * PACT[LA(x)][j][k])} \Big/ {(\sum_{k=1}^{nP(j)} PACT[LA(x)][j][k])} \tag{5}$$

Finally, Cumulative Depth Factor (CDF), which is the sum of DF at each level, is calculated as:

$$CDF(\overline{P_c}, x) = \sum_{j=c}^{nL} DF_j(\overline{P_c}, x) \tag{6}$$

The above-calculated values are used to determine the Path Value (PV) of each student as follows:

$$PV = w_1 * TCF + w_2 * CDF + w_3 * RF \tag{7}$$

where, RF represents the Recommendation Factor extracted from the Recommendation module, w_1, w_2 and w_3 shows the contribution of TCF, CDF, and RF, respectively.

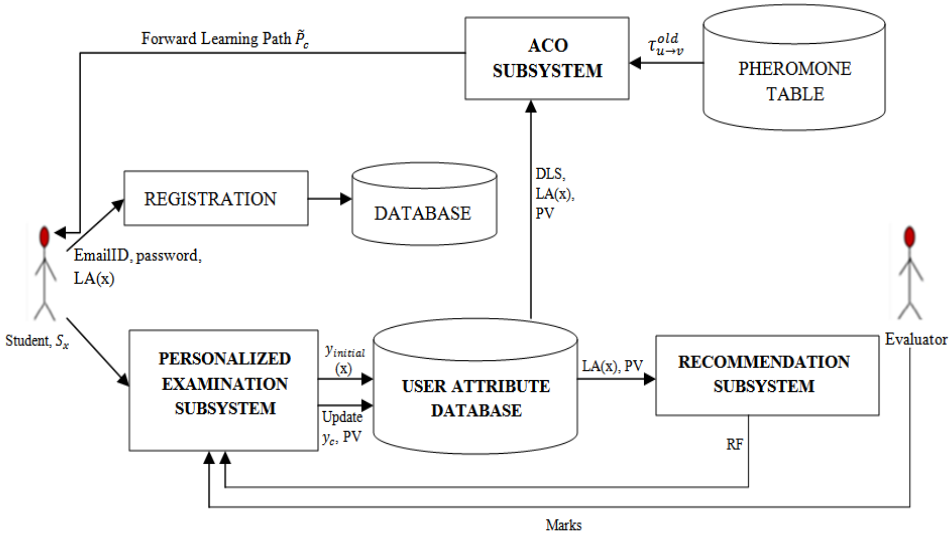

Fig. 1. Architecture diagram of personalized E-learning.

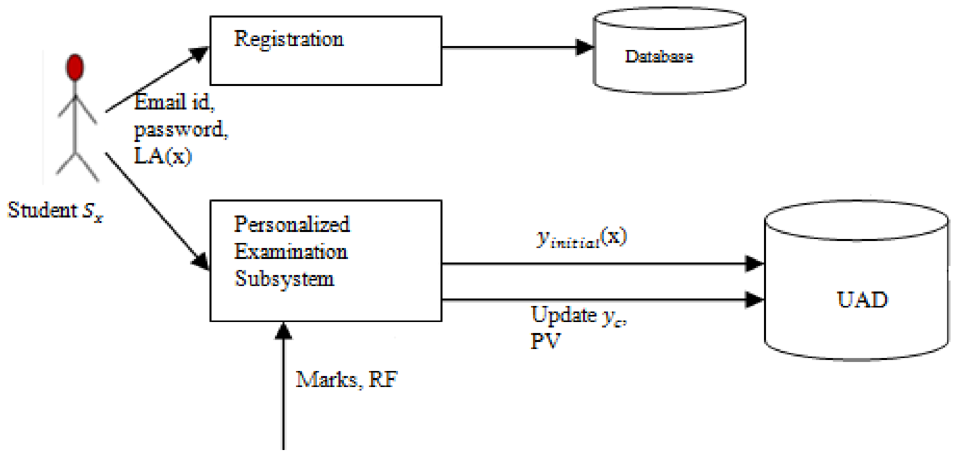

Fig. 2. Personalized examination subsystem.

5. Module 2: ACO Subsystem

Figure 3 shows the ACO Subsystem Module, which takes information about students from the User Attribute Database and recommendation factor from the Recommendation subsystem as input and gives the forward learning path as output.

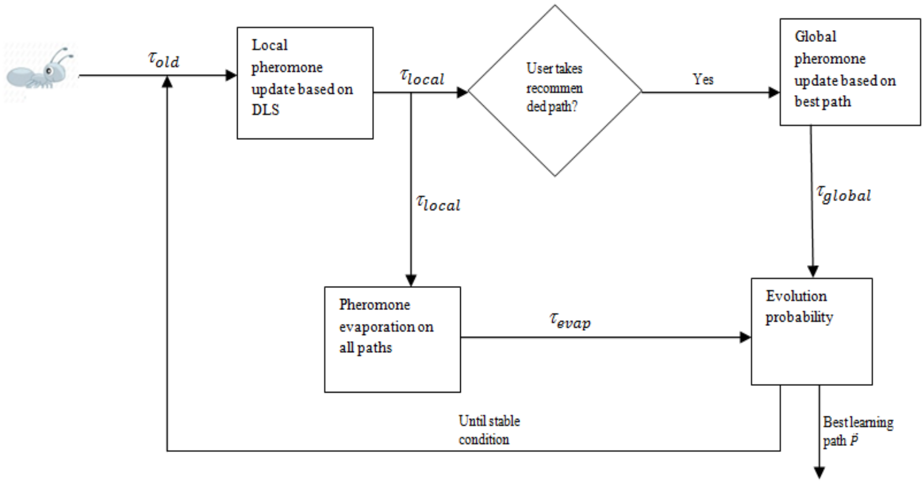

Fig. 3. Workflow of ant colony optimization.

Working of ACO System Module

Figure 4 shows the course graph for the project.

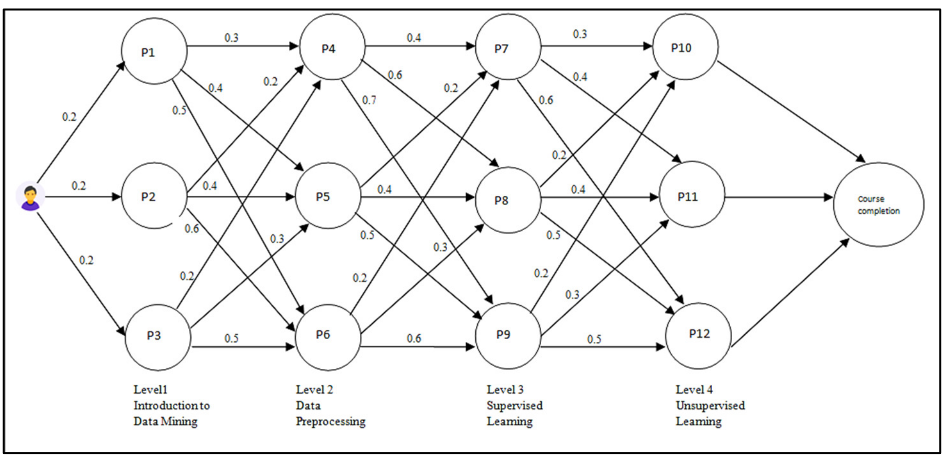

Fig. 4. Course graph.

All the edges are assigned an initial pheromone[19] value (∈). After giving the preliminary test and selecting the learning aim, the user enters level 1, i.e., Introduction to Data Mining. Based on the initial learning ability and learning aim, one of the perspectives, i.e., student, teacher, or researcher, is allocated to the user. All the learning objects of that particular perspective are learned by the user. Users can also go through the learning objects of other perspectives to gain more clarity, but it is not compulsory. After the completion of level 1, a quiz is conducted, and based on the marks of that quiz learning ability (y_j) of the user is updated as follows.

$$y_j(x) = y_{j-1}(x) * \Omega + P_j(x) * (1 - \Omega) \quad (8)$$

Where, Ω is the tuning parameter that determines the contribution of previous learning ability and scaled marks obtained in the quiz in the determination of dynamic learning ability.

Now, based on the DLS calculated earlier in Personal Examination Subsystem, the old value of pheromone is updated locally:

$$\tau_{u\to v}^{new} = \tau_{u\to v}^{old} + (\epsilon * \frac{1}{1-[DLS_v(x)_{y\,u}]})\varphi) + LA(x) \quad (9)$$

Where, $\tau_{u\to v}^{old}$ represents the old pheromone value along edge u -> v, φ is the control parameter which determines the contribution of DLS in calculating the new pheromone value along edge u -> v.

If the user chooses the path having the highest local pheromone value along edge u to v, then the pheromone value of that edge is updated globally as follows:

$$\tau_{u\to v}^{new} = \tau_{u\to v}^{old} + \left(\epsilon * \left(1 + \frac{|PV_{best}(x)|}{\psi}\right)\right) \quad (10)$$

where, ψ is the power parameter which determines the contribution of best path value in the determination of new pheromone value along edge u -> v.

Also, along with time, pheromone gets evaporated along all the edges as follows:

$$\tau_{u\to v}^{new} = \{\frac{\tau_{u\to v}^{old}*(1-\mu) \quad ,if\ \tau_{u\to v}^{old}*(1-\mu)\geq\epsilon}{\epsilon\ ,otherwise} \quad (11)$$

where, μ is the rate of evaporation along all the edges.

Module 3: Recommendation Subsystem

Figure 4 shows the Recommendation Subsystem Module, which takes information about students as input from the Learning Information System and gives the recommendation score for all perspectives at the next level as output. It forms a group of similar peers for a student by taking into consideration learning ability, learning aim, and completed path value at each level of the course. Now, the user having the path value closest to the present user is selected, and the path of that user is extracted from UAD and recommended to the present user. If the present user follows the same path as recommended, the Recommendation Factor (RF) is set to 1; otherwise, it is set to 0, which is further used in the calculation of path value in the Personal Examination Subsystem.

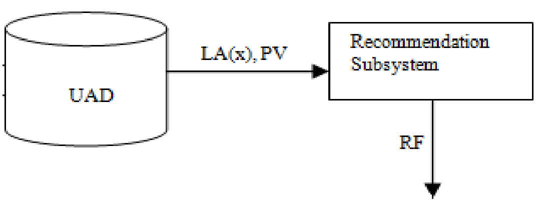

Fig. 5. Recommendation subsystem.

5.1. *Logical requirements*

User Attribute Database (UAD)

This database stores the attributes of the user, such as id, learning aim, learning path, path value, learning ability, etc., which is further used in Recommendation Subsystem. Table 4 shows the structure of the UAD.

Table 4. User attribute database.

Student Id	Learning Aim	Learning Path	y_0	Path Value	y_1	y_2	y_3	y_4
1	Teacher	LP1	0.7	0.342	0.735	0.811	0.835	0.899
2	Student	LP2	0.3	0.572	0.598	0.621	0.623	0.633
3	Teacher	LP3	0.6	0.621	0.633	0.645	0.644	0.685

Perspective Aim Contribution Table (PACT)

This table is used to store the contribution of each perspective corresponding to different learning aims at each level. Table 5 shows the structure of PACT.

Table 5. PACT.

Learning Aim	Levels											
	Level 1			Level 2			Level 3			Level 4		
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Student	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
Teacher	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1
Researcher	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8

Pheromone Value Table (PVT)

This table stores the weight of edges while going from one level to another. Table 6 shows PVT's structure.

Table 6. Pheromone value table.

Perspectives	Levels						
	Level 1			Level 2			
	P4	P5	P6		P7	P8	P9
P1	0.3	0.2	0.2	P4	0.5	0.2	0.2
P2	0.2	0.4	0.2	P5	0.2	0.4	0.2
P3	0.2	0.2	0.5	P6	0.2	0.2	0.6

Question Relevance Table (QRT)

This table shows the relevance of each question at a particular level towards various learning aims. Table 7 shows the structure of the QRT.

Table 7. Question relevance table.

	Relevance values									
	Contribution of question *i* at a particular level j									
Learning Aim	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Student	0.2	0.0	0.1	0.1	0.0	0.1	0.2	0.1	0.1	0.1
Teacher	0.1	0.2	0.1	0.0	0.1	0.2	0.0	0.1	0.1	0.1
Researcher	0.0	0.1	0.1	0.2	0.1	0.0	0.1	0.1	0.2	0.1

6. Experimentation and Results

6.1. *Implementation snapshots*

The snapshots of the implemented app have been demonstrated. Figure 6 shows the implementation of Module1 (Personalized Examination Subsystem). Figure 6.1 shows the extraction of learning aim i.e. student, teacher, and researcher which helps in the determination of forward learning path. Figure 6.2 shows the page to extract information about the user to build the learner's profile. Figure 6.3 shows the prior quiz along with a timer which is used to determine the initial learning ability of the user. Figure 6.4 shows the quiz which is conducted after each level. Figure 6.5 shows the marks obtained in the quiz which is further used to update the dynamic learning ability. Figure 6.6 shows various modules included in the course.

Figure 7 shows the implementation of Module2 (ACO Subsystem). Figure 7.1 shows the forward learning path by the application of Ant Colony Optimization using the learning aim, DLS, PV and UAD. Figure 7.2 shows various learning objects to the student as per the learning aim and preferences. Figure 7.3 shows the content being accessed after selecting a particular perspective. Figure 7.4 shows the code for pheromone updation and evaporation.

6.2. *Testing details*

Our model offers various new features such as dynamic learning ability, ACO generated forward path, and a recommendation from similar peers. A model integrating all these features has not been developed before, so the data of already existing models could not be used. So, we used random data and trained it on a set of 50 students having three Learning Aims in choice by storing the value of various variables in UAD. Based on this trained data, new students having different Learning Aims and different patterns of learning abilities are guided. Since we use the recommendation from similar peers to generate a forward learning path, the impact of this recommendation can be analyzed for students having variations in their learning patterns as follows.

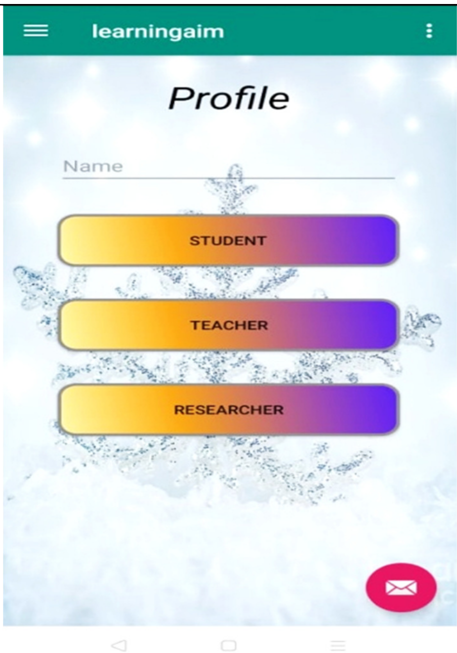

Fig. 6.1. Learning Aim Screen

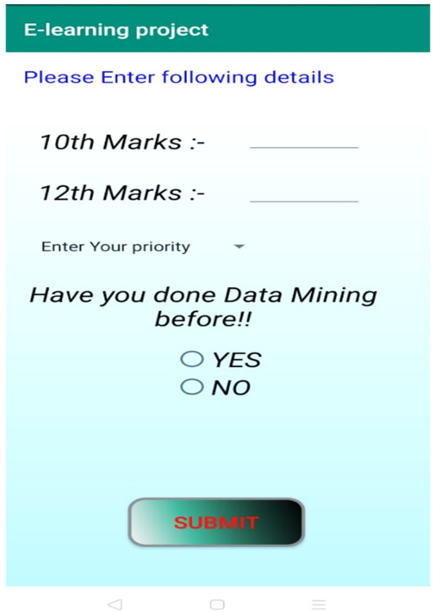

Fig. 6.2. Building Learner's profile

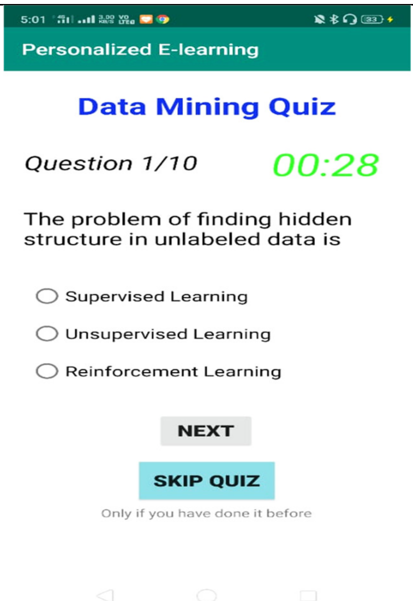

Fig. 6.3. Initial Quiz Screen

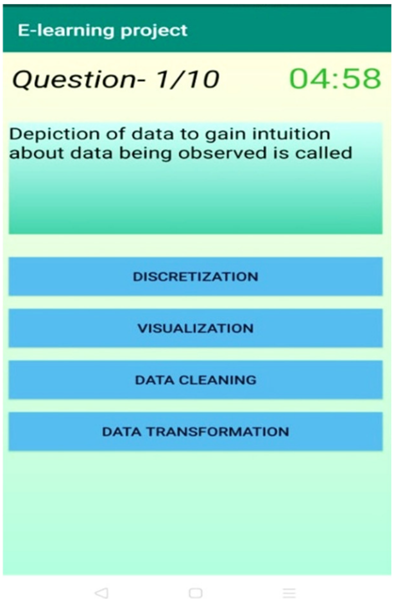

Fig. 6.4. Quiz after each level

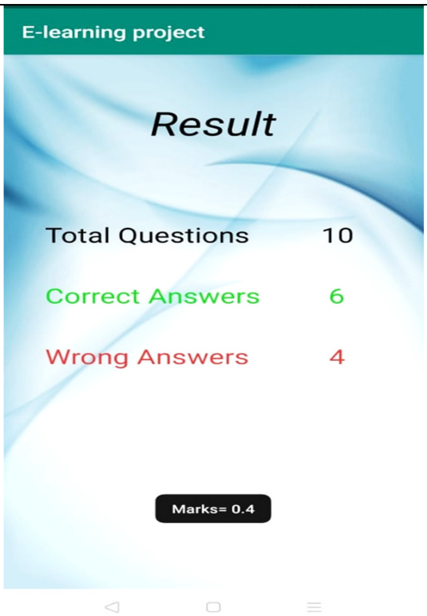

Fig. 6.5. Scaled marks obtained in the quiz

Fig. 6.6. Course Screen

Fig. 6. Snapshots of Module1 (Personalized Examination Subsystem).

Case 1: Students showing persistent improvement in their learning ability
The user starts the course with initial learning ability, $y_0 = 0.1$, and her dynamic learning ability improves by 10% after completion of every level.

Case 2: Students showing boosted improvement

The user initiates the course with low initial learning ability, $y_0 = 0.05$, but later on, the dynamic learning ability shows significant improvement after every level, say 15% after level 1, 30% after level2, and so on.

Case 3: Students showing late improvement

The user starts with high initial learning ability, say $y_0 = 0.4$ but later on shows a significant decrease in the dynamic learning ability after each level, say 20% due to the difficulty suggested to him based on his high learning ability. Finally, the system offers him an easier learning path increasing the dynamic learning ability. Finally, two experiments were conducted on the above test cases:

Experiment 1: Generation of forwarding learning path without any recommendation only based on dynamic learning ability.

Experiment 2: Generation of forwarding learning path with the help of recommendations[8] from similar peers.

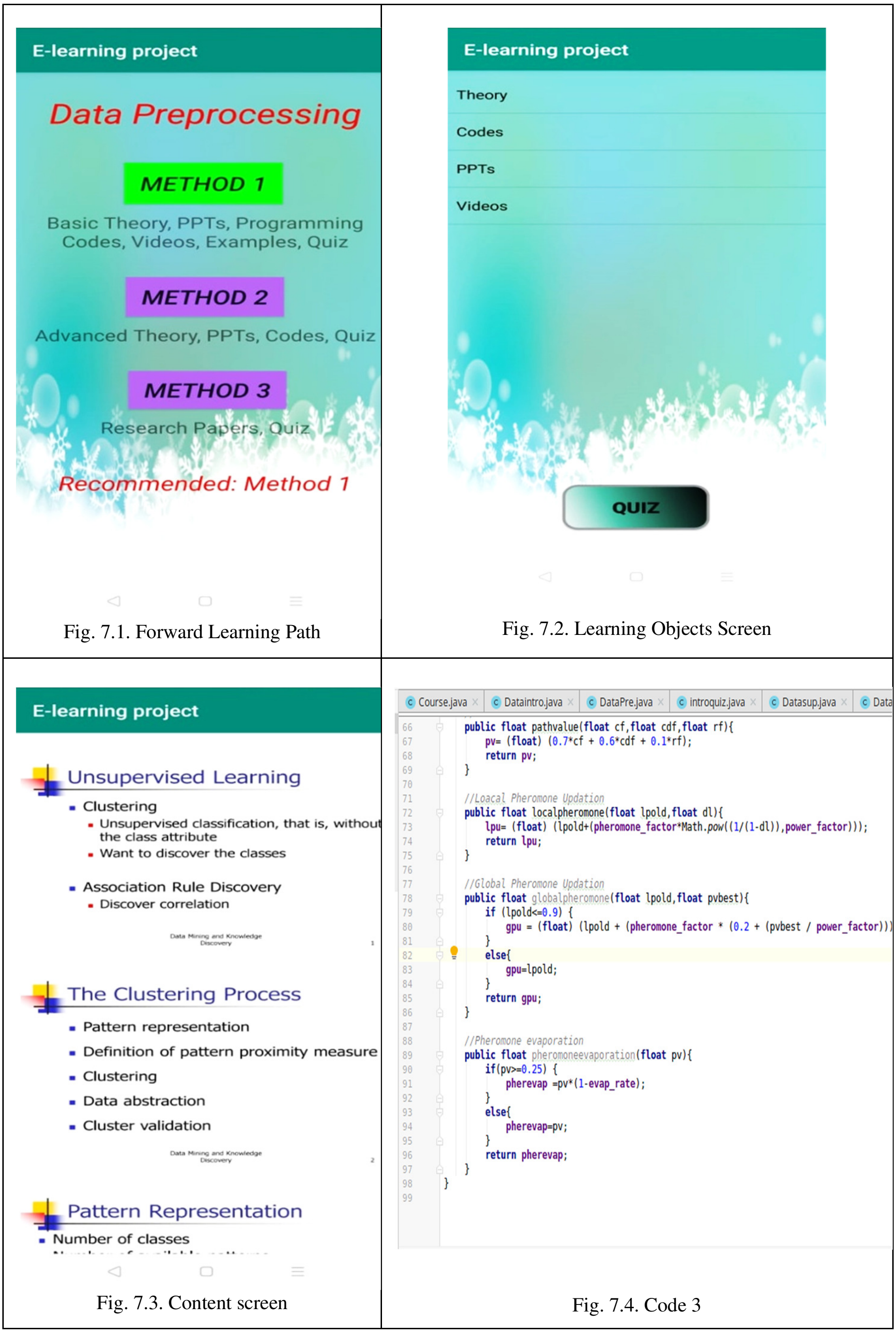

Fig. 7.1. Forward Learning Path

Fig. 7.2. Learning Objects Screen

Fig. 7.3. Content screen

Fig. 7.4. Code 3

Fig. 7. Snapshots of implementation of Module 2: ACO subsystem.

6.3. *Observation*

Experiment 1

This experiment was done to observe the changes in the forward learning path based on the change in its dynamic learning ability after every level.

Case 1: Suppose a student has initial learning ability, $y_0 = 0.3,$ and it improves consistently by 20% after each level. Then, the path generated by the ACO subsystem is shown as:

(1, P1) -> (2, P4) -> (3, P7) -> (4, P11)

Since the y_0 is low, P4 is recommended at level 2 by ACO subsystem as the Difficulty Level (DL) in going from P1 at level 1 to P4 at level 2 is 0.2 only. Later, ACO selects P6, which is the most contributing perspective of level 2 to increase the depth of knowledge of the user. After level 2, the dynamic learning ability increases to 0.36 but is still low, so ACO recommends P7 of level 3 to the user having DL of 0.2, increasing the dynamic learning ability to 0.432. Finally, P11 is recommended by ACO at level 4. due to increased dynamic learning ability after level 3.

Case 2: Pattern similar to Case 1 is shown in the forwarding learning path in case of students showing boosted improvement.

Case 3: Suppose a student has initial learning ability, $y_0 = 0.5$. Based on high initial learning ability, the path generated by the ACO subsystem is shown as:

(1, P3) -> (2, P6) -> (3, P8) -> (4, P10)

Since the user has high y_0, so P3 is recommended by the ACO Subsystem at level1, which is the most contributing perspective. But due to the difficulty associated with the perspective, the dynamic learning ability of users decreases to 0.4, which is still quite high. Therefore, P6 having DL = 0.5 is recommended to the user. The dynamic learning ability of the user further decreases to 0.35. Now, P5 is recommended at level3, which is a bit easier perspective. Finally, P10, which is the most natural perspective, is recommended by the ACO subsystem at level4, resulting in an increase in dynamic learning ability to 0.45.

Experiment 2

Perspectives having high Recommendation Factor (RF)

It has been observed that the perspectives having a high value of RF are always retained in the most optimal forward learning path.

Boost in Path Value (PV)

An increase in path value in all three cases was found while using recommendations from similar peers as this system maintains a balance between dynamic learning ability, recommendation factor, coverage, and depth contrary to the generation of a path without recommendations.

Figure 8 shows the comparison of Total coverage Factor (TCF) and Cumulative Depth Factor (CDF) and Path Value (PV) in Case 1, Case 2, and Case 3 for both of the experiments, i.e., without recommendation and with a recommendation. TCF and CDF don't show any kind of pattern of improvement in all three cases while PV increased rapidly with recommendations.

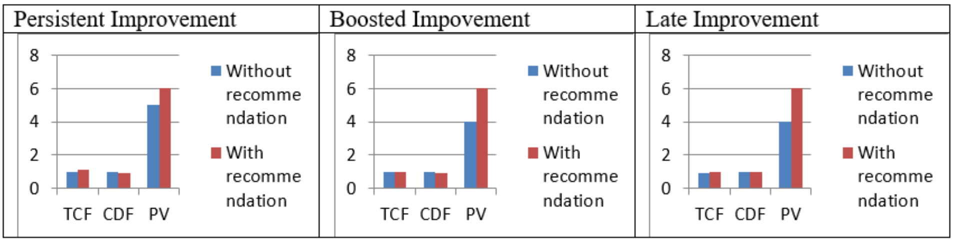

Fig. 8. Comparisons of TCF, CDF, and PV in Case 1, Case 2, and Case 3.

Table 8 shows the experimental part in comparison to other approaches. ACO has been compared with if-then fuzzy rules and JFuzzy logic (the de-facto standard for research and industry applications). The comparison parameters are learning ability, total coverage factor, cumulative depth factor (CDF), and path value (PV). The learning ability, TCF, and PV in the case of ACO are better as compared with fuzzy-logic approaches.

Table 8: Comparison of ACO with fuzzy-logic based approaches.

Methodologies used	Learning ability (γ)	Total Coverage Factor (TCF)	Cumulative Depth Factor (CDF)	Path Value (PV)
ACO	0.713	1.211	0.973	5.794
If-Then fuzzy rules	0.657	1.135	1.021	5.238
JFuzzyLogic (library Java)	0.681	1.082	1.103	4.991

7. Conclusions and Future Work

A system has been proposed, which provides a personalized and adaptive e-learning environment[21] based on Ant Colony Optimization using recommendations from similar peers to generate the most optimal forward learning path. This is a unique approach as it takes care of the dynamically changing learning ability of the learner in recommending the forward learning path. It also uses the learning patterns of past users to provide recommendations to the new user, thereby improving their e-learning experience. These recommendations are extracted from peers having similar Learning Aim and Path Value. It has been found that this system gives priority to the perspective of having the highest recommendation. Thus, this system tries to provide a better e-learning experience to users based on their learning capabilities and preferences.

It is possible to recommend Learning Objects based on the learning style of the user by taking the Felder and Silverman test at the beginning of the course. This will help students to learn as per their learning preferences, thus improving their e-learning environment. Also, the Feasibility of App in both directions, i.e., forward and backward needs, be ensured. The training of data needs to be done on a broader domain having all the varieties of users, including students – Undergraduate and Postgraduate, teachers, and researchers so that the best forward path is recommended no matter what kind of learner is using the App.

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