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Felder-Silverman Learning Style Model, Item response theory, Ontology, Learning ability, Difficulty level

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DEVELOPMENT OF AN ONTOLOGY-BASED ADAPTIVE PERSONALIZED E-LEARNING SYSTEM

Abstract

E-learning has fast become an active field of research with a lot of investments towards web-based delivery of personalized learning contents to learners. Some issues of e-learning arise from the heterogeneity and interoperability of learning content adapting to learner's styles and preferences. This has brought about the development of an ontology-based personalized learning system to solve this problem. This research developed an ontology-based personalized e-learning system that presents suitable learning contents to learners based on their learning style, preferences, background knowledge, and personal profile.

1. INTRODUCTION

Learning is enormously affected by the improvement of Information and Communication Technologies and informed computerized media. E-learning enables access to the training of individuals who think that it's hard to be physically present in the customary study of hall-based learning (Boyinbode & Akintade, 2015; Uhomoibhi, 2006). Personalization is said to exist where training programs are customized to individual learners, based on an analysis of the learners' objectives, current status of

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skills/knowledge, learning style preferences, as well as constant monitoring of progress. Online learning material can be compiled to meet personal needs, capitalizing on re-usable learning objects (Boyinbode & Bagula, 2012).

Some educational issues are taken care of normally through the presentation of a personalized adaptive e-learning system (Adewale, 2006). This system encourages students to learn effectively based on their style of learning and enhance improvement in the performance of the learners. The adaptability of the E-learning platform encourages students to learn with their most preferred method of learning and finish their courses effectively (Adewale, 2006).

2. REVIEW OF RELATED WORK

Kurilovas et al. (2016) developed a personalized learning system based on students' learning styles and application of intelligent technologies, where learners have different features and characteristics such as prior knowledge, intellectual level, interests, goals, cognitive traits (working memory capacity, inductive reasoning ability, and associative learning skills), there came a need for learning behavioral type (according to his/her self-regulation level) and finally learning styles.

The system was designed to perform a systematic review of learning personalization; identify a student with certain learning style, according to felder and silver man learning style model (FSLSM) and finally create a model of personalized intelligent learning system based on students' learning styles, cognitive traits, and other personal characteristics and needs. FSLSM is recognized to be the most suitable for STEM (Science, Technology, Engineering, and Mathematics) and e-learning. Dedicated psychological questionnaire – Sloman and Felder's Index of Learning Styles is used to explore students' learning styles according to FSLSM. The research does not include the creation of pedagogically sound vocabularies of the learning components.

Funda and Aynur (2009) analyzed relations between online learning and learning styles; researchers have investigated that presentation of learning content and learning tools are based on learning styles in the online learning, environments are a factor which impacts the academic achievements of the learner. In the other research approach, researchers have used learning styles as a supportive factor to design the online learning environments for personalized online learning. The hybrid of these research approaches was adopted which suggested that improving the academic achievements of the learners can be achieved by considering the motivation of the learner, demographics factors, teaching strategies, and teaching methods.

Latha and Kirubakaran (2013) presented a Personalized Learning Path Delivery in Web-based Educational Systems using a Graph Theory-based Approach. The absence of a teacher or trainer becomes a bottleneck inappropriately delivering contents to the learner. Developing a system with a novel way of recommending a personalized learning path to a user became important; a graph theory-based approach in web-based learning systems was adopted to make the learning process effective.

Agbonifo and Obolo (2018) developed a Genetic Algorithm-based Curriculum Sequencing Model for Personalised E-Learning System, in which the difficulty level and the relationship degree that exists between various course concepts were recorded to affect the learning ability and the overall performance of the learner. The research focused on enabling the learner to identify the difficulty level of each course concept or curriculum and the relationship degree that exist between them to provide optimal personalized learning pattern to the learner to improve their performance.

Yarandi et al., (2013) proposed an adaptive e-learning approach based on semantic web technology; it is becoming increasingly difficult to ignore adaptation in the field of e-learning systems. Many researchers are adopting semantic web technologies to find new ways for designing adaptive learning systems based on describing knowledge using ontological models; this motivated the development of a personalized adaptive e-learning approach based on semantic (ontology) web technology.

3. METHODOLOGY

Ontology is characterized as a representation of a phenomenon's dynamic model on the world using conceptualization, which helps with distinguishing the allotment of area ideas, using formal definitions regarding adages and the ideas' semantic connections (Chi, 2009). Information portrayal utilizing ontologies encourages sorting out the metadata of complex data assets.

These metadata give syntactic and semantic data about data assets which are encoded as examples in the cosmology. Differential Equations are characterized as ideas or classes. W3C Web Ontology Language (OWL) is a Semantic Web language designed to represent rich and complex knowledge about things, groups of things, and relations between things. The OWL file obtained from the protégé tool is used to extract the concepts or classes that are represented in a specific domain through the domain ontology. These concepts are saved in a vector denoted as $C= [c1, c2, c3..., cm]$ to determine similarities with the XHTML files produced from HTML files. The algorithm used for the extraction of OWL concepts is given:

Algorithm:

Ontology concept extraction
Input: OWL Ontology Document
Output: Vector of Ontology Concepts (C)
BEGIN
1. *Declare Vector (C), OWL Ontology Document, Xpath;*
2. *Define XPATH to get the Ontology concepts from the input OWL Ontology Document*
3. *Pass ontology concepts and store into (C)*
4. *Return Vector of Ontology Concepts (C)*

END

3.1. System Architecture

The ontology-based adaptive personalized e-learning system proposed consists of the following major components as shown in Figure 1.

3.1.1. User Interface

This gives a versatile and easy to use interface for communication with learners. The interface connects user features to the user model ontology, and enables sending the adaptive content from the Adaptive Engine to the user. The user interface additionally sends back the user's reactions to the adaptive engine. For a start-up user, there is an enrollment cycle, where the general and instructive attributes of the user are taken and recorded into the ontological based user model.

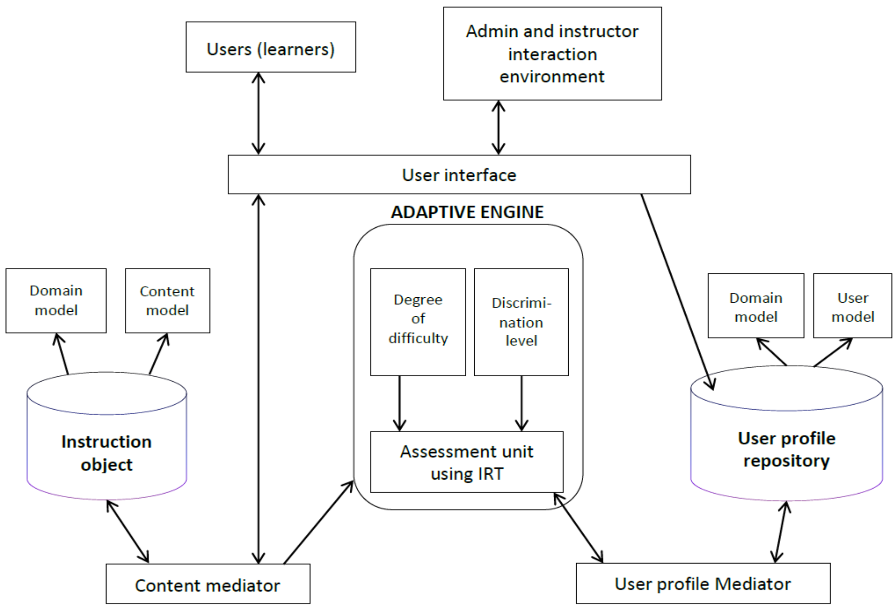

Fig. 1. The Architecture of the System

3.1.2. Personalized Adaptive Engine

This signifies the powerhouse of the e-learning structure which is responsible for presenting personalized learning content anchoring on the material available in the learner's model. The engine merges up instruction objects to produce particular and structured learning content for a particular learner. It obtains facts about learners and learning objects with associated mediators. The engine is also an evaluation element to re-evaluate the stage of knowledge and ability of learners.

This section will subject learners to regular tests and evaluates their performance in the selected topic and also learner's ability based on the item response theory. The user model is updated on the note of the evaluated information acquired from the result of the assessments, which will redefine the profile of the user.

3.1.3. User Profile Mediator

The Mediator is liable for the management of any form of requests, for opening and modernizing the user model repository.

3.1.4. Content Mediator

The Content Mediator is in control of examining the repository and retrieving diverse kinds of instruction objects depending on the diverse instructional role. This mediator also conforms the retrieved Instruction objects into Lessons and marks lessons spontaneously.

The construction comprises two repositories namely Instruction Objects and user profiles. The Instruction Object repository comprises of all learning contents and their metadata based on the content model ontology.

3.1.5. User Profile Repository

This is where the user profile and activities are stored. It houses all users' actions on his/her interfaces.

3.1.6. Domain Model

The domain model is a semantic ontology which is determined by the course creator and structures a coherent scientific classification for the information area. It indicates the subject order of learning objects. The domain ontology contains classes and properties, that portray subjects of an area and educational relationship, between proposed titles or topics. In this system, General Studies Course (GNS) is used for the system.

3.1.7. User Model

The system designs an ontological user model that design the user profile. It includes all the properties of the user(learner). The learner's properties are arranged in two groups including user identification information and learning profiles. User identification information such as names, date of birth, sex, passwords, and emails are kept in the personal information class through data properties which are attached to this class. Other classes and properties of this ontology are designed to characterize the learner's learning profiles such as preferences, learning performance, learning abilities, and learning styles.

The individual learner will also be attached to a set of performance-related data that is presented in performance class via has performance property. Learning performance which contains prior knowledge and gained knowledge can be obtained as a result of technical examination which is taken by individual learners. Ability class will represent the abilities of learners, which are calculated according to item response theory during the learning process. The learning styles of individual learners are recorded in the learning style class based on the Felder-Silverman Learning Style Model (Brusilovsky et al., 2005). This model defines four dimensions namely active-reflective, visual-verbal, sensing-intuitive, and sequential-global for a particular learner. The learning style class presents these dimensions through the learning category class. The learning style of each learner is determined through the result of a questionnaire based on the Felder and Silverman's learning style model.

The learning ability of the learner is calculated using item response theory according to Chen and Chung (2008), which also confirms, that the difficulty level of the recommended content is extremely relevant to learners' abilities. Additionally, the wrong content can result in learner's intellectual confusion in learning practice. In the first step, the learner's ability initiates at a moderate level. In different levels of learning, tests are taken from individual learners regularly and their response is analyzed according to the Item Response Theory (Baker, 2001), which will dynamically estimate and update learners' abilities. In the next level, the right content is recommended based on the updated abilities.

Item response theory is a model-based method designed to choose the most suitable items for learners based on accurate relationships between abilities and item responses. Item response theory is built on the postulation that the likelihood of a correct response to an item is a mathematical function of personalized and itemized variables. The element variable is considered as the item difficulty, item discrimination, and the effect of random guessing. (Baker, 2001).

$$P_i(\phi) = c_i + (1 + c_i)\frac{1}{1+\exp(-a_i(\phi - b_i))}. \tag{1}$$

$P_i(\phi)$ is the probability that an examinee with ability ϕ can respond correctly to the item i. The three-parameter logic function is adapted where:
b_i is the difficulty parameter of item i,
a_i is the discrimination degree of item i,
c_i is the guessing degree of item i,
ϕ is the ability level of the learner.

In this methodology, the item parameters are kept in the Item class of content ontology through some data properties such as the difficulty, discriminations, guessing, etc.

To evaluation, the ability of a learner, the answers of the learner for all items of an exam are distinctly scored. This means that the learner has 1 for a unique answer scored correctly and 0 for the answer gotten wrongly. Hence, there is a response pattern of the form (U_1, U_2, U_3 ... U_j ... U_n) known as test response vector, where $U_j = 1$

is known for a correct answer gotten by the learner for the j^{th} item in the exam. On the contrary, $U_j = 0$ signifies a wrong answer gotten by the learner for the j^{th} item in the exam (Hambleton, Swaminathan & Rogers, 1991). Bock derived the quadrature form to estimate the learner's ability (Baker, 1992):

$$\phi = \frac{\sum_k^q \phi L(u_1, u_2, \ldots, u_n|\phi) A(\phi_k)}{\sum_k^q L(u_1, u_2, \ldots, u_n|\phi) A(\phi_k)}, \tag{2}$$

where ϕ is the estimation of the ability of the learner, $L(u_1, u_2, \ldots, u_n|\phi)$ is the value of likelihood function and $A(\phi)$ represents the quadrature weight at a level below the learner's ability.

$$L(\phi|u_1, u_2, \ldots, u_n) = \prod_{i=1}^{n} P(\phi)^{u_1} \, Q(\phi)^{(1-u)}, \tag{3}$$

where $P_i(\phi)$ represents the chances that the learner answers correctly to the i^{th} item at a level below his ability level ϕ, $Q_i(\phi) = 1 - P_i(\phi)$ signifies the likelihood that the learner answered inaccurately to the i_{th} item at a level below the ability level, $, u_i = 1$ if the result of the i_{th} item is correct and $, u_i = 0$ if the response of i_{th} item is inappropriate (Chen & Chung, 2008). To calculate the difficulty level of the course items, Crocker, and Algina (1986) was adapted:

$$P_i = \frac{A_i}{N_i}, \tag{4}$$

where P_i is the difficulty index of item i, A_i is the number of the correct answer to item i, and N_i is the number of correct answers plus the number of the incorrect answers to item i.

The difficulty of an item is understood as the proportion of persons who answer a test item correctly, the higher this proportion the lower the difficulty level and vice versa. The discrimination level of the items;

$$a_i = D_i = \frac{GH\ correct\ answer - GL\ correct\ answer}{0.5 * N_{large\ group}}, \tag{5}$$

where D_i the discrimination index of item i. $GH\ correct\ answer$ is the number of the correct answer to item i among those with the highest test score. $GL\ correct\ answer$ is the number of the correct answer to items i among those with the lowest test score.

The discrimination level of an item is normal if it's approaching one, hence the item is acceptable, else if the discrimination level of an item is approaching zero, the item is poor and unacceptable.

The guessing degree is calculated by adding up the number of points earned by all learners on an item and divides it by the total number of learner (Abu-Sayf, 1979):

$$G = \frac{P_{total}}{L_{total}}, \tag{6}$$

where G is the guessing degree, P_{total} is the total number of points by the learner and L_{total} is the total number of the learner.

Guessing is discouraged utilizing instructions given on the test and by scoring the test in such a way as to penalize those who guess incorrectly by the use of formula scoring (correction for guessing). Though the procedure has been a source of controversy for many years (Hamzeh, 2005):

$$S = R = \frac{W}{A-1}, \tag{7}$$

where S represents the corrected score, R represents the number of right answers, W represents the number of wrong answers, A represents the number of alternatives per item.

Item Response Theory is used in the high-tech adaptive test to define the best items for learners based on their distinct abilities. Currently, the Computerized Adaptive Testing (CAT) concept has been successfully used in many real applications such as GMAT, GRE, and for the TOEFL.

4. IMPLEMENTATION AND RESULTS

This section defines the implementation of a personalized adaptive e-learning system. The system interface is displayed upon the successful launch of the page.

4.1. Registration Page

The registration page allows new learners to register using the registration form before login in, it's done using the "sign up menu" (Figure 3).

4.2. Home Page

Displays the first page the user comes in contact with when he/she successfully logs into the system, it is the page, where the user signs up and logs in. This is to ensure that only registered and valid users are allowed to perform certain tasks in the portal. A learner can also register and login to the portal to check the delivered content suitable for them based on their learning style (Figure 4).

4.3. FSLSM Learning Style Detector Page

This contains a catalog of questions, each first-time user answers to detect their learning style to enhance the right delivery of content (Figure 5).

4.4. The Dashboard Page

This page contains an overview of the list of departments, and courses present in the system.

4.5. Examination and Test Score Page

This page is the interface for examination concerning the course taking and also helps in displaying the examination scores of the user (Figure 6).

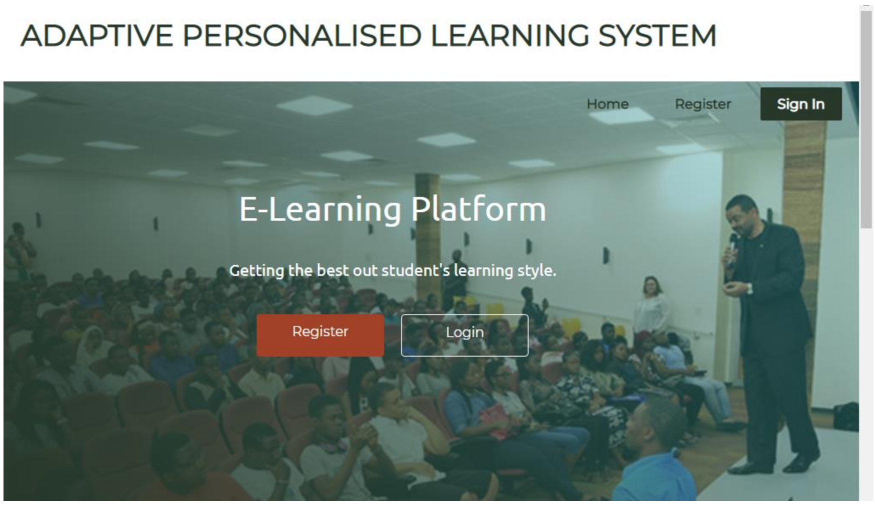

Fig. 2. System Home Page

Users access the system by registering into the system in other to generate the username and password for the user to login with into the system.

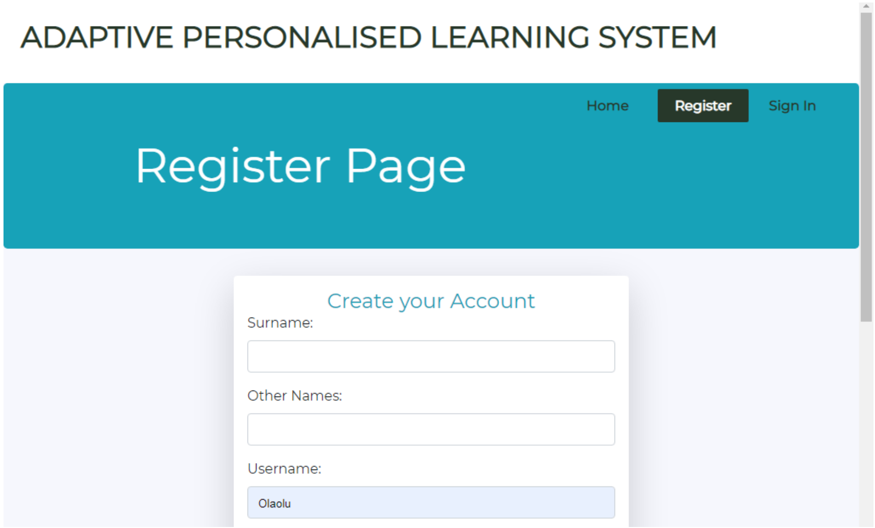

Fig. 3. Register page

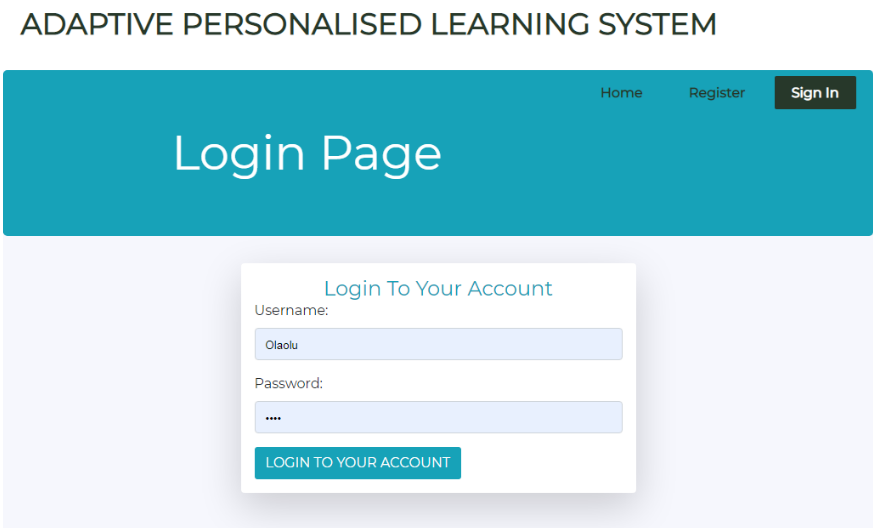

Fig. 4. Showing the Login page for the system

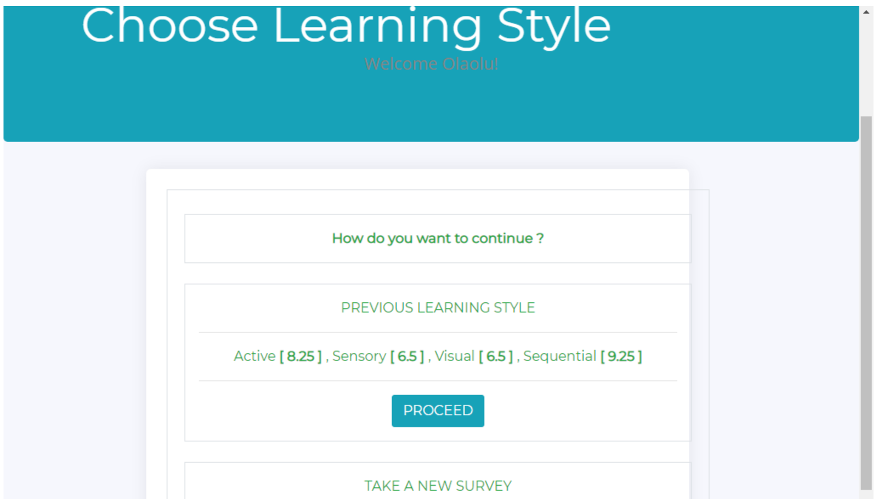

Fig. 5. Showing the record of the learning styles

For a new user, it is mandatory to run a survey which will help the system to capture the learning style of such user, and for an existing user, the learning style has been captured and saved and the user can easily continue with the saved learning style and also has the option of retaking the survey to confirm his or her learning style (Figure 5).In the dashboard of the system, different functions are displayed and the user can easily navigate through the system to enroll (Figure 6).

The user browses courses to check the courses available for enrollment. At the enrolling stage, the user is expected to enroll for a 'beginner' as the proficiency level, because the courses are designed ontologically such that the beginner has courses arranged for that category base on the difficulty level of those courses, which after successful completion of the beginner level, an examination that will show the eligibility of the user to move to the next level, which is the intermediate level is delivered to the user (Figure 7 and 8). Also, there is provision for new users that claim to be at the intermediate or expert level to take an examination of the previous level to determine his/her fitness for that level. A brief examination summarizing the knowledge of the beginner level is given for the intermediate level.

A concise examination for intermediate level is delivered, for the expert level. The eligibility of the user for the level will be determined; if the user failed the examination, he/she cannot proceed to the next level. The system will communicate to the user that he/she is not qualified for the level claimed, please go for the beginner level (Figure 9).

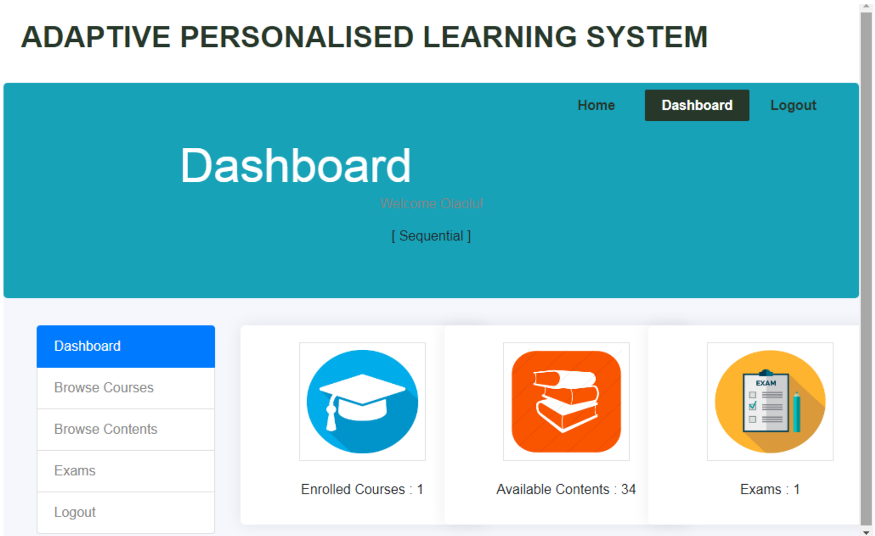

Fig. 6. Showing the Dashboard for the system

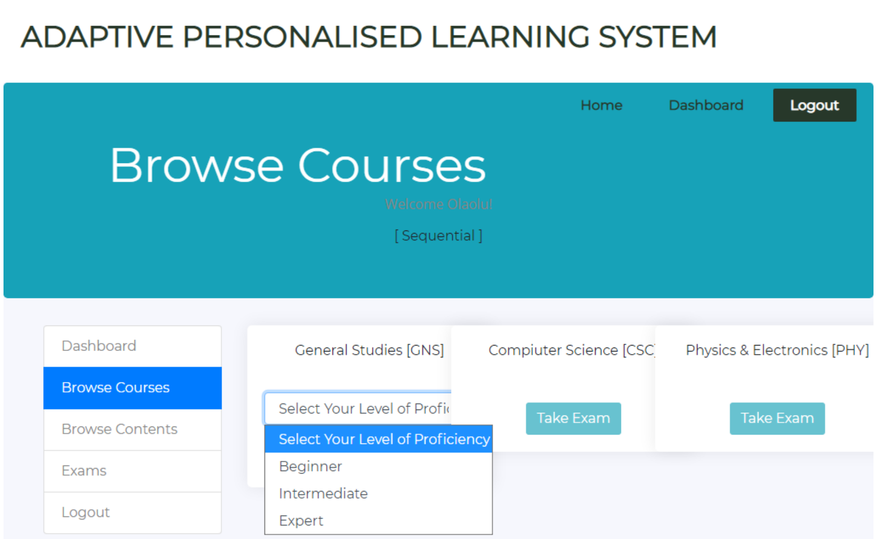

Fig. 7. Showing the Learning Categories

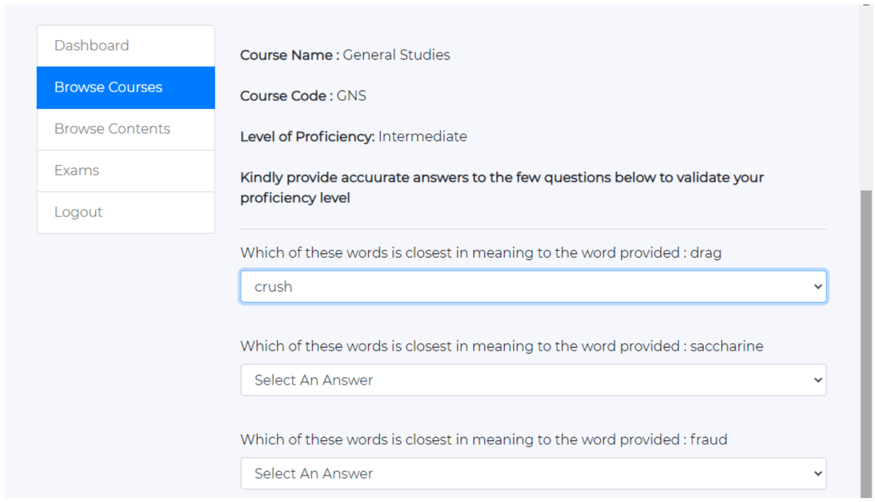

Fig.8. Showing the Eligibility Test Page

Also, if the user is not eligible for the proficiency level he or she claims, it will be revealed in the performance of the user in the eligibility test. The user has just two times, to attempt the eligibility test after which if the user failed, the system will recommend the user to start from the beginner level of the course (Figure 9).

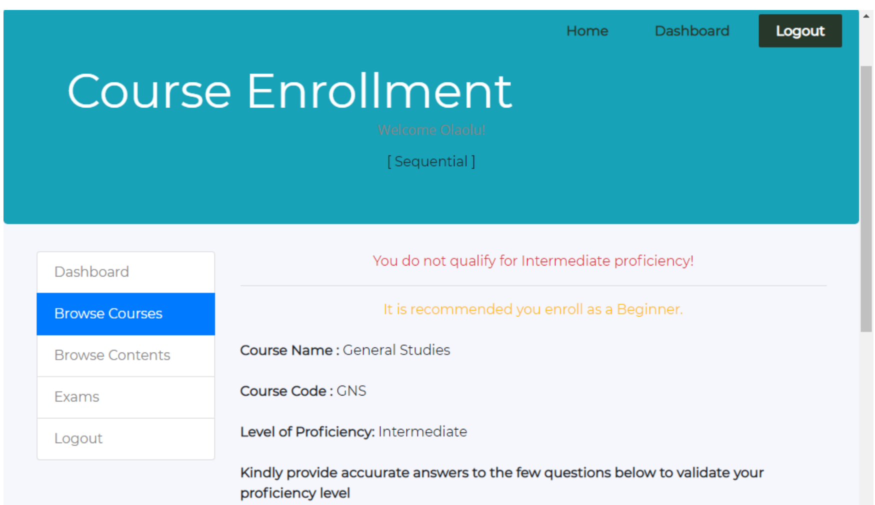

Fig. 9. Course Enrolment

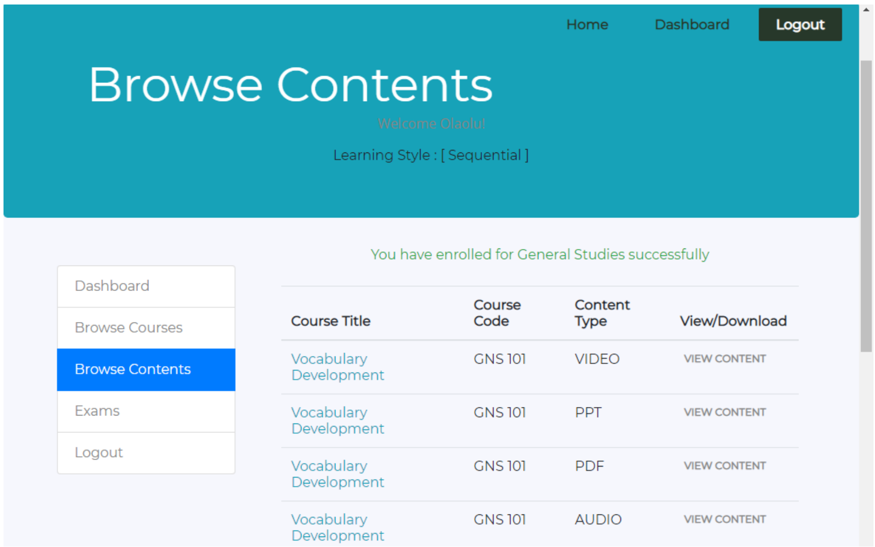

Fig.10. Showing Personalized Content for the Learner

Different types of contents will be delivered to the user based on the learning style of the user. On the successful registration of the user for the beginner level, the system delivers contents to the user based on the learning style, proficiency level, and the profile of the user stored in the user profile repository (Figure 10).

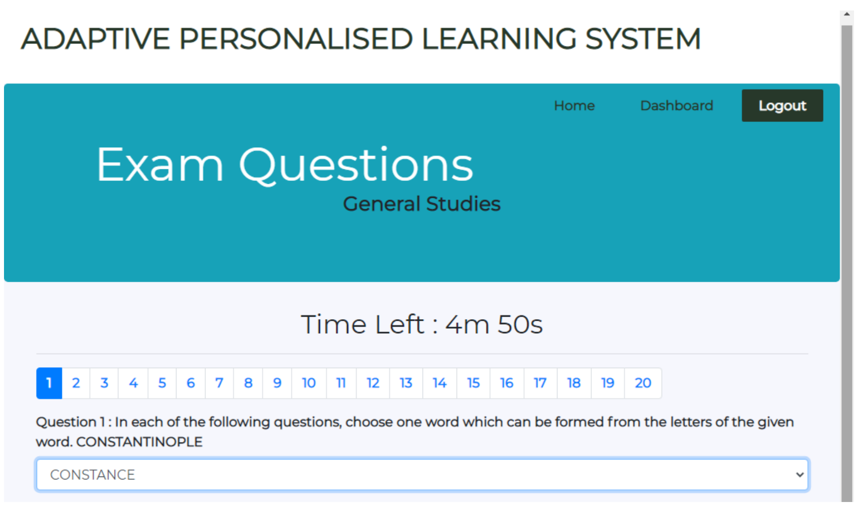

Fig. 11. Page Showing the Examination for the Beginner Level

The user is expected to view or download the various types of contents delivered to the user, after which the user is expected to take examination based on the content delivered (Figure 11).

The performance of the user in the examination taken, is the determinant of the eligibility of the user to move to the next level in the course. The course is slated for three-level, the beginner, the intermediate, and the expert level, such that the performance of the user at each level will show the eligibility of the user for the next level. The performance of the user reflects, the score of the user and the learning ability of the user (Figure 12).

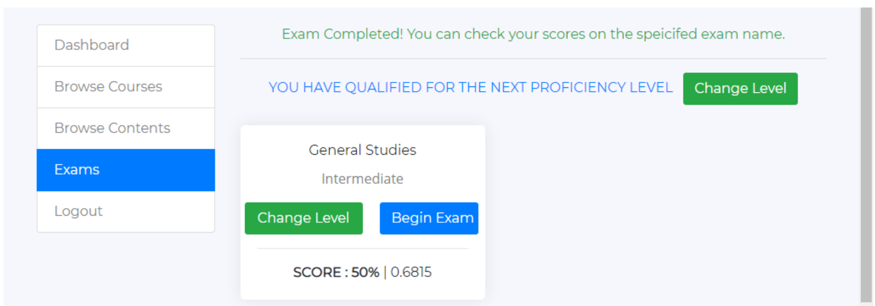

Fig. 12. Showing A Learner Score and Learning Ability Qualified for The Next Level

In Figure 12, the exam score is 50 percent and the learning ability of this user is 0.68 of 1, the system also communicates the eligibility of the user for the next level, but if the performance of the user score is not up to 50% for the next level (Figure 13); then the user cannot proceed to next level (Figure 14).

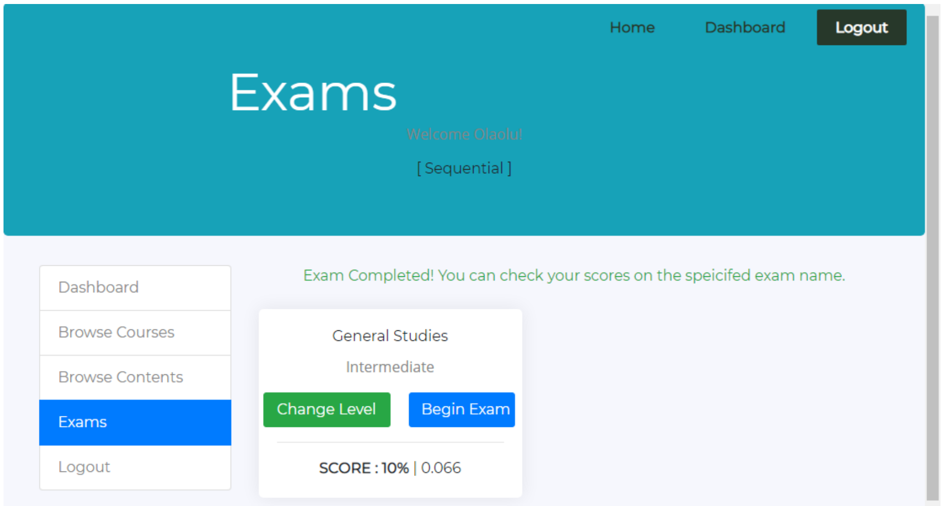

Fig.13. Showing Examination Score and the Learning Ability

On the attempt to move to the next level, the system will display that the user is not eligible and will be taken back to the page, where the same level examination will be re-taken (Figure 14).

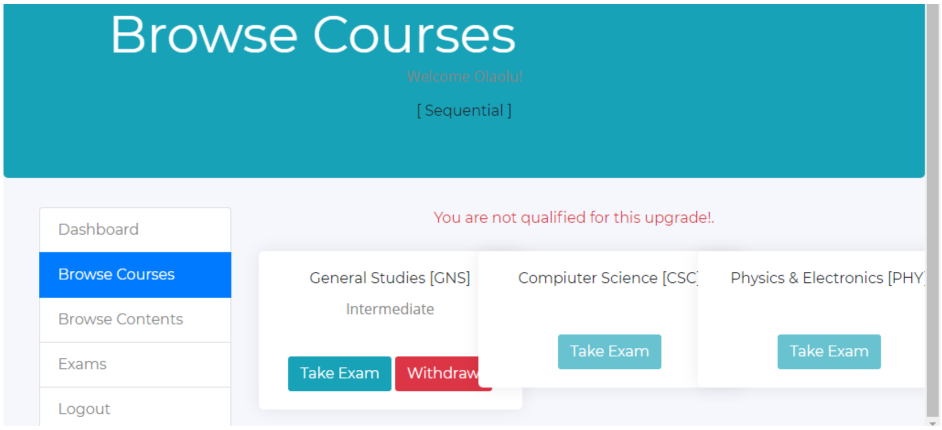

Fig. 14. Showing the System Result

5. EVALUATION

The course used for the case study is General Studies Course (GNS 101), an English course offered by all 100 level students of the Federal University of Technology, Akure, Nigeria. The system was designed for three categories of learners which include, the beginner, the intermediate, and the expert learners.

The learning contents were structures using ontology covering different categories. For the beginner category the contents include: I) Adjectives, II) Adverbs, III) Common Mistakes, IV) Comprehension, V) Direct and indirect Speeches while for the Intermediate Learner category of the general studies the contents include: I) Joining Phrase and Sentence II) Lexis And Structure, III) Noun And Pronouns, IV) Oral Forms, V) Prepositions and Contents for the Expert learners Category include: I) Punctuations Marks and their Uses, II) Spellings, III) Synonyms And Antonyms, IV) Verbs and Tenses, V) Word Combination.

The system was tested with twenty users, willing to respond to the conventional method of learning, so as to be able to carry out the comparative analysis of both methods. The mean performance value of the system was determined by obtaining the summation of the percentage score of all the users at each level divided by the number of users at each level (Table 1 and Figure 15).

Tab. 1. Showing comparison between the personalized system and the conventional system

S/N	PROFICIENCY LEVEL	MEAN PERFORMANCE VALUE
	Beginner	
1	Conventional method	52
2	Personalized adaptive	68.45
	Intermediate	
3	Conventional method	51
4	Personalized adaptive	64.9
	Expert	
5	Conventional method	51.1
6	Personalized adaptive	67.6

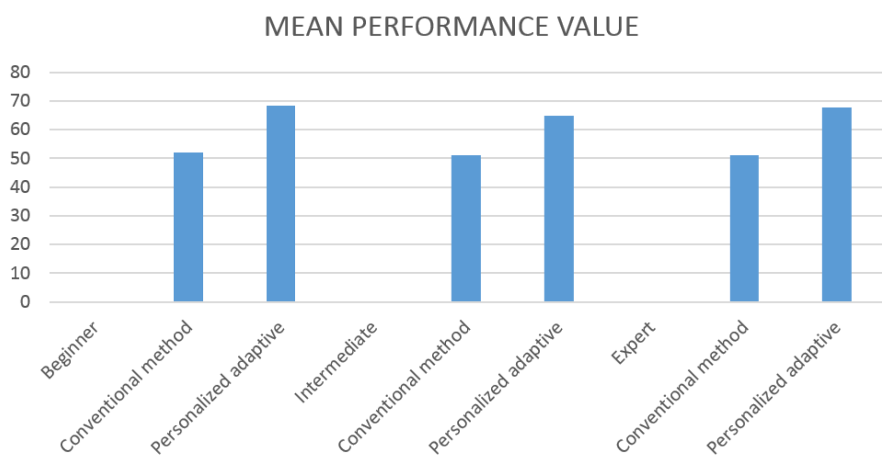

Fig. 15. Mean Performance Value

The system was evaluated with questionnaire filled by the twenty users of the system. The analysis is shown in Table 2 and Figure 16.

Tab. 2. Analysis Table

S/N	REMARKS	SATISFACTORY	GOOD	FAIR	POOR
1	System user-friendliness	10	6	4	0
2	System accuracy	11	7	2	0
3	System efficiency	9	6	3	2
4	System usability	18	1	1	0
5	System effectiveness	9	7	2	2

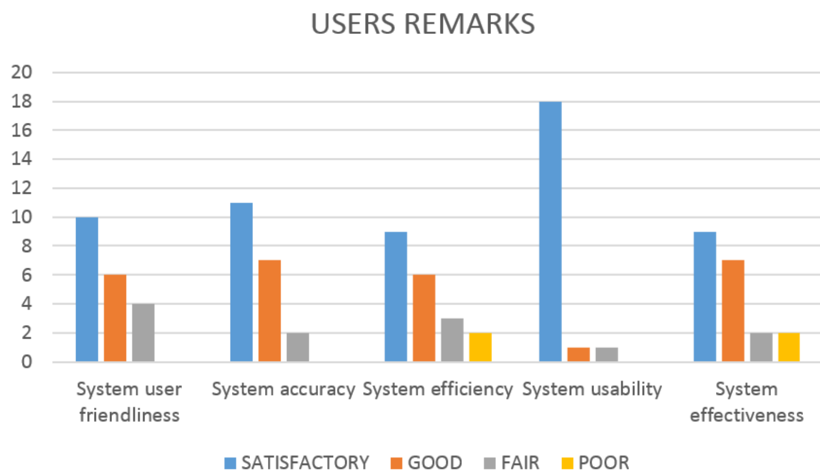

Fig. 16. Overall Performance of the System

Figure 16 shows the result of the evaluation in terms of user-friendliness, accuracy, efficiency, and the effectiveness of the system respectively. The result shows that the system is satisfactory as the majority of the users chose satisfactory as their remarks.

6. CONCLUSION

The personalization and adaptability of a system have been a technique, that has benefited the e-learning environment. However, in most existing personalized adaptive systems, learning contents are not tailored to the learners based on their learning styles. An ontology-based personalized adaptive e-learning system has been developed to offer a variety of personalized learning contents suitable to learners according to their learning styles. This will enhance their learning rate as it increases their learning abilities.

The system allows learners to take a learning style detector test to capture the learner's learning style but in the conventional e-learning system; the learning styles are not captured. The system delivered contents to the learner based on their learning style captured and go through a g-test to capture the learning ability of learners on a particular course. The examination was conducted for each learner within a space of time to determine the performance of the learner and to track the improvement in the learner's learning ability. The personalized adaptive e-learning system was tested using a General Study Course (GNS) as the learning materials with 20 users.

The results from the two methods were compared and the personalized adaptive system has a higher mean performance value at every level than the conventional methods, indicating that the system is more efficient and most preferred to the conventional method. Furthermore, the system was evaluated by 20 users in terms of System user-friendliness, System accuracy, System efficiency, System usability, System effectiveness. It was observed that a higher percentage of the users' remarks fall between satisfactory and good, which shows that the system was acceptable to them.

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