International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8, Issue-1S4, June 2019

# Personalized Learning Model Using Item Response Theory

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***Abstract*— *Many Higher Education Institutions in the Philippines now accept that a blended approach offers countless advantages in most areas of learning. However, learner's ability has been neglected as a significant factor in student's success. Thus various techniques have been developed such as personalization to improve the learning process and accommodate diversity of learners. This study introduces a personalized learning model that recommends Shortest Learning Sequence (SLS) to remediate students with learning difficulty. The learning model was created using Item Response Theory (IRT) implemented in an e-learning environment. Assessments were given during the learning process with levels of difficulty. IRT probabilistically estimates the student's proficiency of the topics taking into considerations the difficulty of the test items. SLS consists of lessons recommended to students, which were ranked accordingly. The one parameter (1PL) model was used to evaluate the test score and the item information was used to rank the lessons. Lessons are reduced until the proficiency level of the student is reached. Results show that the personalized learning model is capable of recommending shortest learning sequences. Hence, reduces the time spent of study. The student's proficiency level was increased through the implementation of the personalized learning model. Thus, the learning outcome was also improved.***

***Index Terms*—shortest learning sequence; item response theory; e-learning; personalized learning model.***

## I. INTRODUCTION

E-learning has long been in existence since 1999. E-learning is often considered as a means of permitting access to learning by using electronic media such as computers, tablets, or mobile phones. Long before the internet was launched, distance courses were being offered to provide students with education on particular subjects or skills. With the introduction of the computer and internet in the late 20th century, e-learning tools and delivery methods expanded. Since then, several schools had been set up to deliver courses online and bring education to people who wouldn't be able to attend college due to geographical or time constraints. In general, e-learning facilitates the delivery of lectures, the administering of quizzes and examinations, and the designation of paper works.

A growing number of business organizations began using e-learning to train their employees. New and experienced workers alike now had the opportunity to improve their industry knowledge base and expand their skill sets. Many e-learning authorities in industry and in schools now accept that a blended approach offers countless advantages in most areas of learning, and good practice has been developed in a hybrid online model [1]. According to the blog posted by the admin of the website CertifyMe.net, entitled the Important eLearning Statistics for 2013, 50% of all college students will be engaged in e-learning by 2015 and that e-learning does not only save money, it also saves time. Therefore, due to the growth of the Internet, an increasing number of individuals are moving to online learning.

Not all learners have the same personal preferences and learning styles [2]. Thus, many researchers have explored different techniques, such as shortest learning path to improve learning process, as well as to accommodate a diversity of learners. An article written by [3] mentioned that the individualized interactivity has contributed significantly to the effectiveness of the e-learning environment. Generally, most personalized systems have been developed to consider learner preferences, interests, and browsing behaviors in providing personalized services. However, learner ability [4] and necessary corrective measures to remediate learning difficulties [5] are usually neglected as important factors in implementing personalized mechanisms. As a result, this paper explores a learning technique to remediate learning difficulties of students in an e-learning environment.

Course contents have been designed to accommodate teaching approaches that support the learning needs of students. This includes students experiencing difficulties in learning. Students having difficulty learning are classfied into the heterogenous group, as they have a wide variety of characteristics, ranging from academic difficulties to cognitive and socio-emotional problems [6]. The term "learning difficulties" is a general one used widely and without much precision. Usually, the term applies to approximately 10 to 16% of the school population and refers to students who have general problems in learning [7]. Most students experiencing these difficulties could participate fully in learning experiences and assessment activities provided by the proposed learning environment.

Assessment plays an important role in learning. It determines whether the abilities and skills of the students in a particular course have been developed. More specifically, assessment is the way the instructors gather data about their teaching and their student's learning. A summative assessment is administered using the e-learning prototype to determine the learning path of the student. Summative examination takes place after the learning has been completed that sums up the teaching and learning process. Questions in the exam are constructed using Anderson and Krathwohl – Bloom's Revised Cognitive Taxonomy. Anderson [8] mentioned in her paper that the taxonomy table emphasizes alignment in terms of student learning and provides in-depth examination of alignment. Questions are

**Revised Manuscript Received on June 10, 2019.**

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generated randomly from the test bank for each student, which ensures that no student has the same series of questions. Multiple choice is the most commonly used type of question for assessment. However, [9] stated that different types of questions must be included in asssessment to encourage deep approaches to learning. Thus, this study employs other question types apart from the standard multiple choice type of question.

A lot of studies have proposed personalization that implements various models like Modified Roulette Wheel Selection algorithm [10] which recommends new learning sequences based on students knowledge and performance; and Item Response Theory (IRT) which recommends appropriate learning contents matching the learner's knowledge and ability [11]. IRT is a theory of how people respond to items. The purpose of this model is to probabilistically explain an examinee's responses to test items via a mathematical function based on his/her ability. This paper explores the use of Item Response Theory to recommend the shortest learning sequences ideally suited for students with learning difficulties that would lessen their time of study.

Thus, this paper provides an alternative way to improve the learning process by recommending shortest learning sequences and to remediate learning difficulties that lessens the time of study. Students take the assessment for the purpose of this personalized learning model. Different question types are employed to encourage different learning approaches. Moreover, questions are aligned according to Anderson and Krathwohl Cognitive Taxonomy. The results of the assessment are analyzed and processed using the formula of One-Parameter Logistic Item Response Theory model.

## II. CONCEPTUAL FRAMEWORK OF THE STUDY

The purpose of the conceptual framework, as presented in Fig. 1, is to show the components or steps by which the researcher implements procedures tailored to the learning needs of each student.

Initially, the student takes a 50-item diagnostic examination to determine his/her knowledge of the course. The test questions are generated randomly from the test bank. Questions are constructed and categorized using Anderson and Krathwohl Taxonomy to measure the cognitive domain of the students. The result of the test determines the first learning sequence (at level 1). The students read and study the lessons from the e-learning course materials. After finishing these lessons, the student takes the summative examination. The result of the examination will be used to determine the shortest learning sequence using Item Response Theory (IRT).

IRT evaluates the ability of the student, taking into consideration the difficulty of the lessons and recommends the shortest learning sequence to him/her. The student can be said to have learned his/her lesson if he/she answers the corresponding test items correctly. Therefore, if the student obtains a passing mark of 85% in the summative examination, the learning goal is achieved. Otherwise, the system will recommend a new learning sequence for the student to read and study again.

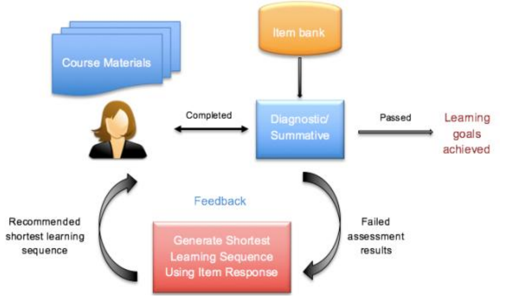


**Fig. 1 Conceptual framework of the personalized learning model**

Fig. 2 demonstrates the generation of the shortest learning sequence or SLS using IRT. Data collected from the results of the exam are used to compute the student's ability probabilistically with regards to his/her answers to test items. The responses of the students to the test items are then converted dichotomously into 1's (correct answer) and 0's (incorrect answer). These are stored in a matrix where the columns are the test items and the rows represent the students. The lesson difficulty is determined using the formula of the odds of success, or the number of correct answers in each lesson (1). On the other hand, the learning ability of the students is estimated based on the odds of the success or the number of correct answers in the test (2). In this case, the lesson difficulty and the learning ability have been identified. Using the one-parameter logistic model, also known as the Rasch model (3), the probability that the student learned a particular lesson is computed based on his/her ability to answer the test items in each lesson with respect to the item difficulty. The result of this determines the lessons that the student needs to review in order for him/her to achieve proficiency of the course. Reinforcement activity is recommended and new learning sequence is generated based on the formula of item information function (4).

During the learning process, as the iteration increases, the learning sequence becomes shorter. This is because the learnt lessons are removed from the learning sequence, meaning that only those topics that the student failed to answer correctly are recommended for a re-study. The iteration process continues until the student passed the summative examination. However, the generation of the personalized learning would usually stop at level 3 because according to [12], the mastery level can be achieved at this level due to the reinforcement process.

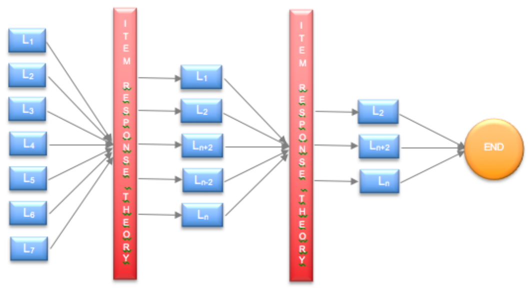


**Fig. 2 Shortest learning sequence generation**

## III. RESEARCH METHODOLOGY

### A. Research Design

The research design refers to all the overall strategy that the researcher chooses to integrate the different components of the study in a coherent and logical way, thereby, ensuring to effectively address the research problem. It constitutes the blueprint for the collection, measurement, and analysis of data [13].

Descriptive research design attempts to describe and explain conditions of the present by using many subjects and a questionnaire to fully describe a phenomenon [13]. The researcher used the descriptive research design in this study. The study describes the use of IRT in recommending the shortest learning sequence. It also describes how the personalized learning model helped improve the learning outcome of the student based on the results of the examination.

### B. Methods and Techniques Used

The course materials for Introduction to Programming using C++ were used as the learning content. The lessons are sequenced accordingly with the course syllabus, reviewed and evaluated by academic coordinators, where the researcher taught. The learning content has been the product of the researcher in her 13 years of teaching the course.

Questions are categorized according to Anderson and Krathwohl Taxonomy, which was published in 2001. Fig. 3 illustrates the Revised Bloom's Taxonomy of the Cognitive Domain defining the levels of thinking. The levels build in increasing order of difficulty from basic, rote memorization to higher levels of critical thinking skills. As shown in the diagram, three changes have been made in the category level. Comprehension was renamed Understand, Synthesis changed places with Evaluation and was renamed Create [8]. Test questions are created and validated based on the 13 years teaching experience of the researcher. The test items were already used in the traditional classroom learning.

Multiple choice question is a widely used and highly regarded question type. However, other cognitive domains may not be measured. Therefore, different types of questions are constructed to encourage different approaches to learning, which includes true or false questions.

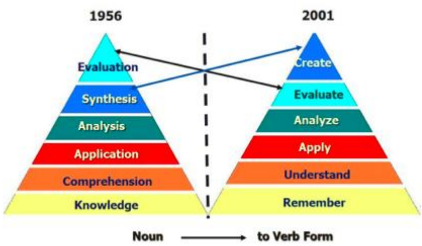


**Fig. 3 Anderson and Krathwol cognitive taxonomy**

It is a repository where all the questions are drawn for the summative examination. Each question in the item bank contains the following properties: question name, description, type, category, and points. Questions from the item bank are selected proportionally for each lesson based on the revised Bloom's cognitive taxonomy. For each lesson, a total of 5 (five) points are randomly picked from the test bank with combinations of easy, moderate and difficult questions. For the purpose of presentation of this study, the 50-item examination was used to evaluate the student's understanding of the course. Since there are ten (10) lessons in the course and each course generates 5-points test items, the researcher purposively used the 50-item examination to have equal distribution of points from each lesson. Furthermore, questions can be dynamically added to the item bank.

### C. Item Response Theory Model

Student's ability cannot be judged based on the number of correct items obtained. Rather, the item difficulty should also be taken into account [14]. Consequently, students can have different levels of ability, and items can differ in many aspects – most importantly, some are easier and some are more difficult [15].

Item Response Theory (IRT) Model is a theory of how people respond to items. It predicts a certain person will give a certain response to a certain item. IRT provides a model-based linkage between item responses and the latent characteristics assessed by a test or scale [16]. IRT models and their corresponding parameter estimation techniques have a long history of development in the psychometrics literature.

The purpose of these models is to probabilistically explain an examinee's responses to test items via a mathematical function based on his/her ability. The goal of IRT is to estimate the learner's ability with regards to his/her dichotomous answers to test items. These test items are scored dichotomously: the correct answer receives a score of one, and each of the distractors yields to a score of zero. Items scored dichotomously are often referred to as binary items [17].

Each lesson has difficulty level based on the incorrect responses on the examination by the learner. Initially, the difficulty level is computed by taking the natural log of the odds of failure (the number of incorrect answers) given by

$$\boldsymbol{b_i = ln\frac{(1-p)}{p}} \tag{1}$$

Equation (1) is the difficulty logit [18] where b is the difficulty of $i^{th}$ lesson and p is the number of correct responses to test items. Negative logit means the lesson is easy, 0 means the lesson is moderately difficult, and positive logit means the lesson is hard.

Student's ability is estimated based on the correct responses on the examination. Ability $\vartheta$ is computed by taking the natural log of the odds of success (the number of correct answers) given by

$$\boldsymbol{\theta_j = ln\frac{p}{(1-p)}} \tag{2}$$

The Ability Logit [18] in (2) is the θ ability of $j^{th}$ student and p is the number of correct responses to test items. Negative logit means the ability level is poor, 0 indicates an average ability level, and positive logit means ability level is high.


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In the One-Parameter Logistic (1PL) Model or Rasch Model, the probability of a correct response is determined by lesson's difficulty and the student's ability by

$$\boldsymbol{P(\theta)} = \frac{e^{(\theta_j - b_i)}}{1+e^{(\theta_j - b_i)}} \tag{3}$$

P(ϑ) determines the probability of a correct answer where θ is the individual ability level of j<sup>th</sup> student, b as the difficulty parameter of i<sup>th</sup> lesson and *e* is an exponential function equal to 2.718281 [15]. 1PL is the simplest IRT model for a dichotomous item that has only item parameter – the difficulty parameter. Fig. 4 shows the graph of the one-parameter logistic function using the Item Characteristic Curve (ICC).

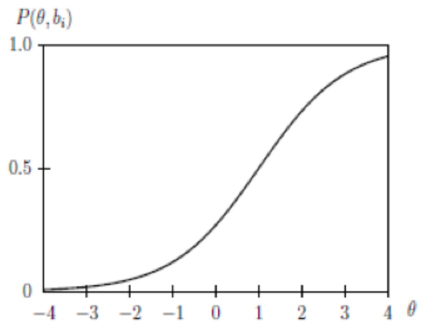


**Fig. 4 Item characteristic curve**

The IRT model illustrates the relationship between the learner's answer and a test item through the Item Characteristic Curve. The standard mathematical model for the ICC is the cumulative form of the logistic function. It defines a family of curves having the general shape of the ICC shown in Fig. 4. The horizontal axis represents the ability of student in a limited range and the vertical axis represents the probability that the student with certain ability can answer the test correctly [17]. It shows how the interaction of student ability and item difficulty influences the predicted probability of a correct response to the item [15].

The Item Information Function (IFF) is related to the accuracy with which ability is estimated. IIF provides information about the ability of the student depending on how closely the difficulty of the item matches the ability of the student. The item information function of the 1PL model is given by

$$\boldsymbol{I_i(\theta, b_i) = P_i(\theta, b_i) Q_i(\theta, b_i)} \tag{4}$$

The item information is used to rank the lessons in recommending the shortest learning sequence where $I_i(\theta, b_i)$ is the item information of i$^{th}$ lesson, $P_i(\theta, b_i)$ is the probability of correct responses on i$^{th}$ lesson, and $Q_i(\theta, b_i) = 1 - P_i(\theta, b_i)$the probability of incorrect responses on i$^{th}$ lesson. As the ability becomes either smaller or greater than the item difficulty, the item information decreases.

### *D. Data Collection*

Student takes a diagnostic examination to determine his/her prior knowledge and misconceptions before beginning a learning activity. The results of this exam are used by the model to generate the initial learning sequence of the student.

The results of the summative examination designed for the course are extracted and fed to the model to evaluate the understanding degree of a learner. Having finished reading all the lessons, the student must answer the corresponding test items. The student is considered to have understood the lesson if he/she answers them correctly. IRT generates the shortest learning sequence by estimating student's ability, ranks the lessons accordingly and recommends the learning sequence to him/her.

## IV. RESULTS AND DISCUSSION

The proposed personalized learning model was implemented in an e-learning environment. A section of 40 college students participated in the conduct of this research. The course contains 10 lessons in the course, Introduction to Programming Using C++. For the purpose of presentation, a 50-item diagnostic examination was given to students to assess their knowledge of the course. Each lesson has a test composed of a total of 5 points which are randomly selected from the test bank with a combination of easy, moderate and hard questions.

**TABLE I**
**EXAMINATION RESULTS**

| Level of Proficiency | Scores | Number of Students |
|---|---|---|
| High | 40 and above | 15 |
| Average | 30 - 39 | 14 |
| Low | Below 30 | 11 |

Table 1 summarizes the results of the diagnostic examination after the test was administered to 40 students. Given the passing rate of 80% (40 out 50 correct items), only few passed the examination. Based on the table, 15 students passed the examination, that is 37.5% of the total takers. They are considered with high proficiency level of the knowledge domain since the threshold value is higher than the normal passing rate, that is 75%. On the other hand, 62.5% (25 students) of the total population have failed the examination. Thus, these students took remedial of the course to increase their proficiency and remediate learning difficulties.

### *A. Algorithm*

```
//Algorithm for IRT
//p[0..n-1] contains the number of correct responses in each lesson
if score < 80 then                                //if score is less than 80 (passing rate)
        a ← ln (score) / (1- score))              //compute student ability logits
        exp ← 2.718281                            //assign a value of 2.718281 to exp
for i=0, i < n loop
        b[i] ← ln ((1 - p[i]) / p[i])             //compute lesson difficulty logits
        prob[i] ← exp*(a–b[i])/(1+exp*(a–b[i]))   //probability of correct responses
        q[i] ← 1 – p[i]                           //probability of incorrect responses
        info[i] ← p[i] * q[i]                     //compute the information item
        increment i by 1
end loop
sort info[i] in ascending order
display the shortest learning sequence
```


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The pseudocode above shows how the equation were used to develop the algorithm for generating the shortest leaning sequence. It begins with comparing the test score to the passing score, which is 80. Then, ability logit and lesson difficulty logit are computed assigned to variables a and b respectively. A loop continues to iterate until the value of n is less than the values of variable i, the total number of items in each lesson. Probability of getting the correct and incorrect responses to test items are estimated, which are stored in the arrays. The item information values are stored in the array info and are arranged in increasing order. These values are the generated shortest learning sequence recommended to students.

### *B. Lesson Difficulty and Student Ability*

The results of the examination were used to assess the learning ability of the student in each lesson. The one-parameter logistic (1PL) IRT model, also known as Rasch model, was used to recommend the shortest learning sequence based on their individual ability taking into account the difficulty of the lessons.

**TABLE 2**

**LESSON DIFFICULTY AND STUDENT ABILITY**

| Student | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | L10 | Ability |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1.39 | -0.41 | -1.39 | -4.00 | -0.41 | 0.41 | 1.39 | 4.00 | -0.41 | -0.41 | 0.00 |
| 6 | -4.00 | -4.00 | -4.00 | -4.00 | -1.39 | 0.41 | -4.00 | 1.39 | 1.39 | -4.00 | 1.15 |
| 7 | -4.00 | -0.41 | -1.39 | -1.39 | -4.00 | 0.41 | 4.00 | 0.41 | 1.39 | -1.39 | 0.41 |
| 9 | -4.00 | -4.00 | -4.00 | -1.39 | -4.00 | 0.41 | -0.41 | 4.00 | -4.00 | 0.41 | 0.94 |
| 11 | -4.00 | 0.41 | -1.39 | -0.41 | -1.39 | -1.39 | 0.41 | 0.41 | 1.39 | 0.41 | 0.32 |
| 12 | -4.00 | -4.00 | -1.39 | -1.39 | -1.39 | 0.41 | -4.00 | 0.41 | 1.39 | -1.39 | 0.94 |
| 14 | 1.39 | -1.39 | -1.39 | -0.41 | -1.39 | 0.41 | -0.41 | -1.39 | -0.41 | -4.00 | 0.66 |
| 16 | 1.39 | -0.41 | -1.39 | -1.39 | -4.00 | 4.00 | 1.39 | 4.00 | -4.00 | -0.41 | 0.08 |
| 18 | -4.00 | -1.39 | -1.39 | -4.00 | -4.00 | 1.39 | -1.39 | 0.41 | 1.39 | 0.41 | 0.66 |
| 20 | 0.41 | 0.41 | -4.00 | -1.39 | -4.00 | -1.39 | 0.41 | 1.39 | -0.41 | 0.41 | 0.41 |
| 21 | -4.00 | -1.39 | -1.39 | 0.41 | -1.39 | -0.41 | -0.41 | 0.41 | -0.41 | 0.41 | 0.58 |
| 22 | 0.41 | -1.39 | -1.39 | -4.00 | -4.00 | 1.39 | 1.39 | 1.39 | -0.41 | -1.39 | 0.41 |
| 23 | -4.00 | -4.00 | -1.39 | -4.00 | -4.00 | -1.39 | 1.39 | 1.39 | -4.00 | 0.41 | 1.05 |
| 25 | -1.39 | -1.39 | 0.41 | -1.39 | -1.39 | 1.39 | -1.39 | 1.39 | 1.39 | -0.41 | 0.24 |
| 26 | 0.41 | -4.00 | -0.41 | -1.39 | -0.41 | -0.41 | 0.41 | 4.00 | 1.39 | -1.39 | 0.16 |
| 27 | -1.39 | 0.41 | -1.39 | -1.39 | -4.00 | 1.39 | -1.39 | 4.00 | 0.41 | 1.39 | 0.16 |
| 28 | 1.39 | -0.41 | -0.41 | 0.41 | -0.41 | 4.00 | -0.41 | 1.39 | 1.39 | -0.41 | -0.41 |
| 29 | -1.39 | 0.41 | -1.39 | 1.39 | -0.41 | 0.41 | 0.41 | 1.39 | 1.39 | -0.41 | -0.16 |
| 31 | 1.39 | -0.41 | -1.39 | -1.39 | -4.00 | 1.39 | -0.41 | 1.39 | 1.39 | -0.41 | 0.08 |
| 32 | -4.00 | -1.39 | -4.00 | -1.39 | -0.41 | -0.41 | -4.00 | 0.41 | -0.41 | -4.00 | 1.27 |
| 34 | -4.00 | -1.39 | -1.39 | -4.00 | -4.00 | -1.39 | -1.39 | 4.00 | -0.41 | 0.41 | 0.94 |
| 35 | 0.41 | -0.41 | -1.39 | -1.39 | -1.39 | 4.00 | -0.41 | 1.39 | 1.39 | -1.39 | 0.08 |
| 36 | -4.00 | -0.41 | -1.39 | -4.00 | -0.41 | 4.00 | -4.00 | 4.00 | -0.41 | -1.39 | 0.58 |
| 38 | -4.00 | 1.39 | -4.00 | 0.41 | -1.39 | 0.41 | 0.41 | 1.39 | 0.41 | 1.39 | 0.00 |
| 39 | 0.41 | -4.00 | -4.00 | -1.39 | -4.00 | -0.41 | -1.39 | 0.41 | -0.41 | -0.41 | 0.94 |
| Average | -1.73 | -1.34 | -1.86 | -1.71 | -2.30 | 0.76 | -0.55 | 1.73 | 0.02 | -0.70 | |

Table 2 shows the lesson difficulty and the student ability based on the correct and incorrect responses of the student's answer to the test items. First, the proportion incorrect is calculated by getting the average of student's incorrect responses for each lesson. The proportion incorrect is then converted into lesson difficulty logits by taking the natural log of the odds of failure using (1). For example, the difficulty level of each lesson for Student 4 are $L_1$=1.39, $L_2$=-0.41, $L_3$=-1.39, $L_4$=-4, $L_5$=-0.41, $L_6$=0.41, $L_7$=1.39, $L_8$=4, $L_9$=-0.41, $L_{10}$=-0.41 respectively.

On the other hand, the student ability is estimated by calculating the average proportion correct in the examination. Converting the proportion correct into student ability logits is done by taking the natural logs of the odds of success using (2). As shown in Table 2, Student 4 has the ability logit of 0, which means that the student has an average ability level.

The Ability column in Table 2 shows the student's ability level of the course. Ability greater than 0 indicates that the student has high proficiency level, ability 0 means an average proficiency level, and ability less than 0 indicates that the student has low proficiency level. Hence, Student 32 has the highest learning ability and Student 29 has the lowest learning ability.

The values in the rows $L_1$ to $L_{10}$ represents the difficulty level of each lesson based on the student's ability. Lesson difficulty is between -4 and +4. That is, lessons with difficulty level -4 are viewed as the easiest, lessons with level 0 are viewed as having moderately difficult, and those that are with difficulty level 4 are the hardest. The results of Table 2 shows that Lesson 5 is the easiest and Lesson 8 is the hardest.

Therefore, the proposed personalized learning model considers both lesson difficulty and the learner ability because these parameters affect the student learning outcome.

### *C. Estimation of Student Learning Abilities*

The probability that the learners can completely understand ($P(\vartheta)$) and cannot understand ($Q(\vartheta)$) the lesson at a level with respect to their ability level are estimated at this point. The acceptable threshold value is 0.80 proportionate to the examination passing rate.

**TABLE 3**

**PROBABILITY OF CORRECT RESPONSES**

| Student | L1 | L2 | L3 | L4 | L5 | L6 | L7 | L8 | L9 | L10 |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 0.20 | 0.60 | 0.80 | 0.99 | 0.60 | 0.40 | 0.20 | 0.01 | 0.60 | 0.60 |
| 6 | 1.00 | 1.00 | 1.00 | 1.00 | 0.93 | 0.68 | 1.00 | 0.44 | 0.44 | 1.00 |
| 7 | 1.00 | 0.69 | 0.86 | 0.86 | 1.00 | 0.50 | 0.01 | 0.50 | 0.27 | 0.86 |
| 9 | 1.00 | 1.00 | 1.00 | 0.91 | 1.00 | 0.63 | 0.79 | 0.02 | 1.00 | 0.63 |
| 11 | 1.00 | 0.48 | 0.85 | 0.67 | 0.85 | 0.85 | 0.48 | 0.48 | 0.26 | 0.48 |
| 12 | 1.00 | 1.00 | 0.91 | 0.91 | 0.91 | 0.63 | 1.00 | 0.63 | 0.39 | 0.91 |
| 14 | 0.33 | 0.89 | 0.89 | 0.74 | 0.89 | 0.56 | 0.74 | 0.89 | 0.74 | 1.00 |
| 16 | 0.21 | 0.62 | 0.81 | 0.81 | 0.99 | 0.01 | 0.21 | 0.01 | 0.99 | 0.62 |
| 18 | 1.00 | 0.89 | 0.89 | 1.00 | 1.00 | 0.33 | 0.89 | 0.56 | 0.33 | 0.56 |
| 20 | 0.50 | 0.50 | 1.00 | 0.86 | 1.00 | 0.86 | 0.50 | 0.27 | 0.69 | 0.50 |
| 21 | 1.00 | 0.88 | 0.88 | 0.54 | 0.88 | 0.73 | 0.73 | 0.54 | 0.73 | 0.54 |
| 22 | 0.50 | 0.86 | 0.86 | 1.00 | 1.00 | 0.27 | 0.27 | 0.27 | 0.69 | 0.86 |
| 23 | 1.00 | 1.00 | 0.92 | 1.00 | 1.00 | 0.92 | 0.42 | 0.42 | 1.00 | 0.65 |
| 25 | 0.84 | 0.84 | 0.46 | 0.84 | 0.84 | 0.24 | 0.84 | 0.24 | 0.24 | 0.66 |
| 26 | 0.44 | 0.99 | 0.64 | 0.82 | 0.64 | 0.64 | 0.44 | 0.01 | 0.23 | 0.82 |
| 27 | 0.82 | 0.44 | 0.82 | 0.82 | 0.99 | 0.23 | 0.82 | 0.01 | 0.44 | 0.23 |
| 28 | 0.14 | 0.50 | 0.50 | 0.31 | 0.50 | 0.00 | 0.50 | 0.14 | 0.14 | 0.50 |
| 29 | 0.77 | 0.36 | 0.77 | 0.18 | 0.56 | 0.36 | 0.36 | 0.18 | 0.18 | 0.56 |
| 31 | 0.21 | 0.62 | 0.81 | 0.81 | 0.99 | 0.21 | 0.62 | 0.21 | 0.21 | 0.62 |
| 32 | 1.00 | 0.93 | 1.00 | 0.93 | 0.84 | 0.84 | 1.00 | 0.70 | 0.84 | 1.00 |
| 34 | 1.00 | 0.91 | 0.91 | 1.00 | 1.00 | 0.91 | 0.91 | 0.02 | 0.79 | 0.63 |
| 35 | 0.42 | 0.62 | 0.81 | 0.81 | 0.81 | 0.01 | 0.62 | 0.21 | 0.21 | 0.81 |
| 36 | 1.00 | 0.73 | 0.88 | 1.00 | 0.73 | 0.01 | 1.00 | 0.01 | 0.73 | 0.88 |
| 38 | 0.99 | 0.20 | 0.99 | 0.40 | 0.80 | 0.40 | 0.40 | 0.20 | 0.40 | 0.20 |
| 39 | 0.63 | 1.00 | 1.00 | 0.91 | 1.00 | 0.79 | 0.91 | 0.63 | 0.79 | 0.79 |

After determining the lesson difficulty and the estimated ability of the student in the course, the probability that the student can respond correctly to the test items in each lesson given the passing rate of 0.80 is identified. This is computed using the values derived from (1) and (2), and the formula in (3).

As shown in Table 3, scores 0.80 and above means that the proficiency level of the lesson has been achieved by the student. Otherwise, if the computed score is below the threshold value, the student reviews the lesson again with a new learning sequence recommended by the model. The items highlighted in red are the lessons that need to be reviewed by the student. These values are the Item Information derived from the probability that the students can completely understand ($P(\vartheta)$) and cannot understand ($Q(\vartheta)$), the lesson with respect to their ability level using the (4). The item information is sorted in ascending order that


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determines the new learning sequence recommended to the learners. For example in Table 3, the new learning sequence for Student 4 is $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$. Therefore, those lessons with scores 0.80 and above are eliminated from the learning sequence, which makes the study time shorter.

Summative examination is given at the end of the course review. As the learning ability increases, the more likely the student can understand the lesson. Therefore, the proficiency level also increases.

Based on Table 3, Student 32 with the highest ability level among the 25 students who failed the examination, has passed all the lessons except for Lesson 8 since it shows that this Lesson is the hardest of all. And Student 29, which was identified earlier with the lowest ability level, has to review all the lessons in the course.

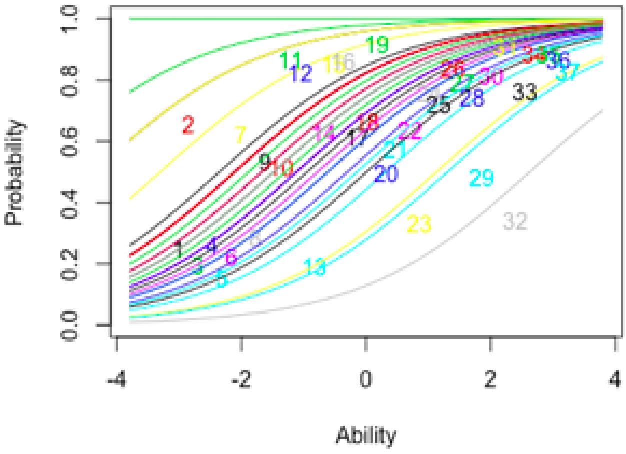


**Fig. 5 Relationship between the lesson and student ability**

The graph in Fig. 5 shows the relationship between the difficulty level of the items in each lesson and the learning ability of the student to answer these items correctly or incorrectly. The higher the ability level, the most likely that he/she can answer the items in the test correctly. Hence, it is more likely that the student can completely understand the lesson.

*D. Recommendation of Shortest Learning Sequence*

The proposed personalized learning model uses the responses of the student for the estimation of his/her ability. If the student gives correct answers to the test items in each lesson, then his/her ability increases. Otherwise, the student's ability will be decreased. Having estimated the student's ability, lessons are sequenced according to the information value illustrated in Fig. 6. This value depends on the matching degree between the difficulty of the lesson and the student's learning ability. The information value is used to arrange the sequences of lessons recommended by the system to the student.

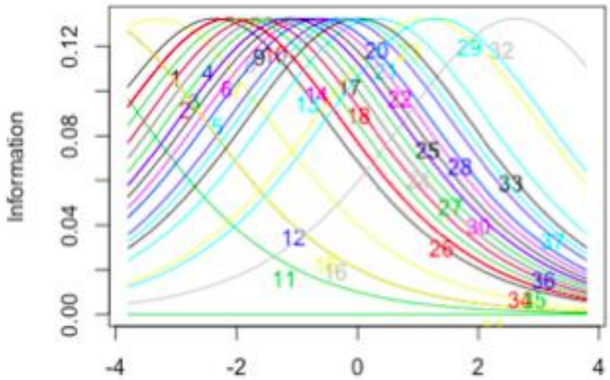


**Fig. 6 Item Information Curve**

**TABLE 4**
**SHORTEST LEARNING SEQUENCES**

| Student | Level 0 | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| 4 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_1 \to L_7 \to L_2 \to L_5 \to L_6 \to L_9 \to L_{10}$ | $L_6 \to L_7 \to L_1 \to L_8$ | |
| 6 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_9$ | | |
| 7 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_7 \to L_9 \to L_2 \to L_6 \to L_8$ | $L_9 \to L_7$ | |
| 9 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_7 \to L_6 \to L_{10}$ | | |
| 11 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_9 \to L_4 \to L_2 \to L_7 \to L_8 \to L_{10}$ | $L_7 \to L_9 \to L_8 \to L_{10}$ | |
| 12 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_9$ | | |
| 14 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_4 \to L_7 \to L_9 \to L_1 \to L_6$ | $L_1$ | |
| 16 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_1 \to L_7 \to L_2 \to L_{10}$ | $L_1 \to L_6 \to L_7 \to L_8$ | |
| 18 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_9 \to L_8 \to L_{10}$ | | |
| 20 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_9 \to L_1 \to L_2 \to L_7 \to L_{10}$ | $L_9$ | |
| 21 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_7 \to L_9 \to L_4 \to L_8 \to L_{10}$ | | |
| 22 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_7 \to L_8 \to L_9 \to L_1$ | $L_7 \to L_6 \to L_8$ | |
| 23 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_{10} \to L_7 \to L_8$ | $L_7 \to L_8$ | |
| 25 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_9 \to L_{10} \to L_3$ | $L_6 \to L_9 \to L_8$ | |
| 26 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_9 \to L_3 \to L_5 \to L_6 \to L_1 \to L_7$ | $L_9 \to L_1 \to L_7 \to L_8$ | |
| 27 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_6 \to L_{10} \to L_2 \to L_9$ | $L_2 \to L_6 \to L_{10}$ | |
| 28 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_1 \to L_8 \to L_9 \to L_4 \to L_2 \to L_3 \to L_5 \to L_{10}$ | $L_4 \to L_9 \to L_1 \to L_6 \to L_8$ | $L_8$ |
| 29 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_4 \to L_8 \to L_9 \to L_1 \to L_3 \to L_2 \to L_6 \to L_7 \to L_5 \to L_{10}$ | $L_4 \to L_8 \to L_9 \to L_7 \to L_2 \to L_6$ | $L_9 \to L_4 \to L_8$ |
| 31 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_1 \to L_6 \to L_8 \to L_9 \to L_2 \to L_7 \to L_{10}$ | $L_6 \to L_9 \to L_1 \to L_8$ | |
| 32 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8$ | | |
| 34 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_9 \to L_{10}$ | $L_8$ | |
| 35 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_9 \to L_2 \to L_7 \to L_1$ | $L_6 \to L_9 \to L_8$ | |
| 36 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_6 \to L_8 \to L_2 \to L_5 \to L_9$ | $L_6 \to L_8$ | |
| 38 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_1 \to L_8 \to L_{10} \to L_4 \to L_6 \to L_7 \to L_9$ | $L_2 \to L_8 \to L_{10}$ | |
| 39 | $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$ | $L_8 \to L_9 \to L_{10} \to L_1 \to L_4$ | | |

Based from the results of the responses of the students to the tests analyzed by the personalized learning model, the shortest learning sequences were generated. Shortest Learning Sequence (SLS) consists of a short series of lessons recommended for the students who undergo reinforcement process in order to remediate their learning difficulty.

As shown in Table 5, 25 out 40 students underwent reinforcement process. At Level 0, the students read all the course materials of the same sequence of lessons $L_1 \to L_2 \to L_3 \to L_4 \to L_5 \to L_6 \to L_7 \to L_8 \to L_9 \to L_{10}$. Students then took the diagnostic examination after they read all the lessons. Students who failed the examination proceed to the next level (Level 1) of reinforcement and the system recommends a shortest learning sequence. Student 4, as presented in Table 5, was given a new shortest learning sequence of $L_8 \to L_1 \to L_7 \to L_2 \to L_5 \to L_6 \to L_9 \to L_{10}$ which is 80% of the lesson was recommended and 20% was successfully passed after the reinforcement. The process continues until the student has successfully passed the examination, which was achieved at Level 3.


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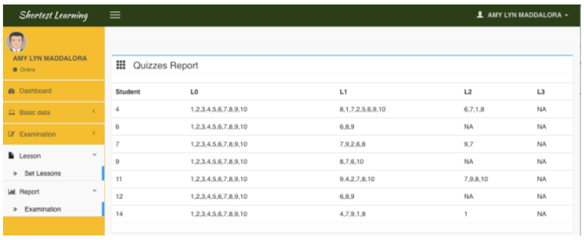


**Fig. 7 E-learning prototype**

With the results presented, notice that the reinforcement process stopped at Level 3 as shown in Fig. 7. The proposed personalized learning model guaranteed that the student would pass the course as the lesson decreases while increasing the proficiency level of the student.

**TABLE 5**
**OVERALL MEASUREMENT OF EFFECTIVITY OF THE PERSONALIZED LEARNING MODEL**

| Grade Remarks | Level 0 | | Level 1 | | Level 2 | | Level 3 | |
|---|---|---|---|---|---|---|---|---|
| Passed | 15 | 37.5% | 7 | 28% | 16 | 88.9% | 2 | 100% |
| Failed | 25 | 62.5% | 18 | 72% | 2 | 11.1% | 0 | 0% |
| Total | 40 | | 25 | | 18 | | 2 | |

Results show that the integration of the personalized learning model to the prototype is considered effective. Among the 40 students assessed in the conduct of this study, as shown in Table 5, 15 or 37.5% passed the course and did not undergo remedial process. Nonetheless, 25 or 62.5% of the students failed the course and took remedial of the course at Level 0.

At Level 1, 25 students who failed the examination took the remedial and 7 or 28% of these takers passed the summative examination which means that they were able to achieve the proficiency level of the course. While 16 or 88.9% of the students successfully passed the examination at Level 2. On the other hand, only 2 or 11.1% of the students failed the summative examination. Lastly, the remaining 2 takers were able to completely understand the lessons by passing the course at Level 3. This means that the personalized learning model is effective in remediating learning difficulty because of the shortest recommended learning sequence of lessons.

The results of the study have been proven effective in improving the learning outcome of the student to remediate learning difficulties through the implementation of the personalized learning model in the e-learning environment.

## V. SUMMARY, CONCLUSION AND RECOMMENDATION

### *A. Summary*

Various techniques have been developed by researchers to revolutionize the teaching operation and improve learning process through personalized learning path. This paper provides an alternative way to improve the learning process by recommending shortest learning sequences and to remediate learning difficulties that lessens the time of study. This study is of great value to academic institutions to enhance the teaching and learning method. The proposed personalized learning model can be used as a means of remediating student learning difficulties, and be able to address their learning needs by recommending individualized course sequencing or personalized lessons.

Diagnostic and summative examiantion are taken by the students to assess their learning of the course. Different question types are employed to encourage different learning approaches. Moreover, questions are aligned according to Anderson and Krathwohl Cognitive Taxonomy. The results of the assessment are analyzed and processed using the formula of One-Parameter Logistic Item Response Theory model. IRT evaluates the ability of the student taking into considerations the difficulty of the lessons and then recommends the shortest learning sequence to him/her. The student is considered to learn a lesson if he/she answers the corresponding test items correctly. Therefore, if the student obtains a passing mark of 85% in the summative examination the learning goal is achieved. Otherwise, remedial of the course is recommended and new learning sequence is generated based on the algorithm developed.

### *B. Conclusion*

Researches in the field of personalization have greatly contributed to the improvement of student learning outcome. Studies have shown that a personalized learning helped learners to learn more effectively and efficiently.

Using the One-parameter Logistic IRT model (Rasch Model), the proposed personalized learning model can estimate the learning ability of the student, taking into account the difficulty level of the lesson. These two parameters are important factors in estimating the likelihood of the student to pass the course. The personalized learning model has been successfully implemented in an e-learning environment that recommends the shortest learning sequence to achieve learning goals. Based on the related literature, studies have shown that the use of IRT is proven to improve the learning process to remediate learning difficulties.

The model recommends the shortest learning sequence to students who underwent reinforcement process to remediate learning difficulty. The study proved that as the recommended learning sequence decreases, the student's learning ability is increased. Hence, the student is guaranteed to pass the course after the reinforcement process. Previous studies have also shown that based on the learner's ability, a personalized learning path can accelerate learner learning efficiency and effectiveness.

In general, the proposed personalized learning model guaranteed that the student would pass the course as the lesson decreases while increasing the proficiency level of the student. The results of the study have proven effective in improving the learning outcome of the student to remediate learning difficulties through the implementation of the personalized learning model in the elearning environment.

### *C. Recommendation*

The researcher has drawn the recommendations for future researchers who will conduct related studies, as well as for the enhancement of the proposed personalized learning model.

The proposed study can be integrated to the e-learning systems of educational institutions who wanted to leverage the use of their system as well as to improve the learning process. This leaning model will be useful to students in remediating learning difficulty.

Further studies are required to improve the personalized learning model. Moreover, future researchers are welcome to explore other IRT models such as the 2PL and 3PL model. Question of different types can be added to encourage different approaches of learning.

The proposed e-learning prototype should be tested and implemented to a wide-array of users since it was only tested on 40 college students. Exploring the possibility of implementing the personalized learning model as a plug-in to an existing e-learning environment should also be considered by future researchers.

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