Fuzzy C-Means Clustering Model for Identification of Students' Learning Preferences in Online Environment

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ABSTRACT
The use of Information and communication technologies has transformed the perceptions of instructors and learners towards a well enabled learning environments. The delivery of earlier computer mediated instruction was more or less similar in approach to conventional classroom education where the mode was one-size-fits-all approach. No sooner than later, the instructional designers began to explore the research findings of learning theorists with respect to differences in learning patterns of students that stimulate enhancement in learning performance. There are over eighty different learning styles and models that have been revealed by different learning theorists. The importance of this is the understanding of instructional designers, educationists and instructors to mediate the learning styles and theories with thoughtful technologies in order to nurture the students through learning process. In the light of this, the research paper adopts Honey and Mumford's learning styles using Fuzzy C-Means (FCM) clustering technique to determine the individual learning preference. The results obtained from this model showed that the technique is suitable in identifying students' learning preferences.

Keywords
Learning styles, students' learning preferences, Fuzzy C-Means clustering, personalization.

1. INTRODUCTION

Learning is described as an active process where learners are actively engaged in constructing knowledge in a meaningful, realistic context through exploration, reflection, and social discourse with others, rather than passively receiving information. It is seen as a spiral process where learners are given increasingly difficult problems and the resources needed to solve them. Learners select information from available resources and then use cognitive strategies such as organization, elaboration, and scaffolding to transform it into new, personal meaning [12]. For learning to be active, it is believed that learners must be given control to learn at the pace that matches with the individual learning interest, background knowledge, learning style and study pattern. The current research issue has been perceived by different researchers with such term as personalization, individualized instruction, customization etc. The main focus of this concept is the improvement over e-learning system.

The importance of personalization has been demonstrated by research endeavour in different areas, where individual differences such as prior knowledge, learning needs, the diversity of learning styles and learning goals provide a significant support for successful personalization. The close links between personalization and learning style are often seen by many researchers. O'Connor [15] argued that students could learn best when their learning can be performed in the modalities which are in accordance with their learning styles. Federico [3] also stated that an understanding of learning styles can improve the instructional procedures and strategies that are accommodated to students' preferences in order to enhance their learning, retrieval and retention. Furthermore, it is suggested that the learning style is the preferred and most effective way students process and acquire the instructional information. It is also one of the valuable resources which need to be utilized for personalizing the e-learning [16].

According to Paneva et al [2], stated that there are several systems that have been reported in the literature for the personalization of E-learning. Each of these systems uses, at the most three personalization parameters. Most of them use the personalization parameters such as learner's level of knowledge, learner's media preference etc. They further strengthened the notion that personalization in current Learning Management Systems tends to be concerned with remembering which courses the user is allowed to view and how they like their pages to be presented. In some cases, users such as learners, teacher and administrators are able to edit their own profile; to maintain their personal calendar (monthly and weekly) which keeps track of their event transactions; to subscribe to forums, etc. They mentioned the following approaches based on user model that can be used to apply the learning personalization:

ι. Personalization, controlled by the learner – It requires direct input of the learner's needs and preferences by filling question forms or by choosing options and alternatives.
ii. Personalization, based on an existing user profile and meta-descriptions of the information content - In this case, the learners' preferences are stored in their profile.
iii. Personalization via searching for a correlation between the learners- Correlation is through the values of the attributes, describing the learner's profile. If there is a strong correlation, there is a possibility that the content for a given profile is suitable for applying to its close (adjacent) profiles.

In the light of this, the research paper focuses on the first option using fuzzy clustering to determine the students' learning preferences that could meet their educational needs.

2. OVERVIEW OF LEARNING STYLES

The research field of learning styles is borne out of learning theories and is both extensive and conceptually confusing as a result of many beliefs, conceptions and terminologies claimed by different theorists of learning styles models. There are many different learning style models, although many of them suffer from a common ancestry and measure similar dimensions. In addition to collection of learning style theories, there is also a wealth of confusing terminology and assessment tools. Many researchers are overwhelmed by the choice of which instruments may be better than the others or which theories may be trusted more than others or which learning styles "work" in any given context. In a review of the psychometric qualities of different learning styles instrument, Curry [14] categorized different research approaches. These were instructional preferences, social interaction, and information processing and cognitive processing style. Curry's onion model as shown in Figure 1 is a good basis for demonstrating the different ways in which learning styles can be categorized, by assigning them to a particular layer in a radial system, with a structure analogous to that of an onion. The innermost layer, cognitive processing style seeks to measure an individual personality, specifically related to how they prefer to acquire and integrate information. Moving outwards, the next layer measures information processing style and examines a learner intellectual approach to assimilation of new information. The layer beyond that examines social interaction, and how students prefer to interact with each other. The outermost layer, of instructional preferences, tends to relate to external factors such as physiological and environmental stimuli associated with learning activities. The layers refer to different aspects of learning style and those most influenced by external factors and most observable are on the outermost layers, but less important in learning. The innermost layers are considered more stable psychological construct, more significant in complex learning and less susceptible to change; however they are less easily measured. Many researchers in the learning styles field have seen Curry's model as a useful, pragmatic way of presenting different models within these broad categories [13].

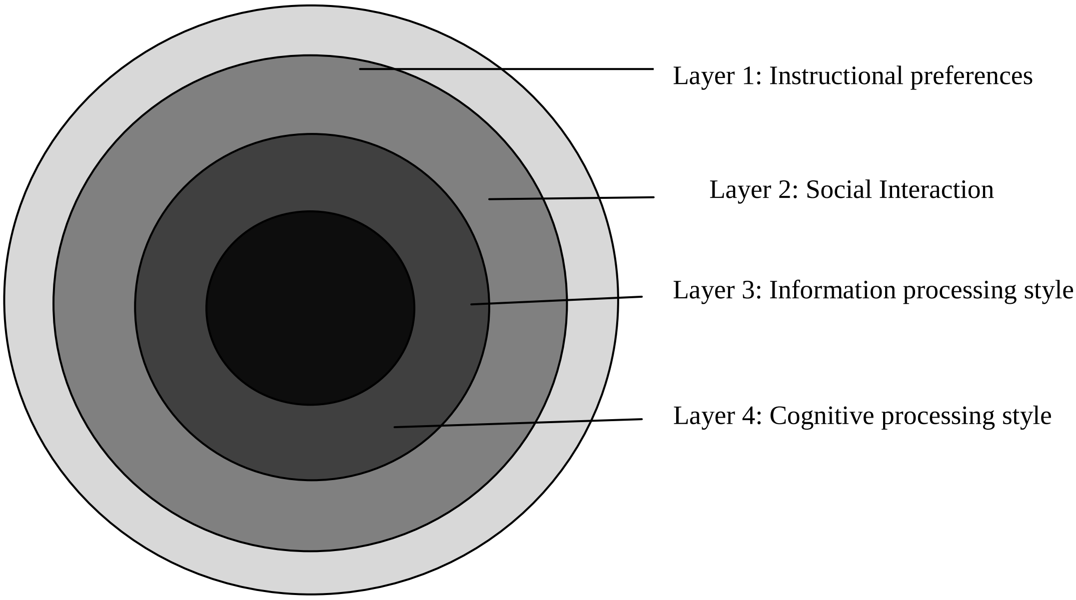

Figure 1: Curry's Onion Model of Learning Styles
Source: Coffield et al [13]

In a review of the study on learning styles, over eighty learning style' models have been proposed, each consisting of at least two different styles. According to recent study, Campell [12] identified many of the models of learning styles from which they were able to select thirteen major models with their associated measuring instruments for analysis. They further classified these into five families along a fixedness dimension. The classification is as follows: learning styles as one component of a relatively stable personality type (e.g Apter and Jackson); learning styles as flexibly-stable learning preferences (e.g Allinson and Hayes; Herrmann; Honey and Mumford; and Kolb); styles as learning approaches and strategies (e.g Entwistle, Sternberg, and Vermunt); constitutionally-based learning styles and preferences(e.g Dunn and Dunn; and Gregorc); and learning styles reflecting deep-seated features of the cognitive structure including patterns ability (e.g Riding).

Learning style is a concept which has provided some valuable insights into learning in both academic and other settings. Mostly, the acceptability of the field by the manner in which individuals choose to approach learning situation is generally recognized as having an impact on performance and achievement of learning outcomes as shown in a study carried out by Mohamad et al [9]. There are a number of learning-related concepts such as perception of academic control and achievement motivation which have been a focus of attention when attempting to identify factors affecting learning-related performance [18]. The focus of this study is based on learning styles developed by Peter Honey and Alam Mumford, based upon the work of Kolb. They identified four distinct learning styles or preferences which are pragmatist, theorist, activist and reflector. According to Kanninen [6], described certain peculiarities in their behaviors: **pragmatist** is a thinker and doer who perceive the experiences abstractly, and then process them actively; **theorist** is theoretical, analytical and thinker who perceive the experiences in an abstract way and integrate them into concepts; **activist** learns through new experiences, opportunities and active experimentation; **reflector** learns best by observing, collecting information about it and thinking through what was learned.

3. OVERVIEW OF CLUSTERING METHOD

Clustering techniques are machine learning mostly unsupervised methods that can be used to organize data into groups based on similarities among the individual data items. A simple formal mathematical definition of clustering is as stated as follows [20]: Let $X \in R^{mxn}$ is a set of data items representing a set of m points x_i in R^n. The goal is to partition X into K groups C_k such that every data that belong to the same group are more "alike" than data in different groups. Each of the K groups is called a cluster. The result of the algorithm is an injective mapping $X \rightarrow K$ of data items X to clusters C_k. There are different types of similarity measure such as distance, connectivity or intensity. Clustering techniques are used in various fields such as machine learning, data mining, pattern recognition, image analysis and bio-informatics [5]. There are several clustering techniques such as K-means, Fuzzy c-means, Hierarchical clustering and Mixture of Gaussians.

Clustering techniques have been applied in several real-life problems which are described briefly in this section. Dhillon et al [1] proposed a new information theoretic divisive algorithm for feature word clustering and apply it to text classification. With the experimental result using Naive Bayes and Support Vector Machines on the 20Newsgroups data set and a 3-level hierarchy of HTML documents collected. It showed that the algorithm monotonically decreases the objective function value by minimizing the "within-cluster Jense-Shannon divergence while simultaneously maximizing the "between-cluster Jensen-Shannon divergence.

According to Mofreh [8], proposed an evaluation methodologies using fuzzy c-means and kernelised fuzzy c-means to find e-learners based on their behavior into specific categories that represent the learners's profiles. The author presented the phases of development as data description, preparation, features selection, and the experiments design using different fuzzy clustering models.

Analysis of the obtained results and comparison with the real world behavior of those learners proved that there is a match with percentage of 78%. Fuzzy clustering reflected the learners' behavior more than crisp clustering. According to Inyang [5], proposed a methodology based on the hybrid of FCM and k-means algorithm and Adaptive Neurofuzzy Inference System (ANFIS) for the prediction of students' academic performances into class of weak, average and good and at-risk levels such as not risky, slight risky, risky and very risky respectively.

4. RELATED WORKS

Wang et al [19] used Kolb's Learning Style Inventory (LSI) as a self-assessment tool aimed at determining student learning style preferences. The instrument consist of 12 statements that describe learning, each with four endings, that individuals rank based on which ending is "most like" or "least like" experience of the individuals and in the order of 4, 3, 2, and 1, without repeating or skipping any. Participants must complete, in rank order, four sentence endings that correspond to four learning mode orientations: concrete experiences (CE), abstract conceptualizations (AC), active experimentations (AE) and reflective observations (RO).

The authors performed calculation process by compiling all of the first endings, second endings, third endings and fourth endings to obtain the scores of CE, AC, AE and RO respectively. The authors also performed a subtraction operation between two learning mode orientations values such as AC-CE and AE–RO to obtain two learning style scores. Two combinations of ranking scores are plotted on a grid to identify the intersection of the scores and thus indicate the preferred learning style quadrant of the learner: diverger, assimilator, converger, or accommodator.

The authors did not explore the use of computational intelligence technique to handle the students' responses from the questions statements in determining their learning preferences especially where there is large number of questions statements to be randomly-ranked and distributed.

Manochehr [10] used the Kolb Learning Styles Inventory (LSI) to measure the learning styles preferences of students. There were two groups of students for learning (e-learning and traditional learning). The LSI test is a 12-item questionnaire in which respondents attempted to describe their learning styles by four levels: diverger, assimilator, accommodator and converger.

A final comprehensive exam was given to the students to test their knowledge based on their learning styles. The responses collected from the students formed the data which were translated and stored as ASCII database file and were analyzed using SPSS. Based on the results of the LSI and final exam, a two way ANOVA procedure was conducted involving two independent variables, the first independent variable was Kolb's learning styles categories and the other was learning methods.

An analysis of student knowledge (final exam grade) for both groups was done. The author's findings revealed that students' learning styles were statistically significant for knowledge performance with e-learning methods and not with traditional methods.

Nguyen [11] discussed extensively the understanding of educationists in the role of learning theories and learning styles with integrating thoughtful technology to nurture students through a learning process in achieving successful learning outcome. Rahimi et al [17] proposed a framework that enhanced learning activities by combining the elements of the students' control with respect to deploying the theory of learning styles and the components of technology-based teaching process. According to McLoughlin [7], carried out a study on three pedagogies such as pedagogy 2.0, online collaborative learning pedagogy (OCLP) and onnectivism. The author's observation was that each has a theoretical framework that has constructivist learning and an emphasis on personalization of the learning experiences at its core.

Hao [4] carried out a study to investigate the student teachers' sense of social presence and the relationship with learning styles in a teacher education course. The Web 2.0 technologies included blogs, wikis, social networking, social bookmarking, and a virtual world. Learning styles were assessed in their relationship with students' feelings. The results indicated that the social networking site achieved the most sense of social presence, and the social bookmarking site the least. The learning styles of reflective, intuitive and global were associated with the social presence of Web 2.0 tools. The findings would help educators gain more understanding of Web 2.0 technologies' impact on student's preference and the relationships between specific Web 2.0 technologies' social presence and individual differences.

5. MODEL DESIGN

The design of the model adopts Honey and Mumford's Learning Styles Questionnaire using clustering technique to uniquely identify students' learning preferences that would improve educational study performance. The architectural view of the model is depicted in Figure 2. There are eighty questions statements that denote features X_i of the personality of a student S, where features are selected to uniquely classify the students into four different personalities (*Pragmatist, Theorist, Activist and Reflector*). Fuzzy c-means clustering technique is adopted for classification of feature selection into four classes of individual learning style. The mathematical notations of fuzzy c-means clustering are described in equations 1-4:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^{m}\left\|X_i - C_j\right\|^2 \qquad 1 \le m \le \infty \qquad (1)$$

$$\sum_{j=1}^{c}\mu_{ij} = 1 \;\; \forall j = 1, \ldots, c;\; i = 1, \ldots, n \qquad (2)$$

$$\mu_{ij} = \frac{1}{\sum_{j,k=1}^{c}\left[\frac{\left\|X_i - C_j\right\|}{\left\|X_i - C_k\right\|}\right]^{\frac{2}{n-1}}} \;\; \forall i = 1,\ldots,n;\; j,k = 1,\ldots,c \qquad (3)$$

$$C_j = \frac{\sum_{i=1}^{N}\mu_{ij}^{m}.X_i}{\sum_{i=1}^{N}\mu_{ij}^{m}} \qquad (4)$$

where $x_1, x_2, \ldots, x_n$ are input feature parameters denoted as vector data sets, which are in form of objects-attributes relation. Objects denote the set of respondents (students) while attributes are the set of responses from students showing the degree of agreement on the set of questions statements. The students respond with selection option type expresses in linguistic terms of four point-likert scale: partially disagree, totally disagree, partially agree and totally agree; each level on the scale is assigned a numeric value from 1 to 4 respectively; m = 2, for each datum X_i, μ_{ij} is a coefficient denoting the degree of being in the *jth* cluster, the cluster is partition into four classes, $C_j = 1,2,3,4$. The sum of those coefficients is defined to be 1 as shown in equation 2. X_i is the *ith* of d-dimensional feature measured data, C_j is the d-dimension cluster of centroid. $\|*\|$ is the Euclidean distance which is the distance between feature measured data and the cluster centroid. Fuzzy partition is carried out through iterative optimization of objective function J_m in equation 1, with updated membership function μ_{ij} and cluster centroid C_j in equations 3 and 4. The iteration will terminate when $\max_{ij}\left\{\left|\mu_{ij}^{(t+1)} - \mu_{ij}^{(t)}\right|\right\} < \varepsilon$ where ε is the termination criterion and t are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

Therefore, at the instance of process classification completion, there is unique identification of students S based on the attributes X_i into classes $C_j = 1,2,3,4$ as represented in equation 5.

$$S_{l,\,x} \in C_j \qquad (5)$$

where $l = 1, \ldots, m$ is the total number of students that interacted and responded to the questions statements at a certain period of time; $x = 1, \ldots, n$ is the total number of attributes; j = 1, 2, 3, 4 (j is the number of classes the students are grouped into). It would be inferred at this point that the highest degree of membership the student is associated with, between the various classes (*Pragmatist, Theorist, Activist and Reflector*) is the strong class the student belongs to.

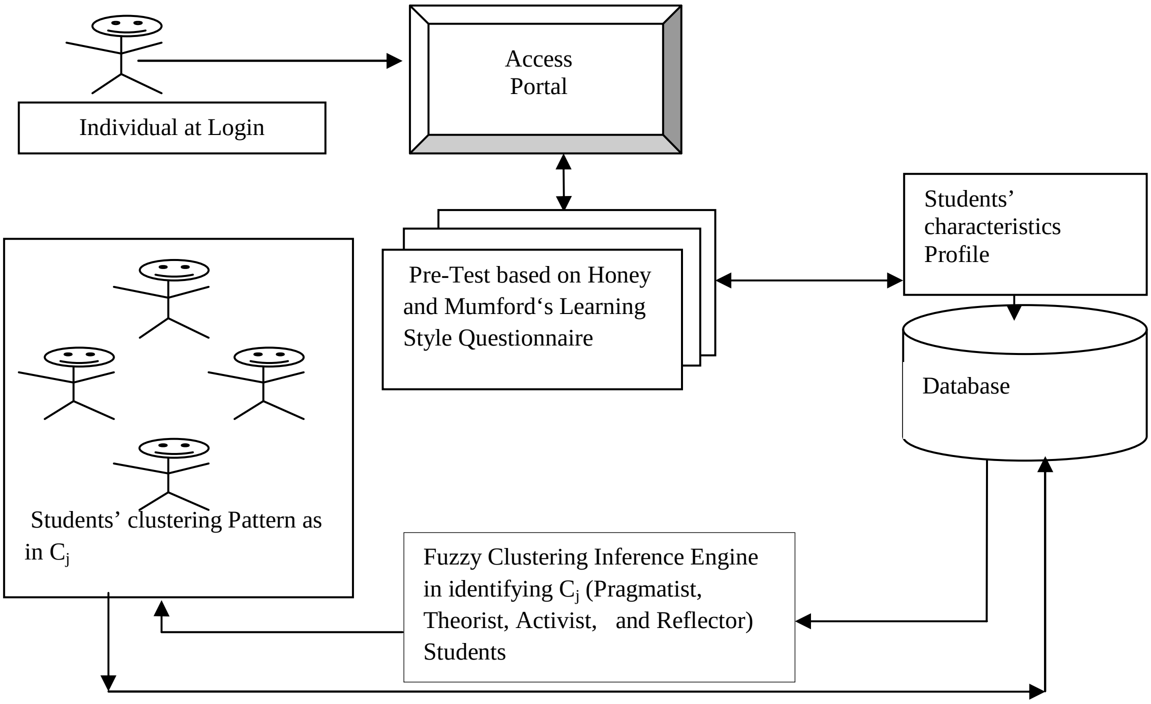

Figure 2: Architectural View of the Model

6. RESULTS AND DISCUSSION

The prototype of this model was tested with using fifty participants of third year students of the Department of Computer Science, Federal University of Technology, Akure. A dataset of these fifty students was collected through submission of filling-in of their personal data and their responses to the questions statements provided via access portal. The fuzzy c-means clustering algorithm was run on the dataset and iterated to converge and terminate at $\varepsilon = 0.00001$ with iterate count which is equal to three. The output of the algorithm is shown in Table 1 which identified each of the students' learning preferences relative to four dimensions of the Honey and Mumford's model (*Pragmatist, Theorist, Activist and Reflector*). Each student has varied degree of membership value of belonging to each of the four dimensions and the highest value was inferred as the likely strong class the student could belong to. The accuracy of this algorithm is obtained considering the total number of students' dataset that are used as input and out of which the algorithm is able to uniquely identify individual student into various classes each belongs to with the varied degree of membership values. Based on this, forty eight out of fifty students (96%) were accurately identified and classified into their respective learning preferences. Two (4%) were not classified accurately which is due to inconsistent input responses pattern from such students with their students' profile identity ((Id): 8 and 29) as shown in Table 1.

Table 1: Fuzzy C-Means Membership Distribution for Students' Learning Preference

	FUZZY C-MEANS MEMBERSHIP DISTRIBUTION						FUZZY C-MEANS MEMBERSHIP DISTRIBUTION				
Id	**Pragmatist**	**Theorist**	**Activist**	**Reflector**	**Strong Preference**	**Id**	**Pragmatist**	**Theorist**	**Activist**	**Reflector**	**Strong Preference**
1	0.22845	0.25877	0.19494	0.31784	Reflector	26	0.27341	0.20920	0.12844	0.38894	Reflector
2	0.27404	0.24986	0.15674	0.31937	Reflector	27	0.24703	0.31066	0.16144	0.28087	Theorist
3	0.29554	0.24200	0.19530	0.26717	Pragmatist	28	0.30391	0.22932	0.21197	0.25480	Pragmatist
4	0.21480	0.24872	0.16058	0.37590	Reflector	29	0.00000	0.00000	0.00000	1.00000	**NULL**
5	0.27264	0.25785	0.18276	0.28675	Reflector	30	0.29688	0.19727	0.13568	0.37018	Reflector

6	0.38251	0.20310	0.15938	0.25501	Pragmatist	31	0.31645	0.24469	0.24469	0.18379	Pragmatist
7	0.29989	0.18929	0.18929	0.25419	Pragmatist	32	0.32996	0.21919	0.19299	0.25787	Pragmatist
8	1.00000	0.00000	0.00000	0.00000	**NULL**	33	0.21698	0.28186	0.21031	0.29038	Reflector
9	0.33267	0.22095	0.14730	0.29907	Pragmatist	34	0.25713	0.24465	0.14823	0.34999	Reflector
10	0.28247	0.25037	0.20276	0.26440	Pragmatist	35	0.27541	0.27251	0.19320	0.25888	Pragmatist
11	0.25490	0.26286	0.22734	0.25490	Theorist	36	0.38603	0.20374	0.16299	0.24723	Pragmatist
12	0.27130	0.21354	0.13031	0.38486	Reflector	37	0.31236	0.20758	0.30652	0.17353	Pragmatist
13	0.25036	0.20237	0.13567	0.41160	Reflector	38	0.32990	0.23474	0.15583	0.27953	Pragmatist
14	0.25230	0.29015	0.28170	0.17585	Theorist	39	0.29696	0.22109	0.16643	0.31552	Reflector
15	0.14017	0.57190	0.08936	0.19857	Theorist	40	0.25762	0.25556	0.26185	0.22497	Activist
16	0.23579	0.27626	0.19181	0.29615	Reflector	41	0.24280	0.22345	0.14342	0.39033	Reflector
17	0.25779	0.27077	0.18632	0.28513	Reflector	42	0.36666	0.26915	0.14795	0.21624	Pragmatist
18	0.21745	0.29729	0.18563	0.29963	Reflector	43	0.29170	0.24309	0.18331	0.28190	Pragmatist
19	0.32693	0.25337	0.20406	0.21564	Pragmatist	44	0.29417	0.22813	0.15525	0.32245	Reflector
20	0.30974	0.22700	0.19381	0.26945	Pragmatist	45	0.27698	0.25140	0.14525	0.32238	Reflector
21	0.23733	0.25085	0.17307	0.33875	Reflector	46	0.29964	0.27310	0.17454	0.25472	Pragmatist
22	0.12131	0.12636	0.69530	0.09303	Activist	47	0.22958	0.24224	0.15050	0.37868	Reflector
23	0.32512	0.23336	0.19420	0.24732	Pragmatist	48	0.29401	0.24048	0.21859	0.24892	Pragmatist
24	0.26177	0.28028	0.21021	0.24775	Theorist	49	0.32800	0.25185	0.23913	0.18222	Pragmatist
25	0.30181	0.25151	0.18172	0.26495	Pragmatist	50	0.30437	0.24243	0.18580	0.26440	Pragmatist

7. CONCLUSION

The design of the model adopted the Honey and Mumford's learning styles using computational intelligence to uniquely match students with their learning preferences. The results obtained demonstrated that the technique is adequately sufficient to achieve the underlined objective. The outcome of the study would enable the instructors to adequately cater for individual students both in technological–mediated learning environment or traditional classroom environment. The role of instructor as advisory counselor would also be adequately discharged to counselee.

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