Journal of Engineering and Applied Sciences 13 (2): 321-327, 2018
ISSN: 1816-949X

Fuzzy Case-based Approach for Detection of Learning Styles: A Proposed Model

[1]Nor Rahayu Ngatirin, [1]Zurinahni Zainol and [2]Nur'Aini Abdul Rashid
[1]School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia
[2]College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, 84428 Riyadh, Saudi Arabia

Abstract: A learning style refers to the way an individual learns. The traditional way to identify learning styles is through a questionnaire or survey. Despite being reliable these instruments have several shortcomings that hinder the learning style identification such as students are unmotivated to fill out a questionnaire and reluctant to provide information. Thus, to solve these problems, researchers have proposed several approaches to automatically detect learning styles. The automatic detection of learning styles is proven to be beneficial to students as it can supply them with learning materials according to their individual preferences. In this study we propose a hybrid approach that combines fuzzy logic and case-based reasoning method to classify students according to their learning styles and preferences. In the context of modeling the learning styles, a student model will be constructed based on the information of student's performance during the online course, personality and their gender. Within this study, we intend to outline our proposed model following the felder-silverman model of learning styles and the Big Five model of personality.

Key words: Learning style, personality, fuzzy logic, case-based reasoning, classification, students

INTRODUCTION

In the past decade, there has been an enormous growth in the field of Automatic Detection of Learning Styles (ADLS). This has happened due to the development of adaptive e-Learning and intelligent tutoring. The traditional way to identify learning styles is through a questionnaire or survey that need to be filled out by students. While these instruments present good reliability and validity it has several shortcomings that prevent the learning style identification such as students are unmotivated to fill out a questionnaire (Akbulut and Cardak, 2012; Dung and Florea, 2012), reluctant to provide information (Kosba *et al*., 2005; Joerding, 1999) and questionnaire only measure learning styles to one specific point of time (Graf and Liu, 2008). These are the several reasons why researchers in the field of e-Learning have expanded their interests on ADLS and student modeling in order to provide personalization according to student's learning styles, preferences and skills (Chrysafiadi and Virvou, 2013).

However, this system still has several open issues which led to some criticism. Firstly, since, they are based on different data, it is difficult to compare the performance of the different approaches (Feldman *et al*., 2015). Secondly, various formula has been used by researchers to compute the precision of the automatic detection system (Feldman *et al*., 2015). If researcher A used formula A while researcher B used a different formula for the computation of the precision, thus both studies cannot be compared. Finally, the precision achieved by several approaches still can be increased to 100% of accuracy (Zatarain *et al*., 2010a, b; Crockett *et al*., 2011; Deborah *et al*., 2015).

In the field of ADLS, learning style model is used to group together students according to their style of learning and preferences of how they prefer to receive and process information (Felder and Silverman, 1988). Numerous learning style models which are widespread within researchers are Felder and Silverman Model (Felder and Silverman, 1988), Kolb Model (Kolb, 1984) and Honey and Mumford Model (Honey and Mumford, 1982). The learning style models help to develop learning materials to the students based on their preferences, experience and learning styles.

Individual learners play an important role in traditional education system and technology-enhanced learning system. Learners come with diversity in their individual needs and characteristics such as different learning styles and preferences, personality traits,

Corresponding Author: Nor Rahayu Ngatirin, School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia

cognitive abilities, prior knowledge, motivation, affective features, skills and meta-cognitive features. These individual differences influence the learning process and one of the reason why some learners find it easy to learn in a particular course, whereas others find it difficult in the same one (Jonassen and Grobowski, 1993). Considering learning styles and personality, investigations are motivated by the relationship between both of the individual differences and how to correlate them in automatic method which can be integrated in technology enhanced learning.

Very limited studies have correlated personality and learning styles in automatic method. Abrahamian *et al.* (2004) classified student's personality using the Myers-Briggs Type Indicator (MBTI) and then relates these types of personality to defined learning preferences in user interface environment. MBTI also has been adopted in Fatahi *et al.* (2015) in order to individualize the learning material structure in e-Learning system. Our research attempt to blend Felder Silverman (FS) learning style model and Big Five (McCrae and John, 1992) (BF) personality model with regard to their advantages as they have not been integrated into any studies. Thus, in this research, we will investigate how individual differences such as learning styles, personality traits and gender can be modelled using Fuzzy Logic (FL) and Case-based Reasoning (CBR) methods to be incorporated in technology-enhanced learning system.

The main contribution of this study is two-fold. First, is to propose a learning style detection model with the integration of personality based on BF personality model. Second, the proposed model combines various techniques such as FL, CBR and fuzzy similarity on student modeling and classification. With this combination, a well-represented student model can be built in order to increase the learning styles detection accuracy.

Felder Silverman learning style model: The FS learning style model is based on Jung's theory of psychological types Kolb Model (Kolb, 1984). In Felder's Model in which developed to describe the learning styles in engineering education, learners are classified into four dimensions: processing (active-reflective), perception (sensory-intuitive), input (visual-verbal) and understanding (sequential-global). An instrument named Index of Learning Styles (ILS) was developed by Felder and Silverman (1988) to identify learning style preferences as:

- Active: work well in groups
- Reflective: work better by themselves or with at most one other person
- Intuitive: like facts, data and experimentation
- Sensory: prefer principles and theories
- Visual: pemember best what they see: pictures, diagrams, time lines, films and demonstrations
- Verbal: remember much of what they hear or read
- Sequential: follow linear reasoning processes when solving problems
- Global: make intuitive leaps and may be unable to explain how they came up with solutions

Big Five personality model: The BF model which was conceived by Tupes and Christal is based on a lexical approach. After decades of intensive research, the psychologists are reaching the consensus on using the BF Model with the five dimensions to be the current definitive model of personality (Schmitt *et al*., 2007). The Big Five Inventory (BFI) (John *et al*., 1991) is a self-report inventory for identifying personality based on the BF model as follows:

- Openness to experience: intellectual, imaginative and independent-minded
- Conscientiousness: orderly, responsible and dependable
- Extraversion: talkative, assertive and energetic
- Agreeableness: good-natured, cooperative and trustful
- Neuroticism: moody, tense, neurotic and not confidence

Literature review: There are many approaches of learning style detection in the literature that are incorporated in the technology-enhanced learning system (e.g., adaptive learning and intelligent tutoring). A number of artificial intelligence techniques such as FL, Neural Network (NN), decision tree and bayesian network have been proposed to automatically detect student's learning styles. FL is commonly adopted solely or being hybrid with other techniques in detecting learning styles.

In a recent researcher Deborah *et al.* (2015) proposed the use of FL to handle uncertainty in learning style prediction of e-Learning students on only processing dimension of FS Model. They evaluated the system for 90 learners and obtained a recognition accuracy of 84%. By changing the number of learners to 120, a recognition accuracy of 92% is obtained. By Crockett *et al.* (2013), student's learning styles were identified using fuzzy classification tree by building a fuzzy predictive model using independent variables which are captured through natural language dialogue. Ghorbani and Montazer (2011) adopted Evolutionary Fuzzy Clustering (EFC) with Genetic Algorithm (GA) for the recognition of learning

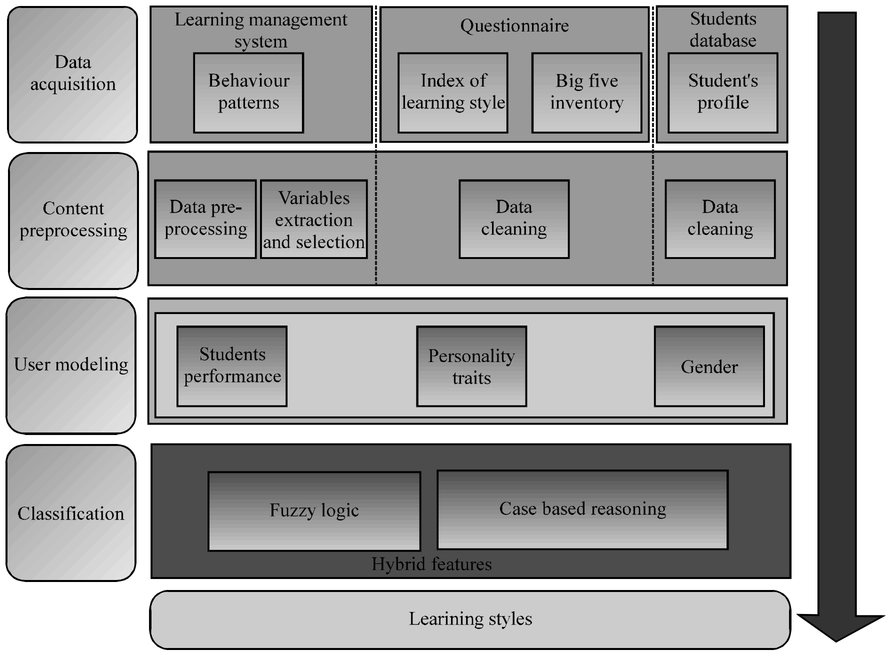

Fig. 1: The proposed model of hybrid learning style detection

styles of e-Learners. The objective of the EFC is to solve both the compactness and separation criteria in clustering problems whereas GA is used to optimize the objective function and to find the center of the clusters. In addition, Abrahamian *et al*. (2004) predicted student's learning styles (sensory intuitive and sequential-global) from behavior cues extracted during conversation obtained through tutorials delivered through Conversational Intelligent Tutoring Systems (CITS) (Fig. 1).

FL was combined with NN by Zatarain *et al.* (2010a, b), where it was trained with different courses under different learning styles and later exported to a mobile device together with an interpreter and the learning objects. Their results only achieved 16% of accuracy to classify all three dimensions (perception, input and understanding) and 66% of accuracy to classify at least two dimensions of FS Model.

CBR on the other hand is not extensively used in ADLS. An accurate classification is needed before a classifier can detect/predict a specific domain problem and an accurate data is crucial in determining an accurate classification. In CBR, the accuracy of the data depends on the case base. It means that all the data entered must be valid and the case base must always be updated (Gonzalez *et al*., 1998). The validation, however is not considered as an independent phase in the CBR cycle but it is designed into the retrieval phase known as a validated retrieval model (Gonzalez *et al*., 1998). Hence, other techniques are needed to do the validation tasks before the cases are stored in the case library, since, it only revised cases using adaptation. A recent researcher by Pandey *et al*. (2014) proposed an adaptive C programming e-Learning system based on different student characteristics combinations to set different levels of errors created and identify remedy to solve the errors and CBR is used for classification of student characteristics and learning performances.

MATERIALS AND METHODS

Proposed model: Based on the previous studies, we propose a model for detecting the learning styles for current and new learners based on hybrid features and technique. The architecture of the proposed model is shown in Fig. 1. Data will be collected from three main sources: ILS and BFI survey forms will be created using the Google forms and will be distributed through the University Info Sharing Facebook Group. These survey forms are expected to collect the subject's (students) answers for the questions regarding their learning styles and personality respectively. Learning management System (LMS) log files. In order to observe pattern of student's traits based on selected variables during online course, the log files will be analyzed. Student's profile Gender parameter along with student's full name and courses enrolled will be extracted from student's database (Fig. 1). The proposed model of hybrid learning style detection.

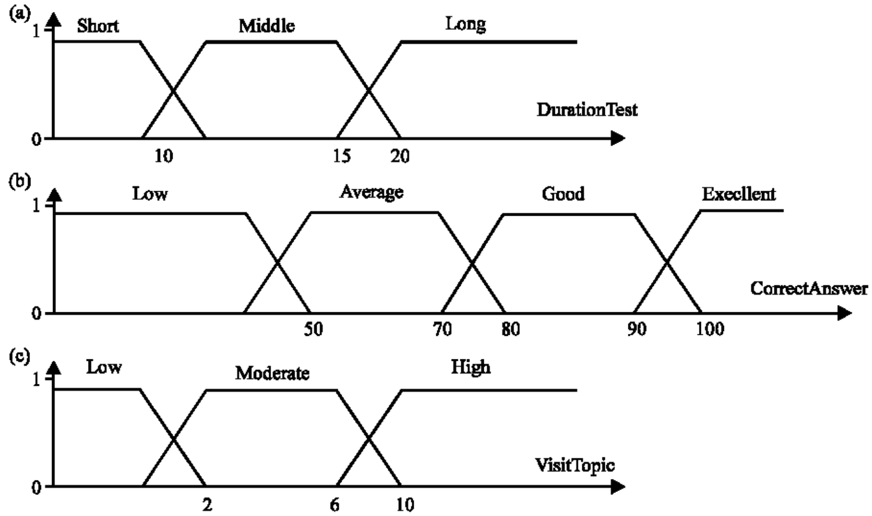

Fig. 2: Fuzzy membership functions for variables: a) DurationTest; b) CorrectAnswer and c) visitTopic

Data from the LMS log files will be observed and pattern of student's traits will be analyzed. The following seven features will be selected and extracted: answer selection order, correct answers, quiz spent time, topic spent time, number of tries until correct answer, number of visits to a question and number of visits to a topic (Zatarain *et al*., 2010a, b). We categorized the seven features as student's performance. Next, another two features, i.e., BF personality traits and gender will be combined with the aforementioned seven features making them as hybrid features. To classify the learning style, a student model will be built based on the hybrid features. In the researcher when students login to the LMS, one version of the learning materials will be given to each of the students according to the initial learning styles from the ILS and they will have to study the provided learning materials for a specific duration (e.g., 30 or 40 min). Next, they will have to answer an assessment (e.g., quiz/test of 30 multiple choice questions) on the studied learning materials. From the results obtained, performance of the students will be calculated. The structure of fuzzy decision-making process of student's learning styles will be built considering two main criteria, linguistic variables and membership functions. Hence, the student model will consist of the aforementioned hybrid features that are stored as linguistic variables, fuzzy sets and fuzzy rules. As an illustration, a FL Model for student classification based on quiz spent time, correct answers, number of visits to a topic, personality and gender is presented here. The steps in applying the FL and CBR Model in this case is:

- Defining input and output values
- Defining fuzzy sets for input values
- Defining fuzzy rules
- Creating and training the fuzzy CBR

Defining input and output values

Input values:

- Duration test [0, ... , 20]
- Correct answer [0, ... , 100]
- Visit topic [0, ... , 10]
- Output values
- Classes of student {Bad 1, Bad 2, Good 1, Good 2, Very good 1, Very good 2, Excellent 1, Excellent 2}

Defining fuzzy sets for input values

Fuzzy sets:

- Duration test: short, middle, long
- Correct answer: low, average, good, excellent
- Visittopic: low, moderate, high

The corresponding membership functions are shown in Fig. 2.

Defining fuzzy rules: The rules and values for student classification are taken from the human teacher. The example of fuzzy rules and linguistic variables used in the reasoning process is as.

Algorithm:

```
IF durationTest is 'long' AND
  CorrectAnswer is 'average' AND
  VisitTopic is 'high' AND
   Personality is 'highExtraversion' AND
   Gender is 'male'
   THEN
 StudentClass is 'good1'
```

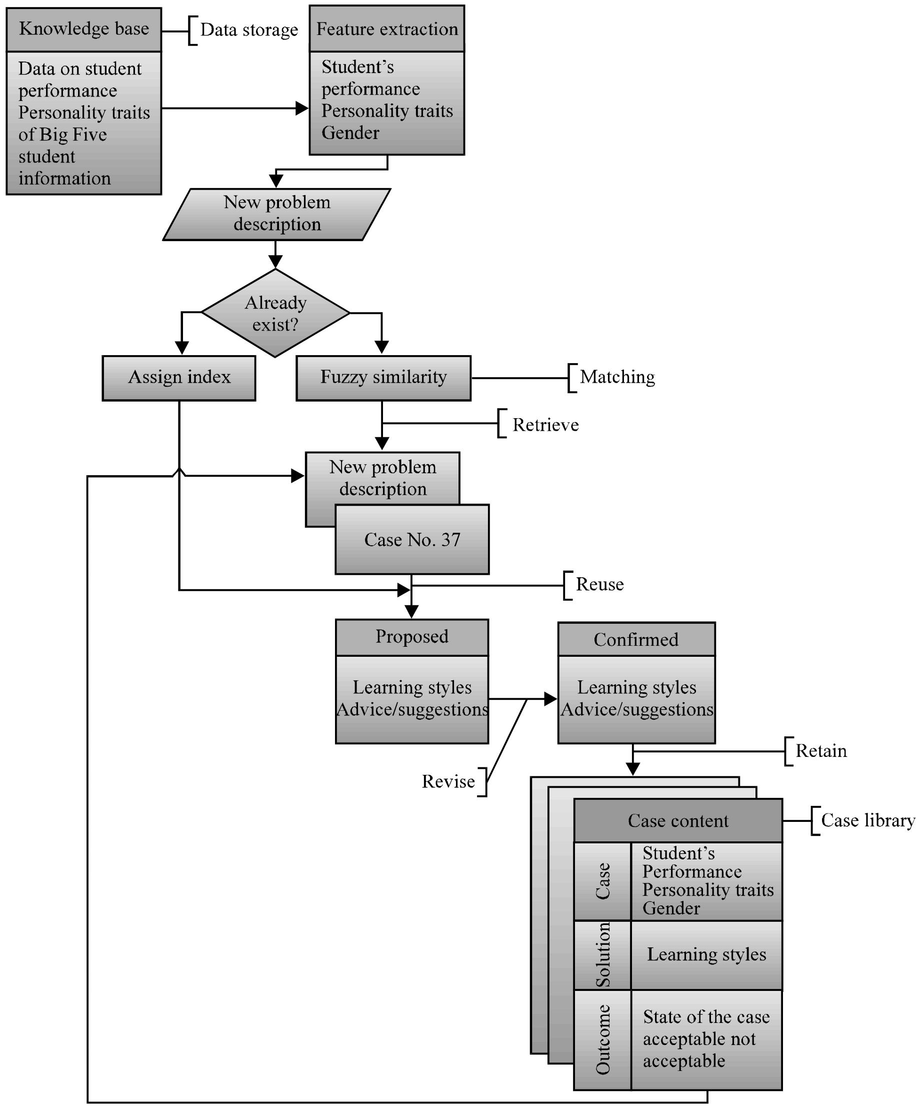

Fig. 3: The reasoning procedure of the proposed fuzzy CBR cycle

RESULTS AND DISCUSSION

Creating and training the fuzzy CBR: When the fuzzy model is defined, the construction of the corresponding fuzzy CBR Model is straightforward (Fig. 3). An example of cases for learning styles classification is shown below. Within the data set, each variable is associated with classifying at least one learning style dimension.

Case 1:

- Student class is 'good 1'
- Then, solution: student is active learner

Case 2:

- Student class is 'good 2'
- Then solution: student is reflective learner

The knowledge base contains the student model that is stored as cases of student's performance, personality traits and gender of a particular student. Features are extracted from the knowledge base before making a new problem case. As a result of the extracted features when a new problem case has been formulated, fuzzy CBR cycle is introduced to solve this new problem case.

Assigning indexes: The indexes are important features that characterize a case and how cases are stored in the case library is based on the indexes.

Case retrieval and matching: When a new case problem is found, the retrieval process will take place by matching the new case against cases in the case library using fuzzy similarity approach.

Case reuse: If a matched case found it will be reuse to solve new case problem. Thus, in this process, FS learning styles will be proposed.

Case revise and adaptation: If a new case does not exactly match the old case, the old case may need to be revised and improve to fit the new one.

Case retain: Once the new case problem is solved, it is stored in the case library for future use. To assess the precision of our method, the following measure proposed by Garcia *et al.* (2007) will be used:

$$\text{Precision} = \frac{\sum_{1=1}^{n} \text{Sim}(LS_{\text{Predicted}}, LS_{\text{ILS}})}{n} \times 100$$

Where:

$LS_{predicted}$ = The Learning Styles Predicted by the proposed method

LS_{ILS} = The Learning Styles from the ILS questionnaire

n = The number of students. The function Sim compares both parameters $LS_{predicted}$ and LS_{ILS}

Sim will return "1" if both are equal and "0" if they are opposite. In order to evaluate the proposed model, we plan to conduct an experiment with undergraduate students who participate with data extraction of LMS log files and student profile whereby they also have to fill up the BFI and ILS questionnaires.

CONCLUSION

In this study, we presented the ongoing attempt of our work in learning style detection model. We reviewed the issues of existing learning styles detection approach. We also presented the underlying theories of learning styles and personality models. A survey of previous learning style detection approaches have been accomplished. Nevertheless, there is still a room for enhancement of the recognition accuracy. The aim is to improve the construction and maintenance of student model and subsequently increase the recognition accuracy. Due to the importance of individual differences that is incorporated in the technology-enhanced learning system, the work will therefore hybridize the FL and CBR methods to detect student's learning styles based on hybrid features, i.e., student's performance their personality and gender.

RECOMMENDATION

For the future research, we are planning to implement the proposed hybrid technique and evaluate the model using real data set.

REFERENCES

Abrahamian, E., J. Weinberg, M. Grady and C.M. Stanton, 2004. The effect of personality-aware computer-human interfaces on learning. J. Universal Comput. Sci., 10: 27-37.

Akbulut, Y. and C.S. Cardak, 2012. Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011. Comput. Educ., 58: 835-842.

Chrysafiadi, K. and M. Virvou, 2013. Student modeling approaches: A literature review for the last decade. Expert Syst. Appl., 40: 4715-4729.

Crockett, K., A. Latham, D. Mclean and J. O'Shea, 2013. A fuzzy model for predicting learning styles using behavioral cues in an conversational intelligent tutoring system. Proceedings of the 2013 IEEE International Conference on Fuzzy Systems (FUZZ), July 7-10, 2013, IEEE, Chester, England, ISBN:978-1-4799-0021-3, pp: 1-8.

Crockett, K., A. Latham, D. Mclean, Z. Bandar and J. O'Shea, 2011. On predicting learning styles in conversational intelligent tutoring systems using fuzzy classification trees. Proceedings of the 2011 IEEE International Conference on Fuzzy Systems (FUZZ), June 27-30, 2011, IEEE, Manchester, England, ISBN:978-1-4244-7315-1, pp: 2481-2488.

Deborah, L.J., R. Sathiyaseelan, S. Audithan and P. Vijayakumar, 2015. Fuzzy-logic based learning style prediction in E-learning using web interface information. Sadhana, 40: 379-394.

Dung, P.Q. and A.M. Florea, 2012. A literature-based method to automatically detect learning styles in learning management systems. Proceedings of the 2nd International Conference on Web Intelligence Mining and Semantics 2012, June 13-15, 2012, ACM, Craiova, Romania, ISBN:978-1-4503-0915-8, pp: 25-39.

Fatahi, S., H. Moradi and E. Farmad, 2015. Behavioral feature extraction to determine learning styles in E-learning environments. Proceeding of the 9th International Conference on E-Learning 2015, July 21-24, 2015, IADIS Publications, Canary Islands, Spain, pp: 66-72.

Felder, R.M. and L.K. Silverman, 1988. Learning and teaching styles in engineering education. Eng. Educ., 78: 674-681.

Feldman, J., A. Monteserin and A. Amandi, 2015. Automatic detection of learning styles: State of the art. Artif. Intell. Rev., 44: 157-186.

Garcia, P., A. Amandi, S. Schiaffino and M. Campo, 2007. Evaluating Bayesian networks precision for detecting students learning styles. Comput. Educ., 49: 794-808.

Ghorbani, F. and G.A. Montazer, 2011. Learners grouping in E-learning environment using evolutionary fuzzy clustering approach. Int. J. Inf. Commun. Technol., 3: 9-19.

Gonzalez, A.J., L. Xu and U.M. Gupta, 1998. Validation techniques for case-based reasoning systems. IEEE. Trans. Syst. Man Cybern., 28: 465-477.

Graf, S. and T.C. Liu, 2008. Identifying learning styles in learning management systems by using indications from students behaviour. Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies (ICALT'08), July 1-5, 2008, IEEE, Zhongli District, Taiwan, ISBN:978-0-7695-3167-0, pp: 482-486.

Honey, P. and A. Mumford, 1982. The Manual of Learning Styles. Peter Honey Publications, Maidenhead, England.

Joerding, T., 1999. A temporary user modeling approach for adaptive shopping on the Web. Proceedings of the 2nd Workshop, 8th International Word Wide Web Conference and 7th International Conference on User Modeling on Adaptive Systems and User Modeling on the World Wide Web, May 11-June 24, 1999, World Wide Web, Toronto and Banff, Canada, pp: 25-30.

John, O.P., E.M. Donahue and R.L. Kentle, 1991. The big five inventory versions 4a and 54. Institute of Personality and Social Research, Berkeley, California.

Jonassen, H.D. and B.L. Grobowski, 1993. Handbook of Individual Differences, Learning and Instruction. 1st Edn., Lawrance Erlbaum Associates, USA., ISBN: 10: 0805814132, pp: 512.

Kolb, D.A., 1984. Experiential Learning: Experience as the Source of Learning and Development. Prentice Hall, Englewood Cliffs, NJ., USA.

Kosba, E., V. Dimitrova and R. Boyle, 2005. Using student and group models to support teachers in web-based distance education. Proceedings of the 10th International Conference on User Modeling (UM 2005), July 24-29, 2005, Springer, Edinburgh, Scotland, pp: 124-133.

McCrae, R.R. and O.P. John, 1992. An introduction to the five-factor model and its applications. J. Personality, 60: 175-215.

Pandey, B., R.B. Mishra and A. Khamparia, 2014. CBR based approach for adaptive learning in E-learning system. Proceedings of the 2014 Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE), November 4-5, 2014, IEEE, Punjab, India, ISBN:978-1-4799-7278-4, pp: 1-6.

Schmitt, D.P., J. Allik, R.R. McCrae and V.B. Martinez, 2007. The geographic distribution of Big Five personality traits: Patterns and profiles of human self-description across 56 nations. J. Cross Cult. Psychol., 38: 173-212.

Zatarain, C.R., M.L.B. Estrada, V.P. Angulo, A.J. Garcia and C.A.R. García, 2010a. A learning social network with recognition of learning styles using neural networks. Proceedings of the 2nd Mexican Conference on Pattern Recognition (MCPR 2010), September 27-29, 2010, Springer, Puebla, Mexico, pp: 199-209.

Zatarain, C.R., M.L.B. Estrada, V.P. Angulo, A.J. Garcia and C.A.R. García, 2010b. Identification of felder-silverman learning styles with a supervised neural network. Proceedings of the 6th International Conference on Intelligent Computing (ICIC 2010), August 18-21, 2010, Springer, Changsha, China, pp: 479-486.