2. RELATED WORKS

[10] describes the 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 the 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 in knowledge, while knowledge, according to the 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, he 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, 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 computer-managed instruction, however, computers are employed to store and retrieve information to aid in the management of education.

There are different theories about 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 learning if the teaching style does not match their learning style. [6][1]. Adaptivity is a frequently used term in education. Adaptivity in learning deals with the ability to modify the presentation of material in response to the 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 organisation 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 based on 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 allows different students to follow individual learning paths and to meet their specific learning/training needs and has received considerable attention. In [9], the paper reviewed the traditional Learning Management Systems and existing Adaptive E-Learning Systems (AES). This review concludes that an efficient and open learning platform requires a combination of the benefits of modern AES, such as adaptability and personalization, and the key features of traditional LMS, such as integration, re-use, and an adequate set of services for both learners and teachers served by one system.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 learner. It is pertinent to note that while personalization aligns the learning process and experience of the learners to fit the learner's profile, adaptivity deals with the ability to modify the presentation of learning material or course in response to the learner's performance. [7] identified adaptation and personalization as two key connected phenomena that must be present in any learning environment in order 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 anymore necessary to the learner, even within the context of determining the learner's learning style. Personalization and adaptability features are required for the development of innovative e-Learning systems that differ from the most commonly used static e-Learning systems [9].

3. MATERIALS AND METHOD

3.1 Data

To curate 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. Their learning styles were determined from the supplied data, and tests were written in accordance with the determined learning style. The 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. A comparison was made to determine the best between the two. Viz-a-viz collection of their biodata and other subsequent interactions were stored in 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]. The 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: Content objects: These represent the learning materials. They come in either text, graphics, diagrams, flowcharts, or video and audio objects. Outline objects: They provide a summary of a chapter. Overview page: Shows the general overview of the course. Self-assessment tests provide the learner with the opportunity to check their acquired knowledge at each stage of the learning process. Exercise objects: These objects provide learners with practise tasks. Examples of objects: These objects provide learners with several examples for learned content. 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 navigation is considered in the behaviour pattern estimation. The following learner's behaviour of FSLSM model dimensions are represented in classical sets as follows: ,B-D1,1. = {uses the group discussion objects, discusses content material with other learners or collaborators}

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

$B_{D1,2}$ = {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}

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

$B_{D2,1}$ = {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}

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

$B_{D2,2}$ = {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}

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

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

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

$B_{D3,2}$ = {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}

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

$B_{D4,1}$ = {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}

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

$B_{D4,2}$ = {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 the message posted, r is the message received, Te is Test written, Mf is a mathematical function, W_t is written text, P_d is Picture / diagram, D_e is a detailed explanation, Co is the course outline.

The computation of the learner's 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 of 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 was made to interact with the software and based on their stored preferences, the system could now track and detect their learning style.

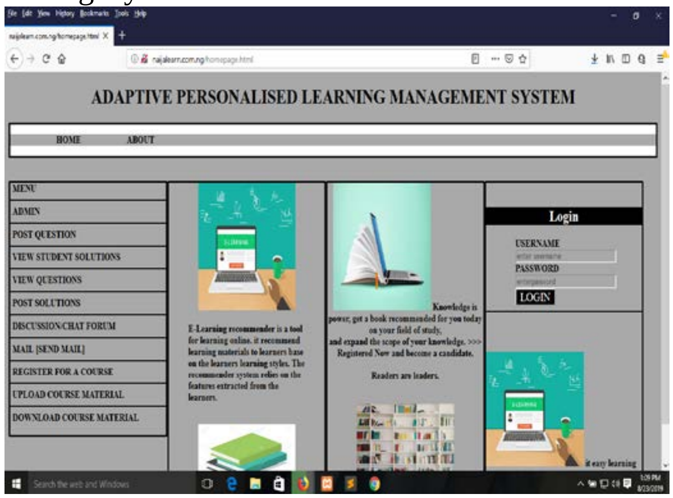

Figure 1: The interface of Adpative Personalised Learning Management System

The result of the students' learning style was first extracted 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 style 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 Questıonare-based Learnıng Style Detected for a particular course-COM 211

S/n	*Student ID*	*Questıonare-based Learnıng Style Detected*	*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*

Table 2: Result of Automatic Learning Style Detected for a particular course-COM 211

S/N	*Student Id*	*Automatic Learning Style Detected*	*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*

Table 3: Performance comparison of automatic learning style detected and the questionnaire learning style detected for a particular course-COM 211

S/n	*Student ID*	*Automatic Learning Style Detected*	*COM 211*	*Questionare Learning Style Detected*	*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

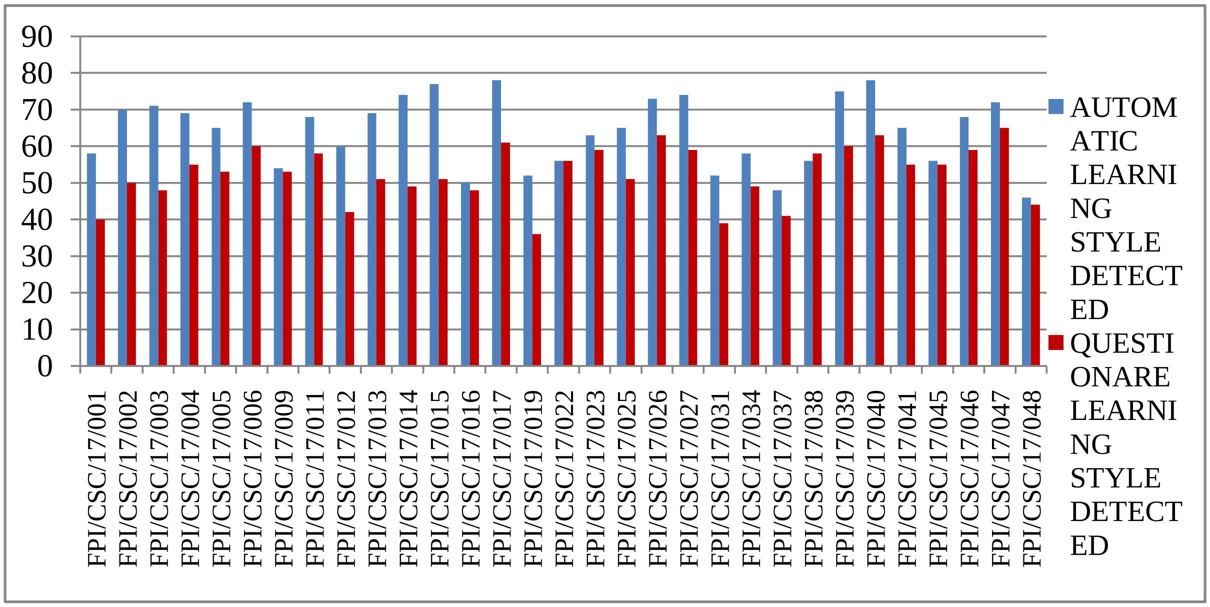

Figure 2: Comparison Performance of automatic learning style detection and using of questionnaire

Table 1 and 2 were used to measure the effect of questionnaire-based 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 a questionnaire in detecting the learning style.

5. CONCLUSIONS

Learning management system focuses on supporting lecturers and/or instructors in creating, administrating, and managing online courses, but there has been less focus on adaptivity for learners. While adaptive systems support learners by providing courses that are in accordance with their needs and abilities, these are rarely used in practice. This paper has discussed these issues by providing an approach for automatic detection learning styles using classical set theories rather than what is obtainable in the traditional learning style of FSLM using the ILS. The work further establishes the collaboration of adaptive and personalised learning techniques 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 performs better in determining learners' learning styles. 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 a different group of learning styles.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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