An automatic adaptive grouping of learners in an e-learning environment based on fuzzy grafting and snap-drift clustering

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Abstract: Adaptive learning systems provide e-learning-based educational services tailored to the needs, preferences and capabilities of learners. The quality of services provided by these systems largely depends on their ability to acquire proper description of learners regarding their personality, behaviour and learning style and to categorise these learners accurately into homogeneous and heterogeneous groups. The ability of an adaptive system to provide a suitable course through suitable presentation is influenced by the accuracy of mentioned grouping process. This paper presents a novel adaptive learning system possessing an automatic and intelligent learner grouping capability. The grouping approach used in this system consists of four stages, identifying the group structures, classifying the learners into the identified groups, detecting the expiration of groups and modifying the groups of learners. This clustering concept is developed by modified fuzzy snap-drift method, and the process of assigning suitable content to identified groups is implemented by a decision tree. The proposed system is implemented on an e-learning course to evaluate its effect on the learning quality. The evaluation of 'academic satisfaction' and 'progress' criteria shows that the proposed system has been able to make significant improvements in e-learning environment.

Keywords: adaptive grouping; adaptive learning system; e-learning; fuzzy grafting clustering; learning style; neural network; snap-drift; technology enhanced learning.

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1 Introduction and theoretical framework

The development of information technology and its diverse capabilities has led to advent and spread of a new form of learning process called *e-learning*. With dramatically improved access to information and application of computing technology to education, e-learning is now expected to adapt the process of learning to its clients (Akbulut and Cardak 2012; Essalmi et al., 2010; O'Donnell et al., 2015).

The process provided by an adaptive learning system to accommodate learning to each learner consists of two phases:

1 identification of specific needs of each learner

2 selection and provision of courses and curriculums based on the identified needs (Botsios, Georgiou and Safouris, 2008; O'Donnell et al., 2015).

But difficulties in precise recognition of each learner's specific educational needs, certain limitations on accommodation of diverse educational content to those needs and lack of access to technologies required to support one-to-one education complicates the provision of a learner-centred learning process, hence customised learning acts as the best alternative to provide the most suitable service for learners with similar needs and requirements (Jin et al., 2006; Bachari, Abelwahed and Adnani, 2011). The aim of this study is thus to develop a new adaptive system with intelligent grouping capabilities enabling it to automatically adapt the educational content to the specifications of learners with similar needs and learning processes.

The rest of this paper is organised as follows: Section 2 describes the concept of adaptive learning and its methods and reviews current adaptive e-learning systems; Section 3 introduces the proposed adaptive learning system and its intelligent grouping method; Section 4 describes and evaluates the process of implementing the proposed system on an e-learning course; and the final section presents the results and conclusion.

2 Adaptive learning system

Adaptive learning refers to the process of accommodating the educational course and curriculum of an e-learning environment to the needs, preferences and capabilities of learners (Akbulut and Cardak, 2012; O'Donnell et al., 2015; Dominic, Xavier and

Francis, 2015; Bachari, Abelwahed and Adnani, 2011). This adaptation can be realised in three forms: adaptive presentation of educational content, adaptive sequencing of its components and adaptive tools of navigation (Papanikolaou et al., 2003; Dominic, Xavier and Francis, 2015).

a **Adaptive content presentation:** In this approach, educational contents will be presented according to learners' characteristics. The aim of this process is to adapt the educational content (in terms of type of medium) to preferences, needs and capabilities of learners and subsequently increase the speed and quality of learning. The Arthur (Gilbert and Han, 2002) and the CS 383 (Carver Jr, Howard and Lane, 1999; Sonwalkar, 2015) are the major adaptive systems of this type.

b **Adaptive content sequencing:** In this approach, the order and sequence by which different sections of educational content will be presented will be tailored to learners' characteristics. Here, the terms order and sequence do not refer to rational sequence (as its presence is a basic prerequisite to learning)but to the order of different content components that have no prerequisite relationships with each other and whose sequence of presentation has significant effect on learning. The ACE (Specht and Oppermann, 1998) and the INSPIRE (Papanikolaou et al., 2003; Dominic, Xavier and Francis, 2015; Chen, Chiu and Huang, 2015) systems are the most important adaptive systems of this kind.

c **Adaptive navigation tools:** The purpose of this form of adaptation is to provide proper orientation for the users of an e-learning environment enabling them to access system resources based on their habits, needs and requirements. This form of adaptation can be achieved by adjusting the visible links that determine the orientation of learning. The AES-CS (Triantafillou, Pomportsis and Demetriadis, 2003) system provides this form of adaptation.

The subject of customised learning and adaptation of educational content in its various forms was first introduced in 1990, but it has undergone significant improvement in recent decade. Next, we review some of the works carried out on this topic.

The 'learn fit' system adapts the educational content to learners. In this system, the Myers-Brigs learning style model is used to describe the learner, who is modelled by a non-automatic procedure implemented through questionnaire. This system uses a Bayesian network to classify learners in different categories and adapt the content and curriculum to their specifications (Bachari, Abelwahed and Adnani, 2011).

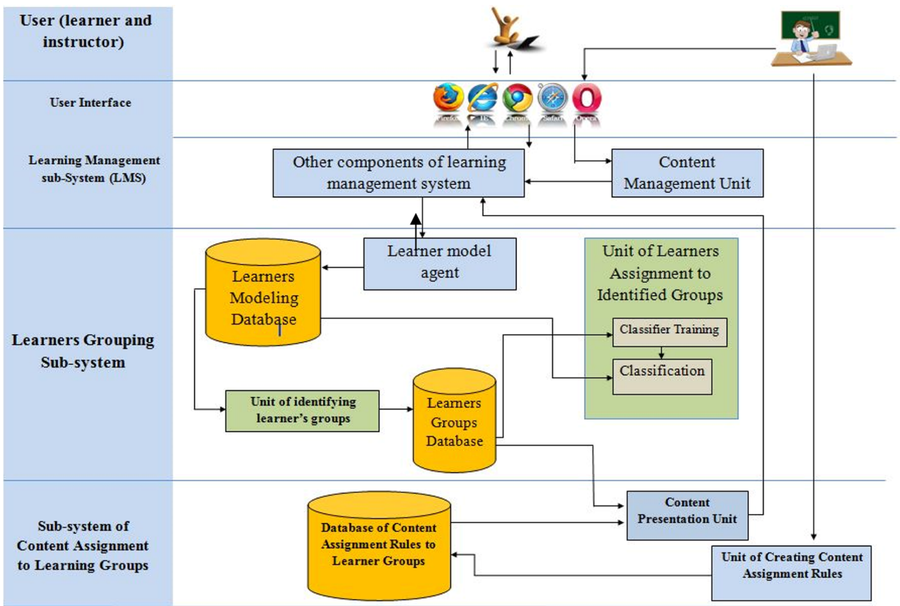
The 'i-learn' system is another form of intelligent e-learning systems that facilitates the task of adapting the content and curriculum to the learners. In this system, the VARK learning style is used to model the learner, and the rule-based classification method is used to categorise the learners and adjust the content (Peter, Bacon and Dastbaz, 2010). In the adaptive system proposed by Minto, learners are modelled by characterisation models (such as Catele-16-PF) and are then classified through K-means clustering (Minetou and SYC, 2005). The adaptive system of Zheng uses a new matrix-based clustering method to classify learners. He believes that the proposed method overcomes the most important shortcoming of K-means, i.e., the indetermination of optimum number of clusters. This study also uses the Catele-16-PF method to model the learners (Zhang et al., 2007). In the system proposed by Yang et al. learners are modelled by character models and a self-organising neural network is used to classify the learners based on their preferences and capabilities (Zakrzewska, 2009).

A researcher who seeks to develop a learner classification method always strive for the best possible combination of speed and accuracy. Many researchers have combined the conventional clustering methods such as K-means and fuzzy C-means with optimisation methods to achieve better accuracy, but this approach leads to sharply increased time complexity, which can have major negative impacts on the quality of the resulting e-learning system. On the other hand, previous researches have neglected to evaluate their clustering results by the criteria that depend on learning styles and models, and this issue obstructs any detailed assessment on the accuracy of these learner classification methods.

3 The proposed learning adaptive system

The proposed adaptive system consists of three subsystems: 'learning management', 'learner grouping' and 'content assignment'. The architecture of this system is shown in Figure 1.

Figure 1 Adaptive e-learning system architecture (see online version for colours)



The 'learning management' subsystem is tasked with the management of educational content and adjustment of their sequence. The 'learner grouping' subsystem is responsible for automatic clustering of learners into homogeneous groups and facilitating the provision of group-tailored educational content. The 'content assignment' subsystem is tasked with establishing the rules of content adaptation for each group and customising the learning process based on these rules. The detailed descriptions of all abovementioned subsystems are presented in the following.

3.1 Learning management subsystem

This subsystem is tasked with maintaining educational content and presenting them to learners. Other tasks of this subsystem include managing user access, logging user activity, monitoring and managing registration, managing finances, setting up courses, deriving lessons from educational content and aggregating these lessons into courses. The learning management subsystem designed in this paper is based on the Persian version of Moodle learning management system (v. 2.5).

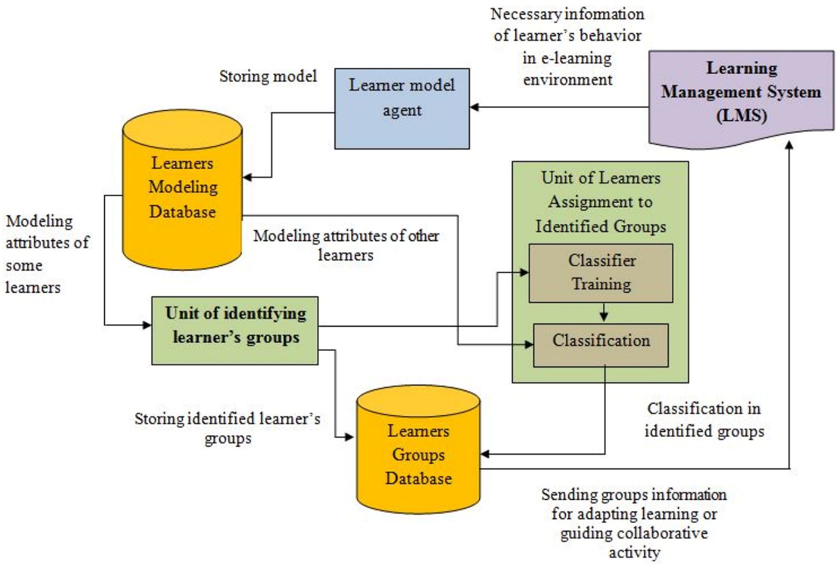
3.2 Learner grouping subsystem

This subsystem is tasked with automatic modelling of learners based on the Felder-Silverman learning style and classifying them into homogeneous groups to initiate the adaptive learning process. The learner grouping process of this subsystem includes four major steps:

- **Initial identification of group structures:** In this step, subsystem identifies the groups of participating e-learners based on a set of clustering criteria. When learner population is large, subsystem can use random sampling to select the learners to be used for cluster identification.
- **Assigning learners to identified groups:** The main objective of this step is to assign other learners to the classes identified in the previous step to generalise the grouping structure to the entire population. Other objectives of this step include assigning those learners who enter the system after structure identification and correcting the class of those learners whose model characteristics have changed or expired. The classifier used in this step first undergoes an automatic training phase, which enables it to classify other learners into identified classes.
- **Detecting changes in group structure:** When characteristics of a classified learner get sufficiently divergent from those of other learners (in the same class), subsystem detects and announces an expired class structure and triggers the reidentification procedure. In this study, subsystem uses Davies-Bouldin index to detect class expiration. Here, the greatest value of Davies-Bouldin index at the grouping made by basic grafting clustering methods is considered as the threshold of expiration.
- **Reidentification of changed group structures:** When an expiration event is announced, subsystem uses a clustering method to identify the new structure of groups.

The proposed grouping subsystem is composed of two processes, 'group identification' and 'learner-class allocation'; one agent, 'learner model' and two databases, 'learner model' and 'learner group'. Figure 2 shows the architecture of this grouping subsystem.

Figure 2 Learners grouping sub-system architecture (see online version for colours)



Modules of this subsystem are as follows:

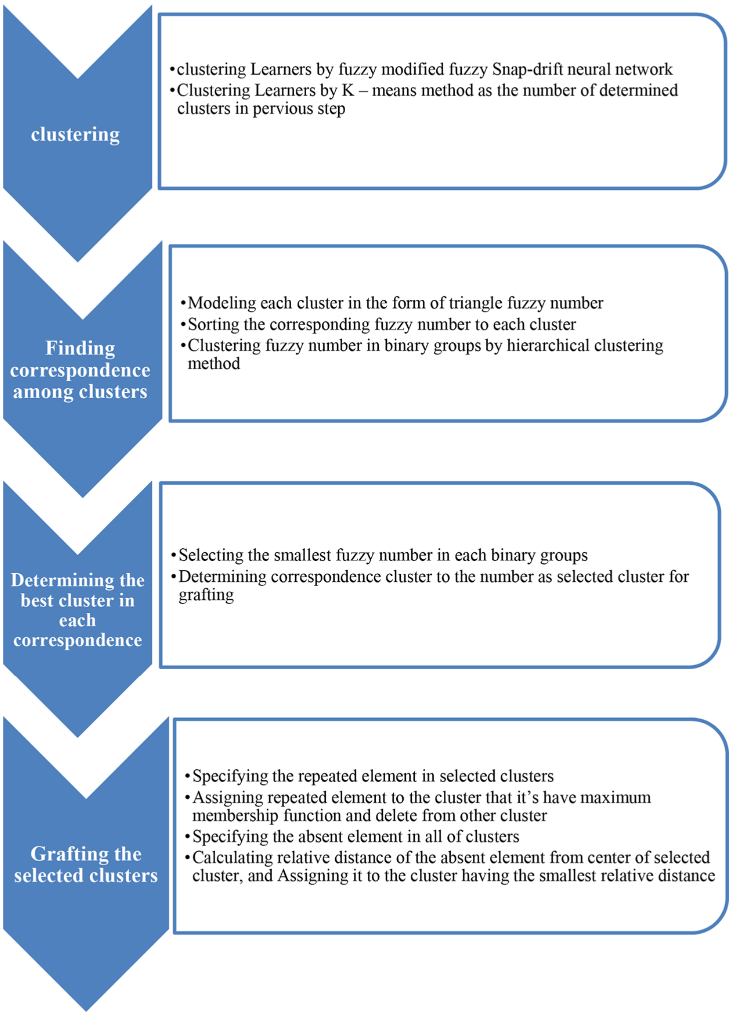
– ***Learner model database:*** All Information regarding characteristics describing every learner are stored in this database, so that it can be used when needed to identify group structures or classify learners into identified classes.

– ***Learner class database:*** The classes identified by group structure identification process and learners in each group are stored in this database. Contents of this database are used when needed to train the classifiers for classification new learners.

– ***Learner model agent:*** The task of this agent is to model each learner based on his/her behaviour in the network. The learner model signifies the characteristics affecting the determination of similarities between learning procedures of different learners. The presented system uses Felder-Silverman learning style to describe the learner model. This learner model agent is a collaboration agent tasked with interacting with learning management system and monitoring learners' behaviour in the network.

– ***Group structure identification subsystem:*** The task of this subsystem is to identify the e-learners' group structures based on the learning style characteristics. This subsystem has a continuous function carried out dynamically throughout the learning process; therefore, another task of this subsystem is to reidentify the classes after a change in structure. Initially, this subsystem does not have access to any data about group structures, so it uses a clustering approach to initiate the process. This paper uses a novel clustering method called modified fuzzy grafting clustering to detect different group structures. While being comprehensive, this method provides memory and time complexities as low as basic clustering techniques. Figure 3 shows the algorithm of this clustering method.

Figure 3 Fuzzy grafting clustering algorithm (see online version for colours)



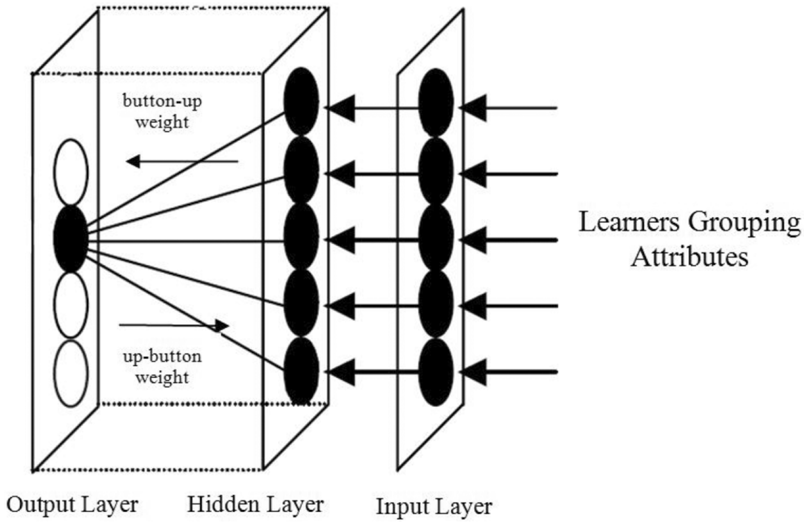
This method first cluster the dataset by a number of simple clustering methods, each capable of identifying different types of data. These methods are called basic grafting methods and should be able to determine the clusters' centres. To achieve an appropriate link between clusters, structure of each cluster should be assessed in conjunction with that of other clusters. Therefore, once clusters of each basic grafting clustering method are obtained, they undergo a fuzzy modelling process, which yields a series of clusters corresponding to the results of basic clustering methods. Then a fuzzy comparison operator determines the optimal clusters in each correspondence.

After selecting the optimal clusters, duplicate and missing elements are allocated to their appropriate clusters, so ultimately a fuzzy combination of several clustering methods detects the group structures with greater precision. The greater diversity of basic grafting clustering methods, i.e., their ability to detect different types of structures, will enhance the accuracy of final clustering; therefore, this study uses K-means technique and modified fuzzy snap-drift neural network as basic grafting methods. The modified fuzzy snap-drift neural network is itself a combination of other clustering method, which are described below.

3.2.1 Modified fuzzy snap-drift neural network

The proposed neural network is a combination of fuzzy ART network architecture and snap-drift learning process. The proposed network consists of three layers; the number of neurons in first and second layers equals the number of inputs (the number of attributes of input pattern) and the number of neurons in third layer is initially 1 but eventually increases to the number of identified clusters. Neurons of first and second layers are linked one-to-one, but the links between neurons of third and second layers are bilateral. We use a sigmoid threshold function for neurons of second and third layers and a linear one for neurons of the first layer (Figure 4).

Figure 4 Modified fuzzy snap-drift neural network architecture



The top-down weights are initialised with half of the range of learners' attributes and the bottom-up weights are determined using Eq. (1) based on the corresponding top-down weights (Brown, Draganova and Lee, 2009).

$$w_{Ij}(0) = \frac{w_{Ji}(0)}{1+N} \tag{1}$$

where $w_{ji}^{(\text{old})}$ is initial value of top-down weights and $N$is the number of input layers. The input vector I enters to the network and the output is calculated in the second layer using Eq.(2) (Brown, Draganova and Lee, 2009):

$$\mu_j = \sum_i w_{iJ}(t)\, i_i \tag{2}$$

The neuron that has max value of μ is selected as winner cluster. The output of the winner neuron is initialised with 1 and the other neuron of F_2 layer is initialised with 0 temporarily. To approve assignment of pattern to the cluster corresponding to winner neuron, in the next step, relative similarity input pattern with selective cluster is calculated using Eq. (3):

$$\text{similarity} = \frac{\left\| I - W_{Ij} \right\|}{\left\| I \right\|} \tag{3}$$

$\left\| I - W_{Ij} \right\|$ is the Euclidean norm of distance between input pattern with centre of winner cluster (up-down weights) and $\left\| I \right\|$ is the Euclidean norm of input pattern. The equation measures relative similarity of input pattern and corresponding pattern of winner neuron. If the measured value is less than that of accept threshold, the pattern is assigned to the cluster. After assigning the input to the cluster, the top-down weights of corresponding neuron should be updated. It is shown in Eq. (4) (Brown, Draganova and Lee, 2009; Lee, Palmer-Brown and Roadknight, 2004).

$$w_{Ji}^{(\text{new})} = (1-p)\left(I \cap w_{Ji}^{(\text{old})}\right) + p\left(w_{Ji}^{(\text{old})} + \beta\left(I - w_{Ji}^{(\text{old})}\right)\right) \tag{4}$$

where $w_{Ji}^{(\text{old})}$ is the current up-down weight between *i*th and *j*th neurons, *p* is the network performance feedback index, *I* is the fuzzy input vector and β is the learning rate constant. So $\cap$ operator is fuzzy intersection which is considered as product operator here. In low performance, the *p* variable is assigned from value 0 and the learning function turns to Eq.(5). The performance evaluation criterion is Davies-Bouldin index. This index is calculated for each epoch. Therefore, if it is greater than 2.5, then the performance is considered bad; otherwise, the performance is considered good,

$$w_{Ji}^{(\text{new})} = \left(I \cap w_{Ji}^{(\text{old})}\right) \tag{5}$$

In high performance, by setting $p = 1$ in Eq. (4), Eq. (6) will be included (Brown, Draganova and Lee, 2009)

$$w_{Ji}^{(\text{new})} = \left(w_{Ji}^{(\text{old})} + \beta\left(I - w_{Ji}^{(\text{old})}\right)\right) \tag{6}$$

After updating up-down weights, the bottom-up weights of network are updated by Eq. (7):

$$w_{Ij}^{(\text{new})} = \frac{w_{Ji}^{\text{new}}}{0/5 + \left\| w_{Ji}^{(\text{new})} \right\|} \tag{7}$$

where $\left| w_{Ji}^{(\text{new})} \right|$ is the Euclidean norm of up-down weight of *i*th neuron (Lee, Palmer-Brown and Roadknight, 2004).

3.3 Subsystem of learners' assignment to identified groups

This subsystem is responsible for assigning learners to the identified groups in which a process is considered in order to automatically detect changes in group structure. This process, based on the expansion of non-convergence in categorising learners, determines the need to reidentify group structures. In this subsystem, quantum neural network (QNN) is used for categorisation; since these types of networks are able to categorise learners with the lowest computational complexity and most accuracy. The high accuracy of these networks in pattern detection is caused by the expansion of parallel power of processing in the networks (Purushothaman and Karayiannis, 1997). The utilised quantum neural network is a three-layer network. This network includes the input n_i, a hidden layer involving n_h multilevel neurons and n_o output neurons. The weight connecting of the ith output neuron to the jth hidden layer neuron with w_{ij} and connecting weight of the jth hidden layer neuron from the kth feature vector is defined in the equations below:

$$\bar{h}_{j,k} = \sum_{l=0}^{n_i} v_{jl} x_{l,k} \tag{9}$$

$$\tilde{h}_{j,k} = \frac{1}{n_s} \sum_{r=1}^{n_s} h_{j,k}^r = \frac{1}{n_s} \sum_{r=1}^{n_s} sgm(\beta_h (\bar{h}_{j,k} - \theta_j^r)) \tag{10}$$

For every k, $x_{0,k} = 1$ and β_h are the slope factors. n_s is the number of energy levels and θ_j^r indicates the jump positions in transfer function. The input of the ith output neuron from the kth input vector is described in the equations below:

$$\bar{y}_{i,k} = \sum_{j=0}^{n_h} w_{ij} \tilde{h}_{j,k} \tag{11}$$

$$\hat{y}_{i,k} = \text{sgm}(\beta_o (\bar{y}_{i,k}) \tag{12}$$

For every k, $\tilde{h}_{0,k} = 1$ and β_o are the sloping factors of output transfer function. The output of each neuron is expressed by the following equation:

$$y = \frac{1}{n_s} \sum_{r=1}^{n_s} \text{sgm}(v^T x - \theta^r) \tag{13}$$

In which, v is the network weight connecting vector, x is the input vector and sgm represents the sigmoid function applied on them. Quantum intervals, which refer to the weight level of the multilevel transfer functions, are determined with the parameter of θ^r jump positions. They are representation of discrete localised cells in feature space, which involve feature vectors whose ambiguity level's approximate number are intended as their membership degree in data set classes (Purushothaman and Karayiannis, 1997).

In order to learn the network, first, the weight connecting should be adjusted by the standard backpropagation algorithm and quantum intervals of hidden layer neurons. The output changes of the pth hidden layer neuron for the mth category of C_m is as follows:

$$\sigma_{p,m}^2 = \sum_{x_k : x_k \in C_m} \left(\left\langle \tilde{h}_{p,C_m} \right\rangle - \tilde{h}_{p,k} \right)^2 \tag{14}$$

$$\left\langle \tilde{h}_{p,C_m} \right\rangle = \frac{1}{|C_m|} \sum_{x_k : x_k \in C_m} \tilde{h}_{p,k} \tag{15}$$

where $|C_m|$ is the Euclidean measure of C_m. The adjustment of θ_q^s parameters is performed according to minimisation of the objective function defined by the $\sigma_{p,m}^2$ set on all categories and all hidden layer neurons in the following form:

$$G = \frac{1}{2}\sum_{p=1}^{n_h}\sum_{m=1}^{n_o}\sigma_{p,m}^2 = \frac{1}{2}\sum_{p=1}^{n_h}\sum_{m=1}^{n_o}\sum_{x_k : x_k \in C_m}\left(\left\langle \tilde{h}_{p,C_m}\right\rangle - \tilde{h}_{p,k}\right)^2 \tag{16}$$

Consequently, the updated θ_q^s equation will become:

$$\Delta\theta_q^s = \alpha_\theta \frac{\beta_h}{n_s}\sum_{m=1}^{n_o}\sum_{x_k : x_k \in C_m}\left(\left\langle \tilde{h}_{q,C_m}\right\rangle - \tilde{h}_{q,k}\right)^2 \times \left(\left\langle v_{q,C_m}^s\right\rangle - v_{q,k}^s\right) \tag{17}$$

such that:

$$\left\langle v_{q,C_m}^s\right\rangle = \frac{1}{|C_m|}\sum_{x_k : x_k \in C_m} v_{q,k}^s \tag{18}$$

$$v_{q,k}^s = h_{q,k}^s(1 - h_{q,k}^s) \tag{19}$$

α_θ refers to the learning tone. Therefore, this network can be regarded as, i.e., first-layer neuron and first- and second-layer weights are classic and only the second-layer neuron follows the quantum computations.

3.4 Subsystem of content assignment to learning groups

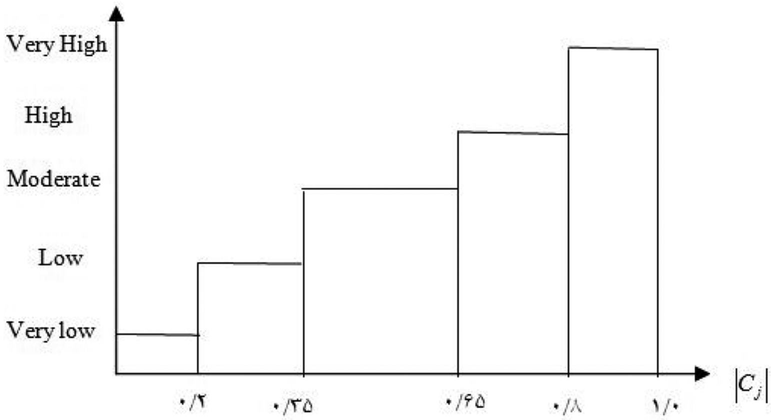
This subsystem is responsible for assigning learning content according to rules extracted from expert and instructor opinion. Such subsystem consists of two units of 'creating content assignment rules' and 'content presentation' and database of 'rules of content assignment to learning groups'.

A - Unit of Creating Content Assignment Rules: This unit is responsible for creating rules of content assignment based on the information entered by the instructor. These rules express the appropriateness of each learning object with the learning style of learning groups with qualitative terms (very low, low, medium, high and very high). For example, if the learning object LO_1 is suitable from expert perspective for learners with learning style of very high intuitive in the perception dimension and high visual in the input dimension, this unit states the rule associated with it as follows:

"If the learner's learning style is very high intuitive in the perception dimension and high visual in the input dimension, then the learning object LO_1 is suitable to present to this learner".

B - Content Presentation Unit: This unit is responsible for determining appropriate content stored in content management unit for each of the learner groups. In this article, decision tree method is used to assign learning content for each group of learners. Each group, at any level of decision tree, evaluates the condition related to one of Felder-Silverman learning style dimensions to reach as suitable content for each group of learners. In Figure 5, the term linguistic variable of the learning style is demonstrated in the learner grouping results as numerical intervals.

Figure 5 Learners group's value in linguistic variable of learning style



According to Figure 5, the normalised amount of the cluster centre Euclidean measure for each group of learners determines the counterpart of that group with each of the amounts of learning style linguistic variables. Based on these counterparts, suitable learning objects are selected to present to each group of learners in accordance with rules defined by experts.

C - Database of Content Assignment Rules to Learner Groups: The content assignment rules to learner groups are stored in this database so as to be used during decision-making to choose suitable content for learner groups.

4 Evaluation of proposed adaptive e-learning system

The efficiency of the proposed adaptive e-learning system, with the smart capacity for grouping learners, was evaluated in order to assess its effectiveness in the improvement of learning environment. For this, a web-based IT enterprise architecture course was held in the form of the proposed learning adaptation system. The characteristics of the learners and the course are presented in Table 1.

Table 1 Specifications of learners and learning course

	Characteristic	*Value*
Learners	Number	40 learners
	Average age	23.2 years
	Standard deviation of age	1.5 years
	Gender	Male and female
Learning course	Number of learning session	12
	Number of learning concept	12
	Number of learning object	56
	Duration of course	6 weeks

In order to evaluate the effect of learner grouping and the proposed method in the improvement of education process, the participants in this course were randomly divided into four groups:

- The first group (G_w) comprised 10 learners who passed the course without the presentation of learning adaptive services. In this group, the learning objects were offered to learners merely by the pre-knowledge order and randomly. In fact, education was not customised for them.
- The second group ($G_{K\text{-means}}$) comprised 10 learners who passed the course as customised and in the form of learning adaptation groups. The learners in this group were categorised using the common K-means method and, subsequently, were presented with suitable learning content based on their group.
- The third group (G_{FGCM_w}) comprised 10 learners who passed the course as customised and in the form of learning adaptation groups. In the course presented to this group, the learners were categorised using the proposed method but without activating the possibility of group modification (reidentification of group structures) and, afterwards, were presented with suitable learning content based on their group.
- The fourth group (G_{FGCM}) comprised 10 learners who passed the course as customised and in the form of learning adaptation groups. In the course presented to this group, the learners were categorised using grouping method and with the possibility of group modification and, then, were presented with suitable learning content based on their group.

To evaluate the impact of using the proposed system in the conducted course, the following criteria are used: 'academic success', 'academic satisfaction' and 'time of presence in the system' (which is complementary of academic satisfaction in system assessment and learners' satisfaction of it). Academic success observes the learning rate of the learner from the presented concepts during the course and academic satisfaction observes the satisfaction rate of the learner from being present in the e-learning environment and the ease in learning concepts of the course.

4.1 Academic success

In Table 2, the mean and standard deviation score of various groups are depicted in a test involving seven theoretical essay questions, three theoretical multiple choice questions and four qualification essay questions.

Table 2 Average and deviation of different groups

	G_w	$G_{K\text{-means}}$	G_{FGCM_w}	G_{FGCM}
Number of learners	10	10	10	10
Mean scores	8.90	13.22	15.63	16.25
Standard deviation of scores	3.26	1.32	1.02	0.98

In order to accurately compare groups with each other, unilateral analysis of variance (St and Wold, 1989) is used and the differences between the results concerning academic success criteria of the learners present in the groups are evaluated.

Table 3 demonstrates the results of final test analysis of variance. According to these results, it is observed that the score of group G_w learners (who are denied customisation) is significantly different from the other groups. Furthermore, the score of group $G_{K\text{-means}}$ learners indicates a significant difference from the third and fourth groups. The difference between learning customisation for $G_{K\text{-means}}$ group and learning customisation for G_{FGCM_w} and G_{FGCM} groups is merely limited to the grouping method used to determine the comparative group of learners; consequently, it can be assumed that using the proposed grouping method in adaptive learning leads to the improvement of learners' academic success. In addition, it is viewed that there is not a significant difference between the learners' scores in G_{FGCM_w} group and G_{FGCM} group. As a result, although the learning style of some learners changes during learning in G_{FGCM} group, this feature does not lead to improving academic development of learners.

Table 3 Final test analysis of variance result

	F statistic	*p-Values (p < 0.05)*	*Significant difference*
Between $G_{K\text{-means}}$ and G_w groups	7.6	3.18	Yes
Between G_{FGCM_w} and G_w groups	8.8	3.18	Yes
Between G_{FGCM} and G_w groups	8.9	3.18	Yes
Between $G_{K\text{-means}}$ and G_{FGCM_w} groups	5.6	3.18	Yes
Between $G_{K\text{-means}}$ and G_{FGCM} groups	4.4	3.18	Yes
Between G_{FGCM} and G_{FGCM_w} groups	3.12	3.18	No

4.2 Academic satisfaction

In order to assess learners' satisfaction from various forms of learning personalisation, at the end of each session, a questionnaire involving four questions were presented to the learners. These questions contain five choices. Its question and objective are shown in Table 4.

Table 4 Academic satisfaction questions

Question number	*Text of question*	*Goal of question*
1	How much did you learn in this session?	Learners grouping, determination of learning style change
2	Was format of lesson's content (voice/video/text) appropriate for you?	Determination group of learners in input dimension, determination of learning style change
3	How much do you satisfy about presented content	Determination group of learners in perception, understand and process dimensions, determination of learning style change
4	Would you like to use the system again?	Overall satisfaction

The mean scores of each learner for each question are provided in Table 5. These amounts for the groups have been evaluated, using one-way variance of analysis statistical method, the results are demonstrated in Table 6. The consequent results indicate that, all in all, grouping of learners and presenting learning content suitable to their adaptive group has effectively enhanced their satisfaction. On the other hand, in an environment where the proposed method is used to group the learners, the learners' satisfaction has had a significant difference compared with the other groups. The effect of detecting change in learning style during learning and regrouping of learners has been positive in the expansion of their academic satisfaction. These results are seen in three out of four questions on academic satisfaction measurement.

Table 5 Result of academic satisfaction questionnaire

Question number	*Index*	G_w	$G_{K\text{-}means}$	G_{FGCM_w}	G_{FGCM}
1	Mean	1.7	3.0	3.8	3.9
	Standard deviation	0.95	0.77	0.77	0.87
2	Mean	2.5	2.9	3.0	3.0
	Standard deviation	1.18	0.70	0.70	0.68
3	Mean	2.5	3.4	4.0	4.0
	Standard deviation	1.65	0.82	0.65	0.68
4	Mean	2.2	3.54	3.7	3.7
	Standard deviation	1.40	0.82	0.88	0.96

Table 6 Analysis of variance result of academic satisfaction

Question number	*Examined goal*	*Compared groups*	*F statistic*	*p-Values ($p < 0.05$)*	*Significant difference*
1	Learners grouping	$G_{\text{K-means}}, G_{\text{w}}$	5.3	3.18	Yes
	Determination group of learners	$G_{\text{K-means}}, G_{\text{FGCM\_w}}$	12.5	3.18	Yes
	Determination of learning style change	$G_{\text{FGCM}}, G_{\text{FGCM\_w}}$	7.2	3.18	Yes
2	Learners grouping	$G_{\text{K-means}}, G_{\text{w}}$	3.9	3.18	Yes
	Determination group of learners	$G_{\text{K-means}}, G_{\text{FGCM\_w}}$	3.2	3.18	No
	Determination of learning style change	$G_{\text{FGCM}}, G_{\text{FGCM\_w}}$	2.6	3.18	No
3	Learners grouping	$G_{\text{K-means}}, G_{\text{w}}$	15.6	3.18	Yes
	Determination group of learners	$G_{\text{K-means}}, G_{\text{FGCM\_w}}$	6.6	3.18	Yes
	Determination of learning style change	$G_{\text{FGCM}}, G_{\text{FGCM\_w}}$	5.6	3.18	Yes
4	Overall satisfaction	$G_{\text{K-means}}, G_{\text{w}}$	9.25	3.18	Yes
	Overall satisfaction	$G_{\text{K-means}}, G_{\text{FGCM\_w}}$	5.6	3.18	Yes
	Overall satisfaction	$G_{\text{FGCM}}, G_{\text{FGCM\_w}}$	4.2	3.18	Yes

4.3 Presence in the system

The time of learners' presence in the system is one of the indicators which can signify its effectiveness in case of learners' satisfaction with an e-learning environment. Consequently, the mean useful time when the learner interacts with the system is calculated and demonstrated in Table 7. As is clear from the results, on average, learners of the groups $G_{\text{K-means}}$, $G_{\text{FGCM\_w}}$ and G_{FGCM} have the most useful time of presence in the system, which, based on the affirmation of learners' academic satisfaction in these systems, indicate that the grouping of learners and the presentation of suitable learning for each group lead to adapting the provided services with the learners' needs and encouraging learners to be present in the system. Among these three groups as well, the participants of groups $G_{\text{FGCM\_w}}$ and G_{FGCM}, for the grouping of which the proposed method has been used, have spent more time than the participants of $G_{\text{K-means}}$ group (for which the grouping method of K-means has been used). This means that the satisfaction level in the learners of these groups is higher than $G_{\text{K-means}}$ group and the proposed method has been able to provide a more absorbing environment for learners.

Table 7 The time of learners' presence in the system

	Total learners		*Learners finishing the course*	
	Number of learners	*Average (hours)*	*Number of learners*	*Average (hours)*
G_{w}	10	6.1	8	9.2
$G_{\text{K-means}}$	10	22.3	10	22.3
$G_{\text{FGCM\_w}}$	10	30.6	10	30.6
G_{FGCM}	10	27.2	10	27.2

5 Conclusion

In this paper, a new adaptive e-learning system is introduced for content adaptation to learners. This system has the capacity to automatically group learners based on their learning style, and a new method is used to enhance the accuracy of grouping learners. The capacities of the proposed adaptive e-learning system include automatic grouping of learners based on the identification of their group structures, and modification of the generated groups through automatic categorisation possibility of new learners and those learners whose traits have altered in the identified groups lead to differentiating this system compared with other learning adaptation systems. The effect of these capacities in improving the e-learning environment is examined by applying the proposed adaptive e-learning system in an e-learning course. The results of the evaluation indicate that this system has a positive effect on improving the learning environment. The proper accuracy and velocity of this system and all of its automation in grouping has made the learning process easy and absorbing; as a result, it has led to academic development and learners' satisfaction.

It seems that focus on the automation of personalisation instruments and the customisation of an e-learning environment, by considering optimal accuracy and velocity, can lead to performance improvement and learner motivation in an e-learning environment. This capacity can improve the main disadvantage of these environments compared with traditional learning environment in the absence of automatic adaptation of the teaching process with the feedbacks from the learner's learning style alterations. Despite the efforts made in this article to apply learners' learning style changes in their grouping modification, the evaluation results do not reveal a significant improvement of the learners' academic satisfaction and development compared with a system without this capacity. This can be caused by factors such as weakness in accurately identifying changes and/or the inadequacy of content diversity for various styles in presenting to them and it is recommended to be investigated in future works.

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