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Intelligent Advisory System for Student Learning Styles' Identification Supporting E-Courses' Designers

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***Abstract*— On designing e-courses, more difficulties appear one of which teachers have to know individual learners behaviour and learning styles in the course. Providing knowledge about learner's learning styles allow deep understanding for both teachers and learners about students' learning process. Teachers help their students to provide high potential to enhance teaching and learning. This paper proposes an approach to apply data mining on a proposed relevant learning styles model. Extracted knowledge is utilized to help teacher in designing learners' e-course. As well as classifying students' preferred learning styles with respect to domain goals attributes. Results show most affected styles in some domain goals and present overall priority for each style in designing e-course. Sequential and rational styles have higher priorities while active and reflective have fewer priorities.**

Keywords- Data mining; Intelligent system; Proposed learning styles model; E-course designing

1. INTRODUCTION

Learning styles (LSs) are educationally popular concept. Students can use their learning styles to become better learners, as teachers vary their instructional approach to engage a range of learning styles [1]. It is difficult for teachers to see how individual students behave and learn in the e- learning system.

Currently, modeling and discovering users' needs, goals, knowledge preferences and motivations are one of the most challenging tasks in e-learning systems that deal with large volumes of knowledge[2]. Regarding the analysis of LSs, data mining (DM) techniques have been widely used to discover useful information from large amount of data [3]. Educational Data Mining (EDM) is well known to focus on the collecting, archiving, and analyzing data related to student learning and assessment. Also EDM enable better understanding of students' performance and enhance teaching and learning process [4]. Effective predictive model was established from the existing student dropout data [5]. Decision tree is used to evaluate student's performance in higher education. Extracted knowledge helps earlier in identifying the dropouts and students who need special attention that allow teacher to provide appropriate advising/counseling [6].

This paper presents a proposed relevant learning styles model (PLSM). This model is inspired from - a survey on the different learning styles models (LSMs) and their reviews [7-17]. Decision tree, is applied on the PLSM to acquire useful knowledge. This knowledge is used for helping teachers in designing e-courses according to the preferred LSs of learners and classifying or predicting their performance.

The paper is organized as follows; section 2 includes LSs, in higher education, and in e-learning. DM and decision tree analysis are presented in section 3. Section 4, includes PLSM building and its application. Applying decision tree to extract rules was presented as section 5. Section 6 includes description of the advisory system. Applications and results are presented in section 7.Finally, conclusions are provided in section 8.

2. LEARNING STYLES

LSs are description of attitudes and, behaviors that affect one's preferred way of learning [18]. LSs are the composite of cognitive characteristics; affective and psychological factors that influence the way individuals interact and respond to learning environments [19].

There are various views on LSs concepts and definitions among researchers and each investigates and observes from various aspects such as psychological, environmental aspects, modality, personality, experiential learning, and brain hemisphere mastery [20].

Many conceptions were commonly discussed to describe and define learning styles [20-22]. Researchers have attempted to construct overviews of LSMs. These are extremely comprehensive works, and are recommended for further reading [7-17].

2.1 Learning Styles in Higher Educations

Some researchers have found out that the cultural context affects students' LSs at the university level [23- 25]. In addition, they noticed that "visual learning style" is the most preferred one by comparing the LSs of American students in some academic colleges with Education, Science, History, Philosophy and Business Management [26-27]. It has been

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found that preferred LSs in different colleges are different [24, 28].Technology provides new capabilities to reconstruct learning environments around specific LSs. There are some possibilities that can be emerged when using LSMs to develop technological applications to university classrooms [29-30].

2.2 Learning Styles in E-Learning

LSs are one of the most important factors that affect enhancing efficient and good quality e-learning [31-32]. More research and studies concerning this aspect makes students' success more. Important recommendation for the ways to enhance learning based on individual differences can be stated as follows [33]:

(a) Various types of sources other than the traditional materials including media sources should be added.

(b) Various formats for the course handouts should be used.

(c) Pre and post supplementary materials for activities in wide range should be used with the content material.

(d) Enough guide-lines should be used with various add-ons.

(e) Adding little fun that gives sense of humor even for adult learners.

(f) Learning strategies have to meet the needs of different LSs rather than sticking to one type of them.

The design of online courses should be mainly concerned with and concentrate on meeting the needs of students of LSs diverse [34-37]. LSs is much more important in e-learning rather than in traditional learning [38]. Briefly, e-instructors' should focus on students' awareness of LSs, consequently, the components of their materials should be directed to all learners and to be varied and rich enough to meet all the different LSs needs [39].

Psychology and cognitive sciences have longtime explored a question, "why humans can assimilate the knowledge received in a better way visually, auditory or through a certain sense?" [40]. IF the employed teaching style is closely matches the student preferred style; learning process becomes easier and more natural results will be improved. Additionally learning time will be reduced [41]. LSs can be summarized as the styles or individual learning techniques that act with its environment, to process, interpret and obtain information, experiences or desirable skills. Data mining can help in acquiring useful knowledge in LSs domain.

3. DATA MINING

DM is defined as the activity that extracts some new nontrivial information contained in large databases. The goal is to discover hidden patterns, unexpected trends or other subtle relationships in data using a combination of techniques from machine learning, statistics and database technologies [42]. Typical inputs include data in various formats, such as numerical and nominal data stored in databases or flat files. The output is the generated new knowledge [43].

Evolutionary algorithms were used as a data mining method for discovering important dependence relationships in students' usage data which may be very useful to both teachers and course designers in enhancing the effectiveness of a given course [44].

Decision tree algorithm was employed for analyzing, students' profiles, to discover the most adaptive learning sequences for a particular teaching content. An optimal learning sequence was recommended in rule for facilitating students' learning processes and for maximizing their learning outcome [45]. An automatic approach was presented by Graf, S.et al for identifying students' LSs in learning management systems as a tool that supports teachers in applying this approach [34]. The approach was based on inferring students' LSs from their behaviour in an online course. Thus, using the data mining technique, being referred to as knowledge discovery in databases (KDD) will lead to elicit an implicit pattern from a volume of data [45].

3.1 Decision Tree

A decision tree is a valuable tool used in the description, classification and generalization of data. It can organize descriptions of data by reducing it into a more compact form. It can also classify discovered data which contains well-separated classes of features and interpret the classes meaningfully in the context of a substantive theory [46]. In generalization and predicting the value of dependent variable through a mapping from observations about independent and dependent variables is useful to get a conclusion about these variables' target value in the future [45].

Decision tree is a tree in which each non-leaf node has associated with it an attribute (feature). Each leaf node has associated with it one of the possible attribute values at the node where the arc is directed from. The best attribute for a node is choosed by random, last-values (smallest number), most-values (largest number), and max-gain (largest information gain) [47].

Studies that provide comprehensive surveys on the application of various decision tree are presented in [46- 48]. Various decision tree algorithms such as CHAID (chi-square automatic interaction detectors) algorithm [49], C4.5 and C5.0 are extensions of the ID3 [50, 2], CART (classification and regression trees) algorithm [51]. In short, decision tree methodology an important tool for data mining researcher and many existing data mining products are based on constructing decision trees from data [46].

3.2 Entropy Measuring Impurity

Given a data table that contains attributes and class of the attributes, we can measure homogeneity of the table based on the classes. If a data table contains several classes, then we say that the table is impure or heterogeneous. There are several indices to measure degree of impurity quantitatively like entropy measure [6].

$$\text{Entropy} = -\sum_{i=1}^{k} \text{pi} \log 2 \text{ pi} \tag{1}$$

Where i is a classes and ρi is the number of class's i occurrences divided by the total number of instances.

4. A PROPOSED LEARNING STYLES MODEL

Building the PLSM includes seven steps as shown in fig.1. These steps are explained as follows:

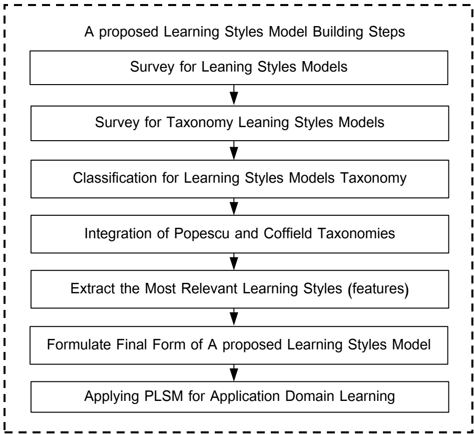

Figure 1. Steps for PLSM building

4.1 Survey for LSMs

LSs as controversial issue has been explained and clarified through reviews of its models and attempts to classify these models. LSMs survey most cited are 87 models. The question is how the LSMs literature should be organized to be posed and which learning styles model is most relevant to be used?

4.2 Survey for LSMs Taxonomy

The existing reviews of the LSMs classification are valuable and helpful for educationists and researchers entering the field at first orientation. However they are less helpful to get a full understanding of the complete LSs and cognitive styles literature. The general points of criticism become clear when comparing the different reviews that can account for this limited workability.

4.3 Classification for Taxonomy LSMs

LSMs overview in literature can be divided into two main categories: one is based on flexibility and stability of the LSs criteria and other is based on integration of the LSs as shown fig. 2.

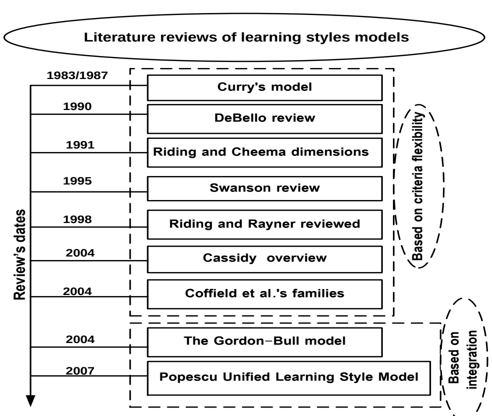

Figure 2. A proposed classification of LSMs as reviewed in literature

4.4 Integration Popescu and Coffield Taxonomies

Popescu et al. tried to address some of the identified criticism issues of LSMs [17]. They synthesized the main models' characteristics in the literature, providing an integrative taxonomy as a unified LSM (ULSM). Furthermore, the ULSM is specifically adapted for e-learning settings. However; large number of LSs still exist, therefore LSs reduction is needed. Coffield had organized LMSs based on 4 criteria's follows [14-15]:

- The LSMs flexibility
- LSMs influence by the context and environment,
- LSMs determination by biological and cognitive constraints.
- LSMs relationship to other scientific concepts and theories.

Coffield's had obtained five LSMs families based on these criteria's as shown in fig. 3.

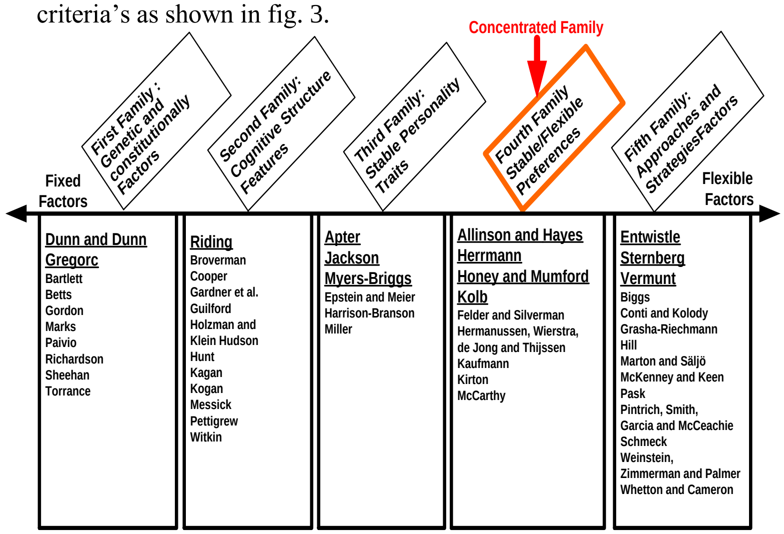

Figure 3. A continuum of Coffield's et al.'s LSMs families shows 13 models fall along a continuum are reviewed [13-14, 66].

4.5 Extracting the Most Relevant LSs Attributes

Extraction of most relevant LSs attributes is a necessary step for knowledge extraction. Based on ULSM integration of Popescu and the 4th family (flexibly/ stable learning preferences) presented by Coffield. The PLSM rates student's LSs using five dimensions as shown table 1. These dimensions are defined by answering five questions; four of them were presented in [42] as follow:

- Which sensorial channel do the students tend to receive information more effectively: (visual style vs. verbal style)?
- What kind of information does the student tend to receive: (intuition style vs. rational style)?
- How does the student make progress (sequential style vs. global style)?

- What is student behaviour around problem-solving: (explorer style vs. adaptor style)?
- How is the information processed: (active style vs. reflective style)? The final five PLSM dimensions are shown in fig.4.

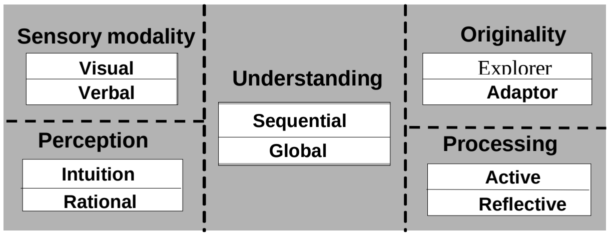

Figure 4. PLSM five dimensions

TABLE 1. DESCRIPTION OF PLSM DIMENSIONS INCLUDED DEFINITION, NUMBER OF PHRASES, AND CHARACTERISTICS.

Dimensions & LSs		Characteristics	Inspired Definition	Number of phrases
Sensory modality	Visual	Pictures, demonstration and expression.	Visual learners prefer to "get more information from visual images (pictures, diagrams, graphs, schematics, demonstrations)" [67]	9
	Verbal	Spoken words, written words, and explanation.	Verbal learners who learn best through explanations with words, verbal lectures, discussion and listening to what others have to say [67]	
Perception information	Intuition	-Bored by details. -Quick but careless. -Dislike repetition. -New ways.	Intuition means characteristic of right-brain orientation, refers to "immediate judgment based on feeling and the adoption of a global perspective [68].	21
	Rational	-Patient with details. -Careful but slow. - Dislike complication. -Existing ways.	Rational means characteristic of left-brain orientation refers to "judgment based on mental reasoning and a focus on detail [68].	
Understanding information	Global	-Jumping directly. - Grasp big Pictures. -Relations /connections	Global learners learn in large leaps, being fuzzy about the details of the subject but being able to make rapid connections between seemingly Scattered subjects [67].	9
	Sequential	-Steady progression. -From Partial materials to whole. -details oriented	Sequential learners tend to gain understanding in linear steps or in small connected chunks, orderly and systematic fashion[67]	
Originality activities	Explorer	Seen as ingenious; unsound, impractical-undisciplined, riskier operation. Doing things differently	Explorer can be defined as Individuals are scored according to their level of apparent desire for novelty [69].	15
	Adaptor	Seen as conforming, safe, dependable – disciplined-efficiency Doing things better	Adaptor Individuals are scored according to their level of apparent desire for familiarity [69].	
Processing information	Active	-Work in group. –Solving activities, practical.	Active learners prefer to process information by talking about it and trying it out [67].	19
	Reflective	-Work alone -Think about materials	Reflective learners prefer to think about information before acting [67].	

4.6 Proposed Learning Styles Formulation

This stage aims to refine phrases' dimension in order to exclude repeated phrases. These phrases were answered by students so that the student LSs can be determined. In addition to estimate validity and reliability for PLSM. The reliability was estimated by Cronbach's alpha value 0.490. It refers to the acceptable reliability of PLSM. According to validity, the drafted PLSM phrases have been presented to some specialists in the field of psychology, curriculum, and teaching methods. The result is reformulation, some of phrases, and agreement percentage is not less than 80%.

4.7 PLSM for Application Learning Domain

This step is divided in two main stages: first stage is the applying PLSM by the students in one of five departments in the specific education faculty as shown in fig. 5. A dataset (DS) suitable for the e.course is obtained. The DS in this stage includes ten main attributes. In the second stage domain goals are included to DS of PLSM. These goals are creative thinking [52], online learning impression [53], and most relevant subject as shown in fig. 6.

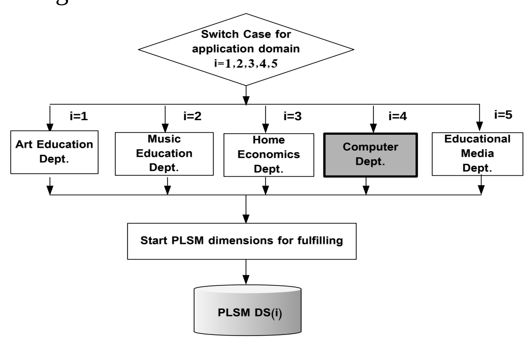

Figure 5. Applications learning domains for building DS of PLSM

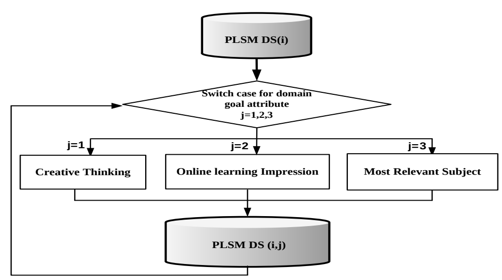

Figure 6. Domain goals are added to DS of PLSM

Finally three DSs of PLSM are established can be tabulated as shown in table2.

TABLE 2. SAMPLE OF BUILDED PLSM DS FOR ADVISORY SYSTEM

Std. No.	PLSM dimensions										Domain Goals
	Vis.	Ver.	Int.	Rat.	Glo.	Seq.	Exp.	Adp.	Act.	Ref.	Creative thinking
Std.No.1	×		×		×		×		×		Strong
Std.No.2	×			×		×		×		×	Moderate
Std.No.3	×		×		×		×			×	Strong
Std.No.4		×		×		×		×	×		Weak
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Std.No.120	×		×		×		×			×	Strong

5. INTELLIGENT ADVISORY FRAMEWORK

The extracted knowledge from DM technique (using decision tree), human expert and literature review knowledge are integrated in a knowledge base (KB). An advisory system using established DSs of PLSM for knowledge extraction is presented. The advisory system has the following steps:

5.1 Preparation of PLSM DSs for knowledge extraction

Processed steps to prepare DSs of PLSM for applying decision tree are shown in fig.7.These steps are

- discretised PLSM features' values,
- eliminated redundant data, and
- determined relevant features to each domain goals.

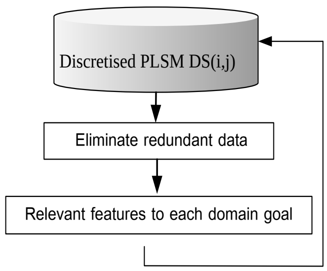

Figure 7. Steps of preparation DSs of PLSM

5.1.1 Discretisation DSs of PLSM Features' Values

Pre-processed data (e. g., discretized, normalized) is requested when data characteristics are not consistent with applying DM methods. Feature reduction is based on discrete data and might be unable to work with continuous data. In addition to entropy-based measures handle nominal or discrete features [54]. The equal width intervals method [55] is used here to discrete. Three ranges of equal size would be to divide as shown table 3.

5.1.2 Eliminate Redundant Data

There are two type instances which were eliminated:

- DSs of PLSM instances have same features values and same goal classifications (data redundant).

TABLE 3. DISCRETISATION AND FEATURES' INTERVALS

Features	Discretisation	Interval
Visual vs. Verbal	Low	$0 \leq X < 4$
	Med	$4 \leq X < 7$
	High	$X \leq 9$
Intuition vs. Rational	Low	$0 \leq X < 8$
	Med	$8 \leq X < 15$
	High	$X \leq 21$
Sequential vs. Global	Low	$0 \leq X < 4$
	Med	$4 \leq X < 7$
	High	$X \leq 9$
Explorer vs. Adaptor	Low	$0 \leq X < 6$
	Med	$6 \leq X < 12$
	High	$X \leq 15$
Active vs. Reflective	Low	$0 \leq X < 7$
	Med	$7 \leq X < 14$
	High	$X \leq 19$

- DSs of PLSM instances have same features values but different goal classification (noise data).

5.1.3 Relevant Feature to Each Domain Goal

In literature, there are various benefits and classified strategies for feature reduction. Most related features for each domain goal are selected, using information gain and gain ratio methods as follow steps:

1-Calculate the information gain and gain ratio value for each feature in DSs of PLSM related to domain goals one after one.

$$Gain\ (S,A) = Entropy(S) - \sum_{v \in values(A)} \frac{|S_v|}{|S|} Entropy(S_v) \qquad (2)$$

Where S is collection of instances, values (A) is the set of all possible values attribute A, and S_v is the subset of S for which attribute A has value v.

$$GainRatio\,(S,A) = \frac{Gain\,(S,A)}{Split\ \ information\ (S,A)} \qquad (3)$$

$$Split\ information\ (S,A) = -\sum_{i=1}^{n} \frac{|S_i|}{|S|} log_2\left(\frac{|S_i|}{|S|}\right) \qquad (4)$$

Where *Split information* is the sum of the entropies of each subset, weighted by the fraction of instances $\frac{S_v}{S}$ that belong to Gain *(S, A)*

2-Discard features do not meet a specified criterion. Information gain and gain ratio (threshold are more than or equal to 30%).

3-Pass the features which were selected to decision tree classifier.

5.2 Rules Extraction

Decision tree is applied on selected features using the ID3 algorithm [6]. This step contains three processes as shown fig. 8. The output of stage is a classification tree which is one way of generating classification IF-THEN rules [55].

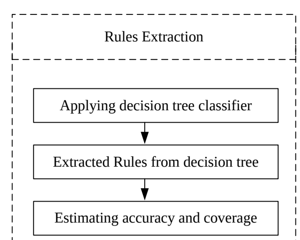

Figure 8. Rules extraction steps

5.2.1 Applying Decision Tree Classifier

To find the information gain for A relative to S, first calculate the entropy of S. Here S is a set of 97 instances have goal's classified as follow:

- Creative thinking goal instances are "Strong", "Moderate", and "Weak". To determine the best attribute for a particular node in the tree we use the measure called Information Gain. The information gain, Gain (S, A) of an attribute A, relative to a collection of instances *S*, Global style has the highest gain; therefore it is used as the root node as shown table 4.

TABLE 4. ADJUSTED INFORMATION GAIN FOR SELECTED FEATURES OF CREATIVE THINKING GOAL

Ranking	features(s)	Info. Gain
7	Visual	49.82
2	Intuition	83.07
4	Rational	82.33
3	Sequential	82.89
1	Global	100
5	Explorer	74.90
6	Adaptor	74.07

This process goes on until all data classified perfectly or run out of attributes. Other goals proceeded in the same steps in applying decision tree.

- Online learning impression goal instances are “Good”, “Average”, and “Poor”. Sequential style has the highest gain; therefore it is used as the root node as shown table 5.

TABLE 5. ADJUSTED INFORMATION GAIN FOR SELECTED FEATURES OF ONLINE LEARNING COURSE IMPRESSION GOAL.

Ranking	features(s)	Info. Gain
5	Verbal	70.70
7	Intuition	56.38
3	Rational	89.95
1	Sequential	100
4	Global	73.01
8	Explorer	49.26
2	Adaptor	92.61
6	Reflective	57.47

- Most relevant subject goal instances are “Excellent”, “V.Good”, and “Good”, and “Fail” Rational style has the highest gain; therefore it is used as the root node as shown table 6.

TABLE 6. ADJUSTED INFORMATION GAIN FOR SELECTED FEATURES OF MOST RELEVANT SUBJECT

Ranking	features(s)	Info. Gain
4	Visual	77.84
6	Verbal	58.24
3	Intuition	85.88
1	Rational	100
2	Sequential	94.36
5	Global	64.52
7	Explorer	57.15
8	Adaptor	56.46

5.2.2 Extracted Rules from Decision Tree

In this subsection, IF-THEN rules were extracted from a decision tree which may be easier for humans to understand, particularly if the decision tree very large. These extracted rules were stored in KB to help teachers for classifying their students into classes. Producing an e-course suitable for learners' preferred LSs, and enhancing the goals related to features are this paper purposes. Sample of extracted rules are shown in table7.

TABLE 7. SAMPLE OF EXTRACTED RULES

Creative thinking goal: IF Global= Low AND Visual =Low AND Sequential=High or Med THEN Class=Weak IF Global= High AND Explorer =High OR Med THEN Class=Strong
Online impression goal: IF Sequential= High AND Verbal =Low AND Adaptor =High THEN Class= Good IF Sequential= Low AND Global =High AND Intuition =High OR Explorer=High THEN Class= Poor
Relevant subject goal: IF Rational= High AND Explorer =Low OR Adaptor =Med THEN Class=Excellent IF Rational= Med AND Verbal =Med THEN Class= V.Good

5.2.3 Estimating Accuracy and Coverage for Extracted Rules

Extracted rules can be assessed by its coverage and accuracy. A rule's coverge is the percentage of instances that are covered by the rule. For rules accuracy, looking for instances that it covers and rule can correctly classify [56]. The coverage and accuracy of rules R can be defined as

$$Coverage(R) = \frac{n\ covers}{|S|} \tag{5}$$

Where n_{covers} is number of instances covered by *R* and $|S|$ number of instances in DS.

$$Accuracy(R) = \frac{n_{corect}}{n_{covers}} \tag{6}$$

Where $n_{correct}$ is number of instances correctly classified by *R*

6. ADVISORY SYSTEM DESCRIPTION

Description of the proposed system can be illustrated through the most important screens are shown in fig.9, fig.10, and fig.11 as follow:

Figure 9: PLSM five dimensions are answered sequentially

Fig. 9 displays PLSM five dimensions. Student answers PLSM dimension's terms to move next dimension. After completion PLSM dimensions answering, student's LSs are identified and stored as shown fig. 10.

Figure 10: Student's LSs are identified then displayed his report

Fig. 11 shows discretization process step in preparation DSs for knowledge extraction.

Figure 11: Discretization DSs of PLSM in preparation stage

7. APPLICATIONS AND RESULTS

This paper aimed to find Firstly: building PLSM for identification student's LSs and storing resulted to DS. Secondly: applying DM technique (decision tree) on established DS for extracting rules set as useful knowledge. Finally: providing teachers in designing a useful e-course to their learners. Building PLSM steps were explained in details. Consequently, first aim was achieved. Information gain and gain ratio was used as feature selection methods to rank features according their relations to domain goals as shown in table 8, 9, and 10. Acceptable features that had information gain and gain ratio higher than 30%, this result indicated to affect PLSM features on each domain goal.

TABLE 8. INFORMATION GAIN AND GAIN RATIO AS PERCENTAGE OF LARGEST VALUE FOR DOMAIN GOAL CREATIVE THINKING

No.	features(s)	Info. Gain	Gain ratio	Ranking
1	Visual	49.82	36.91	7
2	Verbal	37.98	26.52	8
3	Intuition	83.07	74.30	2
4	Rational	82.33	73.30	4
5	Sequential	82.89	74.06	3
6	Global	100	100	1
7	Explorer	74.90	63.76	5
8	Adaptor	74.07	62.73	6
9	Active	0.7058	0.4172	10
10	Reflective	2.8740	1.7141	9

As shows table 8, considering these features in designing course can be help in supporting and improving creativity. These findings agreed to some results of [57] study, which indicates that highly visual, active, reflective, and intuitive students benefit creatively after using multimedia learning tool and. Findings of [58] and [59] differed to recent findings that explorer style isn't more creativity than adaptor style by a large margin.

TABLE 9. INFORMATION GAIN AND GAIN RATIO AS PERCENTAGE OF LARGEST VALUE FOR DOMAIN GOAL ONLINE LEARNING COURSE IMPRESSION

No.	features(s)	Info. Gain	Gain ratio	Ranking
1	Visual	30.43	22.45	9
2	Verbal	70.70	61.48	5
3	Intuition	56.38	46.09	7
4	Rational	89.95	85.56	3
5	Sequential	100	100	1
6	Global	73.01	64.16	4
7	Explorer	49.26	39.11	8
8	Adaptor	92.61	89.24	2
9	Active	7.09	4.81	10
10	Reflective	57.47	47.21	6

Table 9 shows that PLSM features were most features effect on online learning course impression except visual and active features which had ratio less than 30%. Consequently, visual and active features the least effect of Intended domain goal. Therefore, students' online course impression can be improved by supporting course designing according to these features. A study of [60] found Reflective learners were found to be the most successful online learners than active learners and sequential learners also outperformed global learners. While [61] found effects of online learning community on active learners might be as great as on reflective learners. Findings of [62] indicted sensory students demonstrate a higher level of online participation and intuitive students a lower level.

TABLE 10. INFORMATION GAIN AND GAIN RATIO AS PERCENTAGE OF LARGEST VALUE FOR DOMAIN ACADEMIC ACHIEVEMENT

No.	features(s)	Info. Gain	Gain ratio	Ranking
1	Visual	77.84	74.23	4
2	Verbal	58.24	53.35	6
3	Intuition	85.88	83.29	3
4	Rational	100	100	1
5	Sequential	94.36	93.21	2
6	Global	64.52	59.86	5
7	Explorer	57.15	52.24	7
8	Adaptor	56.46	51.54	8
9	Active	9.09	7.58	10
10	Reflective	9.42	7.86	9

Table 10 shows that feature active and reflective was the least effect of academic achievement in computer programming and rest of PLSM features had accepted ratio. Enhancing students' academic achievement in computer programming can be happened if course designed according to these result. These findings disagreed to [63] which found reflective strategy was suggested to facilitate the development of templates: schema's representing patterns of code associated with specific programming problems. While recent findings agreed to the results [64] which indicated that increasing support for sensing and visual learners have a greatest benefit for the course. Moreover result in [65] which was sequential learners in general performed better than random learners.

Decision tree learning algorithm was applied on features which were selected to extract rules related to each domain goal were displayed above. Consequently, second aim was achieved.

Regarding provide teachers in designing useful e-course to their learners. Overall advice is presented in final stage of a proposed approach, which was features priority or ranking at three domain goals. PLSM features were ranked based on average of gain ratio related to three domain goals. Teacher should be taken in consideration features' priority when e-courses designing were began as show table 11.

Average ratio will be dividing into three areas as follow: High concentrate is Ratio>80, Medium concentrate is Ratio<=80 and Ratio>60 and Low concentrate is Ratio<=60. Sequential and rational styles have high concentrate. Global, intuition, and adaptor styles have medium concentrate. Where explorer, verbal, visual, reflective, and active styles have low concentrate. Consequently, third aim was achieved.

8. CONCLUSIONS

This paper introduced a proposed most relevant learning styles model and using it to apply decision tree for extracting knowledge. This applicable Knowledge can be exploited in classifying e-course learners according to preferred students' learning styles. Teachers perform identified styles as initial step before design their courses. The evaluation of the approach good results, showing that the approach is suitable for identifying learning styles with respect to domain goals attributes. The proposed approach developed for designing undergraduate students' e-course general rather than for one specific academic. The extracted knowledge about students' learning styles showing students that have different preferences and ways in which they learn. Furthermore, learning styles help teachers in understanding why and when students may have difficulties in learning. In addition, the knowledge can be used for making students themselves aware of their own learning styles to enhance understand about strengths and weaknesses in their learning process. The proposed approach which using data mining is an important step for enhancing and fitting e-courses designing based on students' preferred learning styles. Future work will deal with developing presented approach in identifying learning styles to automatic way for enhancing adaptivity in LMSs, and fit their learning styles based on their prior behaviour in the course.

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