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Automatic Detection of Learning Styles Based on Classical Set Theories in Adaptive Personalised e-Learning System

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Abstract

Learning management system focus on supporting lecturers and/or instructors in creating, administrating and managing online courses; even as witnessed in this COVID-19 era. Meanwhile, there as been less focus on adaptivity and personalisation through automatic detection of learning styles of learners. İt is a general believe that a learner's ability to learn relies to a large extent on what the learner already knows and understands, and the acquisition of knowledge should be an individually tailored process (preferences) of construction devoid of location and time. The learning style provided by Felder-Silverman learning style model (FSLSM) provided some level of determining learners' learning style. However, its deficient in the dynamism requires for automatically detecting learners' learning style. The paper, therefore expoit the Fuzzy and classical set theories on the FSLSM for automatic detection of learning styles for Learners. Self-reported Index of Learning Styles (ILS) questionnaire was administered to 31 randomly selected students of National Diploma level II of the department of Computer Science, Federal Polytechnic, Ile-Oluji. Four courses were used as a pilot study. The students were further made to interact with our designed adaptive and personalised learning management software with the automatic detection scheme embedded. Both the ILS questionnaire and learning style extracted from the software were analysed. The result shows that automatic detection of learning styles based classical set theories scheme performs better than the traditional FSLSM.

1. INTRODUCTION

Learning theories are conceptual framework describing how information is absorbed, processed, and retained during learning. Cognitive, emotional, and environmental influences, as well as prior experience, all play a part in how understanding, or a world view, is acquired or changed and knowledge and skills retained. Those who advocate constructivism believe that a learner's ability to learn relies to a large extent on what the learner already knows and understands, and the acquisition of knowledge should be an individually tailored process of construction.

To identify an individual's learning styles, the self-reported Index of Learning Styles (ILS) questionnaire is most frequently used [1]. The ILS contains eleven questions for each dimension of the model. For the eight learning styles, each distinguishes between balanced, moderate, and strong style expressions. An individual learner's expressions on each of these styles are not to be seen as preferences fixed for life, but as variable ones, depending on the learning context. [2] broadly categorized learning styles into three "categories:" Visual Learners, Auditory Learners and Kinesthetic Learners. By recognizing and understanding learning styles of a learner, better suited techniques can be used. This definitely could improve the speed and quality of learning.

Nowadays, personalised learning services are a key point in the field of online learning as there is no fixed learning path which is appropriate for all learners [3]. However, traditional learning systems ignore these services requirements and deliver the same learning content to all learners.

This approach may not be effective for learners with different backgrounds and abilities. In order to get maximum performance from any learner, there is need to enable the delivery of learning content according to particular learner's needs. However, the individual learners play a central role in traditional as well as technology enhanced learning. Each learner has individual needs and characteristics such as different prior knowledge, cognitive abilities, learning styles motivation, and so on. These individual differences affect the learning process and are the reason why some learners find it easy to learn in a particular course, whereas others find the same course difficult [4]. The individual differences called for adaptive e-Learning to the personalised system. The adaptive e-learning is a process where learning contents are delivered to the learners in an appropriate way at an appropriate time based on the learners' needs, knowledge, preferences and other characteristics. This means that the appropriate contents are delivered to the learners in an appropriate way at an appropriate time based on the learners' needs, knowledge, preferences and other characteristics [5]. Felder pointed out that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style [6][1]. Personalization and Adaptivity are two phenomena that mostly occur in recent learning management systems. [7] identified the key words for a learning environment that are able to motivate, engage and inspire learners as adaptation and personalization. These two words are strongly connected, adaptation is based on personalization.

This paper considers four dimensions of the Felder-Silverman learning style model (FSLSM), a traditional model for determining learning style which is based on Index of Learning Styles (ILS) questionnaire. İt provided some level of determining learners' learning style. However, its deficient in the dynamism requires for determining learners' learning style automatically. Therefore, the paper investigate the possibility of automatic detection of learning style of learners. The paper further stressed that adaptive and personalisation allow the learner to access the most appropriate, interesting and challenging learning activities, and to avoid learning materials already acquired by the learner, but no longer necessary to him. The two features are necessary in the field of e-learning because of its importance in the learners. Adaptive learning gives different students the opportunity to follow individual learning paths and to meet their specific learning/training needs and has received considerable attention [8]. [9] also reaffirmed that personalization and adaptivity features have advantages over the traditional Learning. The two can both be implemented in learning management systems through adaptive learning technology. Aside the automatic detection of learning style of learners, a link between personalization and adaptive learning styles in achieving modern online learning pedagogy could be achieved even as the world is faced with the global challenge of COVID-19 and e-learning is becoming critical tool to sustaining education and learning processes.

2. RELATED WORKS

[10] describes training as a learning process. This process involves gaining knowledge, improving the skills that may lead to a change in attitudes and learning behaviours that will enhance the performance of a particular learner. Training has been described by [11] as a change in level of various skills. [11] draws a distinction between training and education, with education being a change of knowledge and training a change of skills.

[11] defines education as a change of knowledge, while knowledge according to Oxford English Dictionary is the fact or condition of being instructed, or of having information acquired by study or research; acquaintance with ascertained truths, facts, or principles; information acquired by study. [12] in his evaluation of the effectiveness of the e-learning experience in Saudi Arabia categorized the definitions of e-learning from three different perspectives: the distance learning perspective, the technological perspective and also from the perspective of e-learning as

pedagogy. Also, the computer-based learning comprises the use of a full range of hardware and software generally that are available for the use of Information and Communication Technology and also each component can be used in either of two ways: computer managed instruction and computer-assisted-learning. In computer assisted- learning, computers are used instead of the traditional methods by providing interactive software as a support tool within the class or as a tool for self-learning outside the class. In the computer-managed instruction, however, computers are employed for the purpose of storing and retrieving information to aid in the management of education.

There are different theories on how individuals learn, as proposed by different scholars In the same way, implementing e-learning requires a clear understanding of how e-learners learn. According to [13], learning theories can be influential in e-learning. [14] have categorised learning theories into behavioural theory, cognitive theory and humanistic, social and affective learning theories. Such theories support different models of Instructional Design (IS) or Instructional Systems Design (ISD), which mainly focus on exploiting the efficiency and usefulness of instruction, by reflecting on the learning experience through determining the learners state and needs and by setting up the objectives of instruction

Learning styles are unique ways by which an individual learner assimilates, learns and understands a course. It describes the overall behaviour of a learner's learning path. Different learning styles are based on various learning theories. Considering learning styles, investigations are motivated by educational and psychological theories, which argue that learners have different ways in which they prefer to learn. Furthermore, Felder pointed out that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style [1,6].

Adaptivity is a frequently used term in education. Adaptivity in learning deals with the ability to modify the presentation of material in response to learner's performance. In its simplest form, adaptivity is often referred to as a branching technology, where a learner's actions and responses in a task can be calibrated to determine the level and scope of the next activity. Adaptive Learning features are embedded at various levels of content organization in adaptive learning systems (ALS). Four levels are proposed in [15] namely: Learning Object, Sequence, Course, and Set of Courses. The author argued that only the first two levels are suitable for building Adaptive Learning features that are available on every Learning Management System platform. The benefits of adaptivity in learning management systems include; timely learning, platform portability, flexibility, engages learners, rewarding, interactive and quality learner progression.

[16] opined that for an e-learning system to be considered adaptive it should be capable of: monitoring the activities of its users; interpreting these on the basis of domain-specific models; inferring user requirements and preferences out of the interpreted activities, appropriately representing these in associated models; and, finally, acting upon the available knowledge on its users and the subject matter at hand, to dynamically facilitate the learning process. [8] stated that adaptive learning gives different students the opportunity to follow individual learning paths and to meet their specific learning/training needs and has received considerable attention. In [9], the paper reviewed at first the traditional Learning Management Systems and existing Adaptive E-Learning Systems. The conclusion of this review is that a combination of the advantages of modern AES, such as adaptability and personalization with the key features of traditional LMS which are integration, re-use and an adequate set of services for both learners and teachers served by one system is necessary so as an efficient and open learning platform to be developed. In order to fulfil this combination, the proposed approach was to select an open source traditional LMS (Moodle) and upgrade its capabilities focusing on adaptation and

personalization. In line with this goal, the available open source e-learning platforms were evaluated by mainly studying whether and to what extent adaptivity and personalization features are supported by these systems. Moodle obtained the best results in general as well as in the specific adaptation evaluation criterion. The authors therefore suggested an extension of the selected platform in a way that the courses adapt to the unique strengths, learning objectives, knowledge levels, and learning styles of each individual learner was feasible.

It is pertinent to note that while personalization aligns the learning process and experience of the learners to fit learner's profile, adaptivity deals with the ability to modify the presentation of learning material or course in response to learner's performance. [7] identified adaptation and personalization as two key connected phenomena for any learning environment being able to motivate, engage and inspire learners. The authors opined that the two allow the learner to access the most appropriate, interesting and challenging learning activities, and to avoid learning material already acquired by the learner, and then not any more necessary to the learner, even within the context of determing learners learning style. Personalization and adaptivity features are necessary for the production of innovative e-Learning systems differentiating from, the mostly used, static e-Learning systems [9].

3. MATERIALS AND METHOD

3.1 Data

For the purpose of curating data for this work, four courses were selected from the curriculum of the National Diploma (ND) programme of Computer Science. Each course consists of chapters, content objects, an outline, conclusion, example(s), exercise(s) and a self-assessment test(s) object. Each chapter has 3 self-assessment tests, questions, examples. A discussion forum object is provided for the course. At the end of the course, a learner is presented with an examination to access the effectiveness of the learning style detected. Thirty-one out of the number of students offering these courses were selected for the pilot test. The Index of Learning Style (ILS) questionnaire developed by Felder and Silverman was administered to the selected students, thier learning styles were determined from the supplied data and tests were written after a course has been taught in accordance with the determined learning style, also same was done after the students were subjected to the developed system to determine the effectiveness of the learning styles gotten from the developed system. Comparison were made to determine the best between the two. Viz-a-viz collection of their biodata and other subsequent interaction were stored on the learning application database.

3.2 Methods

FSLSM is based on traditional learning rather than online learning. To apply FSLSM in online environments, some sort of mapping between the behaviour in traditional environments and in online environments is necessary [17]. Classical set is used to handle the automatic detection of learning styles.

3.3 Learners' Learning Style Estimation

The following objects (features) stated below are designed as classical sets. Then equations(1-8) were used to test each of the features to handle the automatic detection of learning styles in the adaptive LMS. They include:

i. Content objects: These represent the learning materials. They come in either text, graphics, diagram, flowchart, video and audio objects.
ii. Outline objects: They provide a summary of a chapter.
iii. Overview page objects: Shows the general overview of the course.
iv. Self-assessment tests object: Provides the learner with the opportunity to check their acquired knowledge at each stage of learning process.

v. Exercises object: These objects provide learners with practice tasks.
vi. Examples objects: These objects provide learners with a number of examples for a learned content.
vii. Discussion forums objects: These objects offer shared collaboration and participation between learners during a learning session.

The use of content, outline, overview, exercises, self assessment test examples and discussion forum objects; and the number of visits and time spent by learners on these objects are used to estimate the level of behavioural patterns. Also, regarding navigational behaviour, how often or rarely learners skip learning objects via the navigation is considered in the behaviour pattern estimation.

The following learner's behaviour of FSLSM model dimensions are represented in classicat sets as follows $B_{D1,1}$ = {uses the group discussion objects, discusses content material with other learners or collaborators}

$$B_{D1,1} = \sum_{i=1}^{n} x_i/t \tag{1}$$

$B_{D1,2}$ = {works only with content material objects, doesn't collaborate with other learners, reads comments of other learners in forums but doesn't comment or contribute}

$$B_{D1,2} = \sum_{i=1}^{n} r_i/t \tag{2}$$

$B_{D2,1}$ = {uses more of real life examples objects, spends lesser time on content object, performs more of self assessment tests and exercises, checks answers of self assessment test more often, performs better at questions about facts}

$$B_{D2,1} = \sum_{i=1}^{n} Te_i/t \tag{3}$$

$B_{D2,2}$ = {uses more of equations, spends more time on abstract and mathematical formulations of course content objects, spends more time on course content objects, performs less number of self assessment tests, spends less time on examples, performs better at questions about concepts and theories}

$$B_{D2,2} = \sum_{i=1}^{n} Mf_i/t \tag{4}$$

$B_{D3,1}$ = {uses more of picture, diagram and flowchart objects, tends to answer more questions about that involves graphics, diagram}

$$B_{D3,1} = \sum_{i=1}^{n} Wt_i/t \tag{5}$$

$B_{D3,2}$ = {uses more of written text course content objects, uses more of spoken content object, rarely uses visual aid objects, answers more questions dealing with text}

$$B_{D3,2} = \sum_{i=1}^{n} Pd_i/t \tag{6}$$

$B_{D4,1}$ = {selects the learning materials step by step, learns from parts to whole material, doesn't skip much of some course materials, uses more of detailed explanation object, answers more questions dealing with details, spends less time visiting and dwelling on the course outline or overview}

$$B_{D4,1} = \sum_{i=1}^{n} De_i/t \tag{7}$$

$B_{D4,2}$ = {selects content materials at random, the number of skipped learning objects via the navigation menu is high, uses more of the course outline object, uses more of course overview object, finds connections between different areas of course material, answers more questions dealing with overview knowledge}

$$B_{D4,2} = \sum_{i=1}^{n} Co_i/t \quad (8)$$

Where t is time spent, x is message posted, r is message received, Te is Test written, Mf is mathematical function, W_t is written text, P_d is Picture / diagram, D_e is detailed explanation, Co is course outline.

The computation of the learning style is carried out at the first login session of the learner. It is worthy of note that unlike other related works which determine learning style preference using results from the Index learning Style (ILS) questionnaire, this extended framework determines learning style preference based on levels of behaviour(s) and actions exhibited during the first login session by a learner. The estimated learning style outcome will determine which learning style preference a learner exhibits and subsequently determine the number of learning objects to be personalised to the learner.

4. RESULTS AND DISCUSSIONS

The randomly selected thirty-one (31) students were made to fill the Index of Learning Style (ILS) questionnaire. The analysis of the questionnaire, their biodata and other interactions with them were collected and stored on the designed e-learning web-based software-Adaptive Personalised Learning Management System (see figure 1). Thereafter, each of the students were made to interact with the software and based on their stored preferences, the system could now track and detect their learning style.

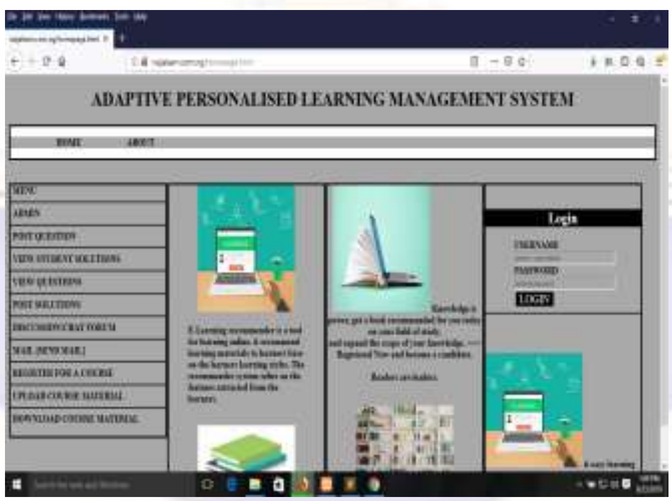

Figure 1: The interface of Adpative Personalised Learning Management System

The result of the students learning style was firstly exracted from the ILS to determine the students learning style as presented in Table 1 for questionaire based learning style detection, while Table 2 shows the automatic learning stlye detected as extracted from the designed adaptive personalised e-learning software (See figure 1). The two results were compared as presented in Table 3.

Table 1: Result of QBLSD for COM 211

S/n	Student ID	QBLSD	COM 211
1	FPI/CSC/17/001	GL	40
2	FPI/CSC/17/002	GL	50
3	FPI/CSC/17/003	AC	48
4	FPI/CSC/17/004	SQ	55
5	FPI/CSC/17/005	IN	53
6	FPI/CSC/17/006	SE	60
7	FPI/CSC/17/009	SQ	53
8	FPI/CSC/17/011	AC	58
9	FPI/CSC/17/012	SQ	42
10	FPI/CSC/17/013	GL	51
11	FPI/CSC/17/014	GL	49
12	FPI/CSC/17/015	VE	51
13	FPI/CSC/17/016	VI	48
14	FPI/CSC/17/017	VI	61
15	FPI/CSC/17/019	RE	36
16	FPI/CSC/17/022	VE	56
17	FPI/CSC/17/023	RE	59
18	FPI/CSC/17/025	SE	51
19	FPI/CSC/17/026	VI	63
20	FPI/CSC/17/027	AC	59
21	FPI/CSC/17/031	RE	39
22	FPI/CSC/17/034	AC	49
23	FPI/CSC/17/037	IN	41
24	FPI/CSC/17/038	GL	58
25	FPI/CSC/17/039	SE	60
26	FPI/CSC/17/040	VI	63
27	FPI/CSC/17/041	SQ	55
28	FPI/CSC/17/045	VI	55
29	FPI/CSC/17/046	VE	59
30	FPI/CSC/17/047	VI	65
31	FPI/CSC/17/048	VE	44

QBLSD-Questionare-based Learning Style Detected

Table 2: Result of ALSD for COM 211

S/N	Student Id	ALSD	COM 211
1	FPI/CSC/17/001	AC	58
2	FPI/CSC/17/002	AC	70
3	FPI/CSC/17/003	VI	71
4	FPI/CSC/17/004	GL	69
5	FPI/CSC/17/005	VI	65
6	FPI/CSC/17/006	AC	72
7	FPI/CSC/17/009	SQ	54
8	FPI/CSC/17/011	VE	68
9	FPI/CSC/17/012	VE	60
10	FPI/CSC/17/013	AC	69
11	FPI/CSC/17/014	SE	74
12	FPI/CSC/17/015	AC	77
13	FPI/CSC/17/016	VI	50
14	FPI/CSC/17/017	SE	78
15	FPI/CSC/17/019	VI	52
16	FPI/CSC/17/022	VE	56
17	FPI/CSC/17/023	RE	63
18	FPI/CSC/17/025	VI	65
19	FPI/CSC/17/026	VI	73
20	FPI/CSC/17/027	AC	74
21	FPI/CSC/17/031	VI	52
22	FPI/CSC/17/034	VE	58
23	FPI/CSC/17/037	SE	48
24	FPI/CSC/17/038	GL	56
25	FPI/CSC/17/039	AC	75
26	FPI/CSC/17/040	SQ	78
27	FPI/CSC/17/041	GL	65
28	FPI/CSC/17/045	VI	56
29	FPI/CSC/17/046	SQ	68
30	FPI/CSC/17/047	VI	72
31	FPI/CSC/17/048	VE	46

ALSD-Automatic Learning Style Detected

Table 3: Performance comparison of automatic learning style detected and the questionnaire learning style detected for a

S/n	Student ID	ALSD	COM 211	QLSD	COM 211
1	FPI/CSC/17/001	AC	58	GL	40
2	FPI/CSC/17/002	AC	70	GL	50
3	FPI/CSC/17/003	VI	71	AC	48
4	FPI/CSC/17/004	GL	69	SQ	55
5	FPI/CSC/17/005	VI	65	IN	53
6	FPI/CSC/17/006	AC	72	SE	60
7	FPI/CSC/17/009	SQ	54	SQ	53
8	FPI/CSC/17/011	VE	68	AC	58
9	FPI/CSC/17/012	VE	60	SQ	42
10	FPI/CSC/17/013	AC	69	GL	51
11	FPI/CSC/17/014	SE	74	GL	49
12	FPI/CSC/17/015	AC	77	VE	51
13	FPI/CSC/17/016	VI	50	VI	48
14	FPI/CSC/17/017	SE	78	VI	61
15	FPI/CSC/17/019	VI	52	RE	36
16	FPI/CSC/17/022	VE	56	VE	56
17	FPI/CSC/17/023	RE	63	RE	59
18	FPI/CSC/17/025	VI	65	SE	51
19	FPI/CSC/17/026	VI	73	VI	63
20	FPI/CSC/17/027	AC	74	AC	59
21	FPI/CSC/17/031	VI	52	RE	39
22	FPI/CSC/17/034	VE	58	AC	49
23	FPI/CSC/17/037	SE	48	IN	41
24	FPI/CSC/17/038	GL	56	GL	58
25	FPI/CSC/17/039	AC	75	SE	60
26	FPI/CSC/17/040	SQ	78	VI	63
27	FPI/CSC/17/041	GL	65	SQ	55
28	FPI/CSC/17/045	VI	56	VI	55
29	FPI/CSC/17/046	SQ	68	VE	59
30	FPI/CSC/17/047	VI	72	VI	65
31	FPI/CSC/17/048	VE	46	VE	44

Tables 1 and 2 are used to measure the effect of questionnaire-based learning learning style and automatic learning style detection of a learner respectively. The result as presented in Tables 1-3, using COM 211 (Computer Programming using OO Basic) as a typical example for determining the effectiveness of the two learning styles shows that, ten (10) students have the same learning style in both automatic and questionnaire while twenty one (21) students have different learning styles detected. From *Figure 2*, it is clear that 29 out of 31 students performed better in automatic detection than using questionnaire in detecting the learning style.

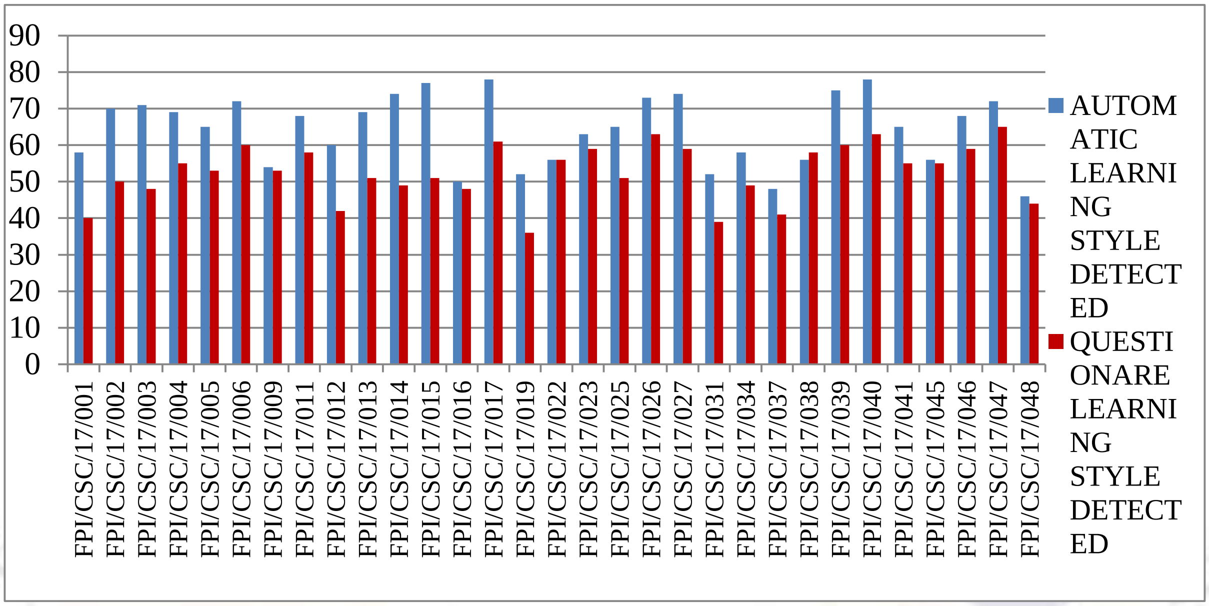

Figure 2: Comparison Performance of automatic learning style detection and using of questionnaire

with their needs and behavious which are rarely used in practice. This paper has discussed this issues by providing an approach for automatic dectection learning style using classical set theories than what is obtainable in traditional learning style of FSLM using the ILS. The work further establish the collaboration of adaptive and personalised learning technigues into the automatic learning style detection (ALSD) scheme as provided in the paper. The comparative analysis between ALSD and FSLM for learning style shows that ALSD perform better in determing learners' learning style. Adaptive and personalised learning techniques with ALSD could be embedded into learning management applications. We suggest that focus can be made on the automatic detection of learning styles by using more features to classify the learners into different group of learning styles.

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