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Immersive Intelligent Tutoring System for Remedial Learning Using Virtual Learning Environment

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A B S T R A C T

Intelligent Tutoring System (ITS) has been widely used in supporting personal learning. However, there is an aspects that have not become focus in ITS, namely immersive. This research proposes an Immersive Intelligent Tutoring (IIT) model based on Bayesian Knowledge Tracing (BKT) for determining the learner's characteristics and learning content delivery strategies using genetic algorithms. The model uses remedial learning with a faded worked-out example. This study uses a 3-Dimensional Virtual Learning Environment (3DMUVLE) that implements immersive features to increase intrinsic motivation. This model was built using a client / server architecture. The server side component uses the MOODLE, the client side component uses OpenSim and its viewers, and the middleware component uses the Simulation Linked Object Oriented Dynamic Learning Environment (SLOODLE). Model testing is performed on user acceptance using a combination of Technology Acceptance Model (TAM) and Hedonic-Motivation System Adoption Model (HMSAM) and the impact of the model in learning using statistical test. The results showed 83% of the learners felt happy with the learning. Meanwhile, the evaluation of the impact on learning outcomes shows that the use of this model is significantly different from traditional learning.

A R T I C L E I N F O

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1. INTRODUCTION

Integration of Information and Communication Technology (ICT) in learning has changed the paradigm and learning scenario. These changes concern the place of learning, face-to-face strategy, the introduction *of* blended learning, the increasingly blurred differences in terms of formal, non-formal, and informal learning (Humanante-Ramos *et al.*, 2015). ICT supports easy access to e-learning for both teachers and students. Hardware and software support make e-learning accessible anywhere and anytime (ubiquitous learning). Like classroom learning, e-learning also consists of learning materials and delivery strategies of these materials to learners.

Nowadays, e-learning emphasizes personal learning. Personal learning applies student-centered learning and supports the self-directed learning process. This is in line with (Humanante-Ramos *et al.*, 2015) who states that learners are unique in which they have their own interests, limitations, and capabilities.

However, PLE still has many limitations, especially in personalization. Personalization can be obtained through the learning activities by analysing log files (quantitative approach), the characteristics of learners such as WFCL (Settouti *et al.*, 2007), REDIM (Choquet & Iksal, 2007). Besides learning content, personalization is related to the generation of content maps.

The remedy is a learning clinic to help learners who have difficulties in learning. The learning process is more focused on each person as a learner, but still pay attention to the curriculum. The flow of remedial learning is an assessment-learning-reassessment. Many methods are used in remedial learning such as tailoring personalized learning materials according to each student's strengths and weaknesses (Lin *et al.*, 2018), Reciprocal Teaching.

Effective remedial learning provides personalized handling of learning to each learner's specific needs. The main process is to identify the learners' difficulties during learning. The track record data is used to make decisions for effective learning actions. The use of technologies such as machine learning or artificial intelligence is very helpful for the automation of processes, such as identifying the characteristic and capacity of learners and determining the appropriate learning content as well as strategies for delivering the learning materials. The use of machine learning methods in personal remedial learning includes genetic algorithms (Lin *et al.*, 2018), affective tutoring (Lin *et al.*, 2014), and fuzzy sets (Dai & Huang, 2015).

On the other hand, learning requires motivation from the learner. Intrinsic motivation that comes from oneself has a positive impact on the learning process. The motivation is driven by the anxiety of being unable, race condition, and happiness in the learning process. Virtual Learning Environment provides these three things because of the rich presentations, user-friendly interaction techniques, and adaptive capabilities (Alam *et al.*, 2017). Also, the ability to collaborate with other users (Khlaisang & Songkram, 2019) and provide immersion (Kozhevnikov *et al.*, 2013), enjoyment, curiosity, and better knowledge gain (Rosmansyah *et al.*, 2019).

Adaptive remedial learning is the method used in this study in helping learners with such difficulties. It is called adaptive because this model provides differentiated learning for different learners according to the student model (Brusilovsky & Peylo, 2003). The remedial form in this study is drilling with a step-by-step process of completion. In this study, the step in discussing problem-solving is immediate feedback on the execution of the question. The screening of the problem-solving steps is adjusted to the learner's needs in accordance with the BKT value they have. The screening category of the steps for solving the problem consists of three things, namely: one show, two shows, and three

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shows. Drill method is a worked-out example (Skudder & Luxton-Reilly, 2014) and faded of completion steps (Salden *et al*., 2009).

ITS aims to provide customized teaching and feedback to learners (Juárez-Ramírez *et al*., 2014). ITS supports personal learning by applying Artificial Intelligence (AI) which has the functions of: 1) Comfortable cognitive processes, 2) Continuous cognitive adaptation, and 3) Controlling question and answer interactions (Samuelis, 2007). IIT has several important components, which are: 1) pedagogical module; 2) learning module; 3) domain module; and 4) interface. This study aims to improve ITS by adding Immersive, remedial and author components for remedial learning in a virtual learning environment. The proposed model emphasizes personal interactions as immediate feedback.

2. STUDY LITERATURE

This sub-chapter will describe the literature on remedial learning, personal learning systems, and virtual learning environments.

2.1. Remedial Learning

Remedial learning is a learning clinic to help learners who have difficulties in participating in learning. Generally, learning material is material that is considered as not understandable by students. Learning is done by knowing the weaknesses of the learners through a assessment. In general, the assessment is done using quizzes or tests. Furthermore, based on the test results, an analysis is carried out either manually by the instructor or automatically by the system. Students are directed to teaching materials that correspond to the results of the analysis. The effectiveness of remedial learning can be achieved by making flexible learning for each learner who has his own unique character, interests, limitations, and capabilities (Humanante-Ramos *et al*., 2015).

2.2. Intelligent Tutoring System

Computer-based learning has disadvantages because it is done in a large number and ignores the needs, goals, and abilities of learners, even though every learner has a different background, ability, and learning style (Das & Pal, 2011). Personal learning using adaptive learning and ITS is a system that can be used for that. Definition of ITS is an AI application for education (Samuelis, 2007) which has some functions, namely:

1. Comforting cognitive process,
2. Continuing cognitive adaptation, and
3. Controlling the interrogation of questions and answers.

The ITS is an intelligent system that is able to provide adaptation in learning for learners. As a system, the ITS has several important components. This sub-section, the components of ITS will be described based on the researchers, as shown in **Table 1**.

Table 1. ITS components.

Researcher	Components
(Kavitha *et al*., 2012)	a. Data Gathering b. Finding the Learner Ability c. Question Classification and Accumulation d. Intelligent Question Accumulation and Assigning
(Feng *et al*., 2009)	a. Interface b. Expert c. Student d. Tutor

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Table 1 (Continue). ITS components.

Researcher	Components
(Das & Pal, 2011)	a. Layer of information gathering b. Layer of decision c. Layer of tutorial d. Layer of assessment e. Layer of analysis and evaluation
(NKambou *et al*., 2010)	a. Domain model b. Tutoring model c. Student Model d. Interface

2.3. Virtual Learning Environment

The VLE is one alternative in learning. The benefits of VLE are useful for teachers and learners. For teachers, VLE provides statistical logs that are useful for subsequent learning analysis (Lavigne *et al*., 2015). Meanwhile, VLE provides fun learning for learners because it accommodates them with rich presentations, user-friendly interaction techniques, and adaptive capabilities (Alam *et al*., 2017). VLE currently supports personal learning, especially the learning which is in accordance with the learners' needs and preferences. The adaptation can be divided into 3 parts, namely: adaptation to student models, adaptation to teaching strategies and learning content, and adaptation to mechanisms (Scott *et al*., 2017).

Adaptation to the student models is in the form of identification, representation, and updating information about the learner. Adaptation of learning strategies is in the form of selecting learning techniques and learning material content that is unique to each learner. Adaptation mechanism is carried out on presentation and navigation. Currently VLE is using 3D dimensions and multi-users to add learner immersion (Khlaisang & Songkram, 2019).

3. METHOD

3.1. Participants

The respondents in this study were the students of ISOLA Elementary School which is located at Jalan Gegerkalong Girang No. 12 Bandung, Indonesia. The number of respondents in experiment class is 31 students which consist of 14 boys and 17 girls. The number of respondents in control class is 24 students which consist of 11 boys and 13 girls. The students are the six graders of Lab School Elementary, Universitas Pendidikan Indonesia.

3.2. Learning

This study involved two study groups, namely: the control class and the experimental class. The control class used conventional learning while the experimental class used 3DMUVLE-based remedial personal learning. Remedial learning follows the path displayed in **Figure 1**.

In **Figure 1**, the assessment and re-assessment are in the form of a quiz. Meanwhile, the learning applies adaptive learning in accordance with the conditions of each learner. The generator of questions in the quiz uses genetic algorithm. The learning uses the drill method of applying an adaptive faded worked-out example as an immediate feedback explanation.

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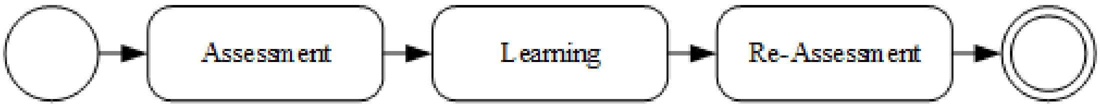

Figure 1. Flow of remedial learning.

3.3. Personal Remedial Learning System Design in 3DMUVLE

3.3.1 Design assessment

Assessment is a step to test the learner's understanding of the material that has been given. In this study, the assessment was carried out three times, as follows: 1st assessment (pre-test) that was conducted to find out the learner's knowledge before learning and 2nd assessment (quiz) that was conducted to determine the learning progress. If the learner had not been able to complete the quiz (the result was smaller than the threshold value), then the learning would be repeated. 3rd assessment (post-test) was done to test the learner's performance when the learning was complete. Post-tests were conducted to test the learner's understanding of material comprehension.

The question in this study is automatically generated using a genetic algorithm following the flow chart as shown in **Figure 2**. The solution contains chromosomes that model a package of questions consisting of a set of questions which has an ideal composition.

Determination of the fitness value objective function to achieve the ideal composition, namely: 25% of questions in the category of knowledge, 50% of questions in the category of understanding, and 25% of questions in the category of application based on Bloom's Taxonomy. The formula for objective functions is the maximum function of f (x, y, z) where x is abs (25-percentage composition of types of easy questions * 100), y is abs (50-percentage composition type questions are * 100), and z is abs (25-percentage composition of difficult types of questions * 100) by approaching or according to the ideal composition.

F(x,y,z)= X + Y +Z=300, with function f(x), f(y), and f(z) as follows:

1. Variable X is the composition of questions with category C1, with the following values:

$$X=\begin{cases} \frac{\sum_{i=1}^{n} x_i}{nX} x1100, \sum_{i=1}^{n} x_i \leq nX \\ \frac{\sum_{i=1}^{n} x_i - nX}{nX} x100, \sum_{i=1}^{n} x_i > nX \end{cases}$$

2. Variable Y is the composition of questions with category C2, with the following values:

$$Y=\begin{cases} \frac{\sum_{i=1}^{n} y_i}{nY} x100, \sum_{i=1}^{n} y_i \leq nY \\ \frac{\sum_{i=1}^{n} y_i - nY}{nY} x100, \sum_{i=1}^{n} y_i > nY \end{cases}$$

3. Variable Z is the composition of questions with category C3, with the following values:

$$Z=\begin{cases} \frac{\sum_{i=1}^{n} z_i}{nZ} x100, \sum_{i=1}^{n} z_i \leq nZ \\ \frac{\sum_{i=1}^{n} z_1 - nZ}{nZ} x100, \sum_{i=1}^{n} z_i > nZ \end{cases}$$

The chromosome selection process uses the roulette wheel method, while Operation Cross Over is one-cut point, and Operation Mutation is replacing one of the allele with a random value. The number of chromosomes that undergo mutations is determined based on the probability of mutations which is 10%.

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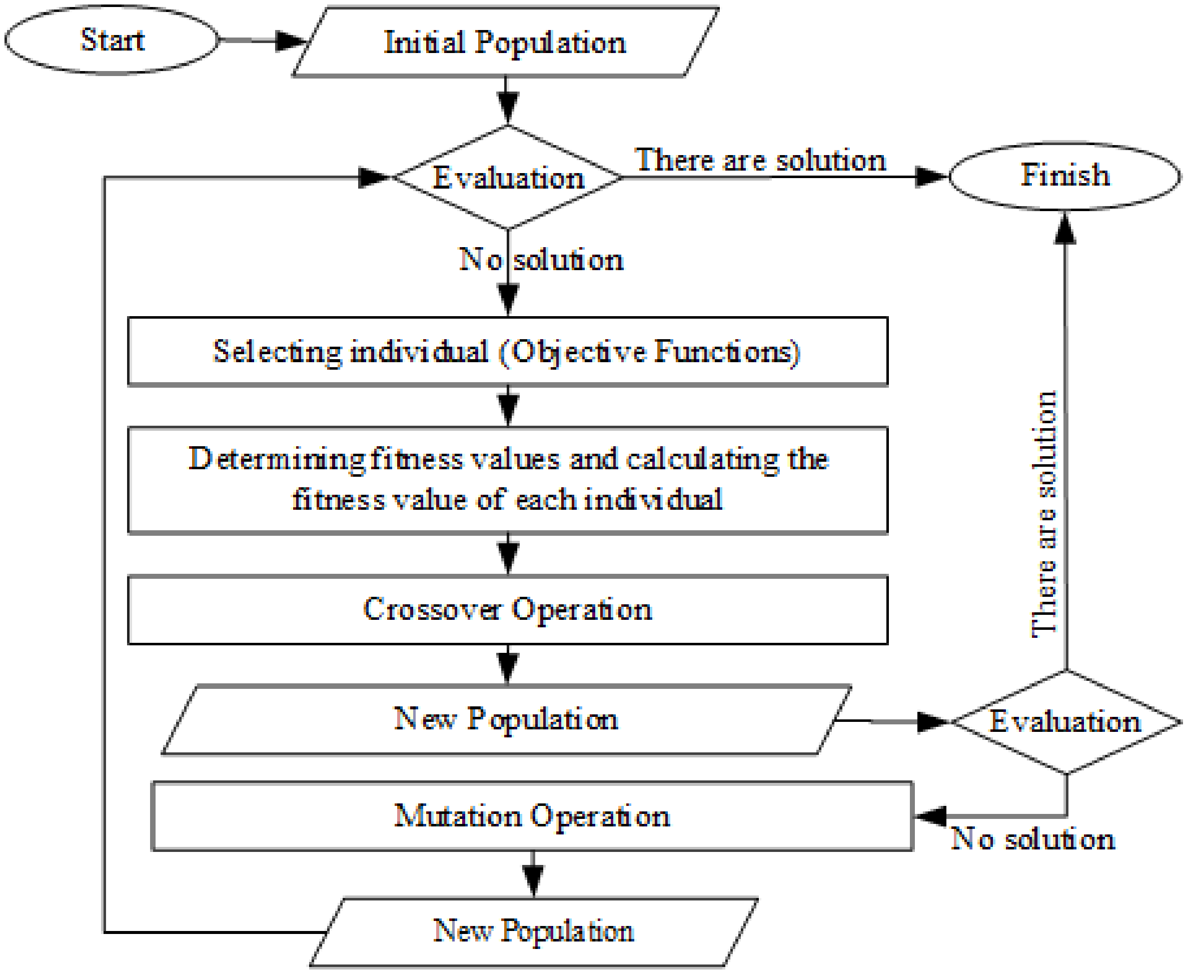

Figure 2. Flowchart of genetic algorithms.

3.3.2 Design material

Teaching is carried out with the example of worked-out method. Each exercise has steps to solve it. Worked-out example has three steps, namely: problem statement, solution design, and implementation. The problem statement is the first step in which the problem is determining which solution will be sought. The solution design is the sequence of problem-solving steps. The implementation is the steps in which the sequence of steps is implemented according to the problem. The examples of worked-out example in the subject of fractions can be seen in **Table 2**.

3.3.3 Design student model

There are many approaches to modelling learners. Learning cognitive models and predicting their abilities are difficult to work. This happens because of the uncertainty of different levels of knowledge and learning strategies. BKT was introduced by Corbett and Anderson 1995 (Van De Sande, 2013). Implementation of BKT is carried out in two ways, namely: in full the Hidden Markov Model (HMM) and associated Markov chain. BKT predicts the possibility that the learner applies his ability correctly in solving problems. The BKT model typically calculates the learner’s performance using the residual sum of squares (RSS) test. BKT has 4 parameters, namely:

1. P (L0): initial probability of learner knowledge before learning.
2. P (G): the probability of the learner answering correctly even if he doesn't understand, the term used is guess.

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3. P (S): the probability that the learner answers incorrectly even though he understands, the term used is slip.
4. P (T): probability to learn abilities, if the learner has these abilities. The value of P (T) is constant.

This model consists of the knowledge possessed by the learner which symbolized by K and how the learner's work in solving problems is in accordance with the knowledge they have which symbolized by C as shown in **Figure 3**.

Table 2. Worked-out example.

Problem Statement	Solution Design	Implementation
Mrs. Yati bought 3 1/4 kg of rice, then she cooked 1.5 kg. Mrs. Yati bought other 2 3/4 kg of rice. The weight of Yati's rice now is ...	1. Write what is known 2. Write what is asked 3. Write the completion steps	1. Known: rice Yati = 3 1/4 kg + 2 ¾ kg, rice used = 1.5 kg 2. Asked: The remaining rice is available 3. Answer: 3 1/4 + 2 3/4 - 1,5= 3 1/4 + 2 3/4 - 1 ½ 4. 13/4 + 11/4 - 3/2 = 13/4 + 11/4 - 6/4 5. (13+11-6) /4 =18/4 6. 4 2/4 = 4 ½
Sugar price is 4/3 the price of rice. Price of rice is 2/5 that of eggs. The difference of prices between sugar and rice is Rp. 2,400, -. The price of eggs is ...	1. Write what is known 2. Write what is asked 3. Write the completion steps	1. Known: Sugar = 4/3 rice, Rice = 2/5 eggs, Sugar-rice = 2,400 2. Asked: Egg Price 3. Answer: Sugar-rice = 2,400 4. 4/3 Rice-rice = 2,400 5. 1/3 rice = 2,400 6. Rice = 2,400 x 3 = 7,200 7. Rice = 2/5 eggs 8. Eggs = 5/2 Rice 9. Eggs = 5/2 x 7,200 = 18,000
Mother has a 5 1/2 m cloth, it is given to aunt 2.4 m, and 3/4 m is used for sister's clothes, the mother cloth is now	1. Write what is known 2. Write what is asked 3. Write the completion steps	1. Known: Mother's cloth 5 1/2m, given to aunt 2.4m, used for sister clothes 3/4m 2. Asked: how much is the mother's cloth now? 3. Answer: 5 1/2 - 2,4 -3/4=5 1/2 - 2 4/10 - ¾ 4. 11/2 - 24/10 - ¾ 5. (11x10)/(2x10) - (24x2)/(10x2) - (3x5)/(4x5) 6. 110/20 - 48/20 - 15/20 7. (110-48-15)/20 8. 47/20 = 2 7/20 = 2,35

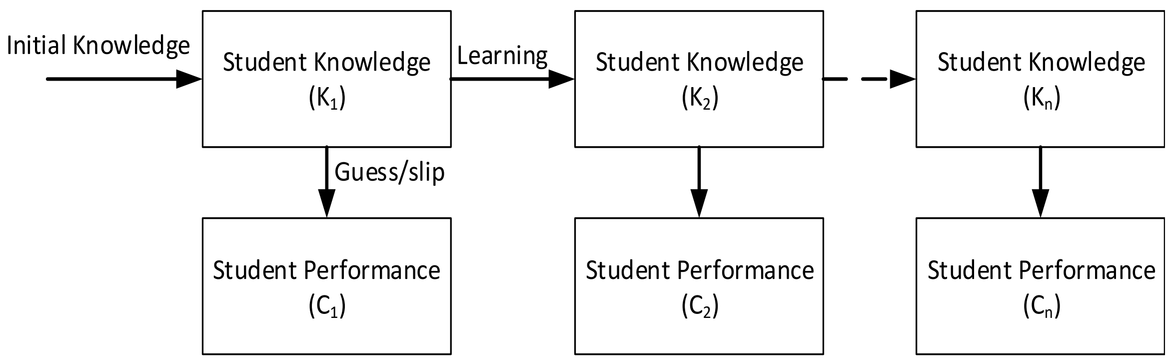

Figure 3. BKT model (Gong *et al*., 2011).

P (Ln) is a conclusion about the learner's knowledge of the n^{th} opportunity to apply skills:

1. Predict whether the learner answers correctly at the n^{th} time
$$P(correct_n) = P(L_n).\left(1 - P(S)\right) + (1 + \left(1 - P(L_n)\right).P(G)$$
2. Predict whether the learner answers incorrectly at the n^{th} time
$$P(incorrect_n) = P(L_n).P(S) + \left(1 - P(L_n)\right).\left(1 - P(G)\right)$$
3. Observation of the learner's response on the n^{th} opportunity (correct)
$$P(L_n \mid correct_n) = \frac{P(L_n).(1 - P(S))}{P(correct_n)}$$
4. Observation of the learner's response on the n^{th} opportunity (wrong)
$$P(L_n|incorrect_n) = \frac{P(L_n).P(S)}{P(incorrect_n)}$$
5. Learner's knowledge after learning
$$P(L_n) = P(L_{n-1}|evidence_{n-1}) + \left(1 - P(L_{n-1}|evidence_{n-1})\right).P(T)$$

Fading is the elimination of zero to n steps for solving problems. According to Reisslein et al., (2006), the fading has two methods, namely forward and backward. Forward fading removes the solution steps from step one ton while backward fading removes the solution steps from step n to one. In this study, the fading method used is the backward method. In this case, fading is carried out in the form of screening the solution according to the learner's cognitive conditions. In addition, the learning diagnoses were carried out using the BKT method. Learner's cognitive values are categorized into three, as follows:

a. Smaller or equal to 0.3,
b. Smaller or equal to 0.7,
c. Greater than 0.7.

Based on these categories, the solution steps are carried out by these rules:

a. If BKT <= 0.3, the number of shows is 3 times with portions (n steps x 1/3),
b. If BKT <= 0.7, the number of shows is twice with portions (n steps x 1/2),
c. If BKT > 0.7, then the number airs 1 time by serving n steps of the solution.

The presentation of this solution is direct feedback to the learners' actions in their learning. Feedback is done directly after the learner answers the question. The feedback provided is an explanation in the form of a solution step from solving the question. An example of displaying the completion of the problem is shown in **Figure 4**.

PROBLEM: Mrs. Yati bought 3 1/4 kg of rice, then cooked 1.5 kg. Mrs. Yati bought another 2 3/4kg. The weight of Yati's rice now is …

1. Known: Mrs. Yati rice = 3 1/4 kg + 2 ¾ kg, rice used = 1.5 kg
2. Asked: The remaining rice is available

3. Answer : 3 1/4 + 2 3/4 - 1,5= 3 1/4 + 2 3/4 - 1 ½
4. 13/4 + 11/4 - 3/2 = 13/4 + 11/4 - 6/4

5. (13+11-6) /4 =18/4
6. 4 2/4 = 4 1/2

Figure 4. Screening of problem solving based on BKT value.

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3.3.4 Process of personal remedial learning

Based on the discussion in sub-chapter 3.3.1 to sub-chapter 3.3.3, it can be concluded that personal remedial learning can be seen in **Figure 5**. **Figure 5** shows the remedial learning process. learning begins with the presentation of the material followed by a quiz. If the quiz score is greater than or equal to the Minimum Completeness Criteria value, the next process is post-test. Meanwhile, if the quiz score is less than the Minimum Completeness Criteria value, remedial learning begins. The process starts from generating questions using genetic algorithms. Next, students work on the problem, and from the results of working on these questions, it can be seen the cognitive characteristics of students using BKT. Based on the BKT value, immediate feedback explanatory using a faded worked-out example. If the remedial learning process is complete, the next step is back to the quiz. The process is repeated if the results are still below the Minimum Completeness Criteria value.

4. RESULT AND DISCUSSION

This study integrates remedial learning, VLE, and ITS into IITS. The proposed model is shown in **Figure 6**. This model is called IIT because it adds an immersive module that provides enjoyment of learning. Immersion is achieved by: 1) providing a fun virtual interface and 2) learning processes that provide immediate explanatory feedback. This model consists of components as follows: interface modules, pedagogic modules, domain modules, student modules, author modules, remedial modules, and immersive modules. The interface module serves as an interaction between the system and the instructor and learner. In this case, the interface module uses 3DMUVLE. The pedagogy module serves as a smart learning strategy. This module applies remedial learning to the learning path: assessment-learning-reassessment.

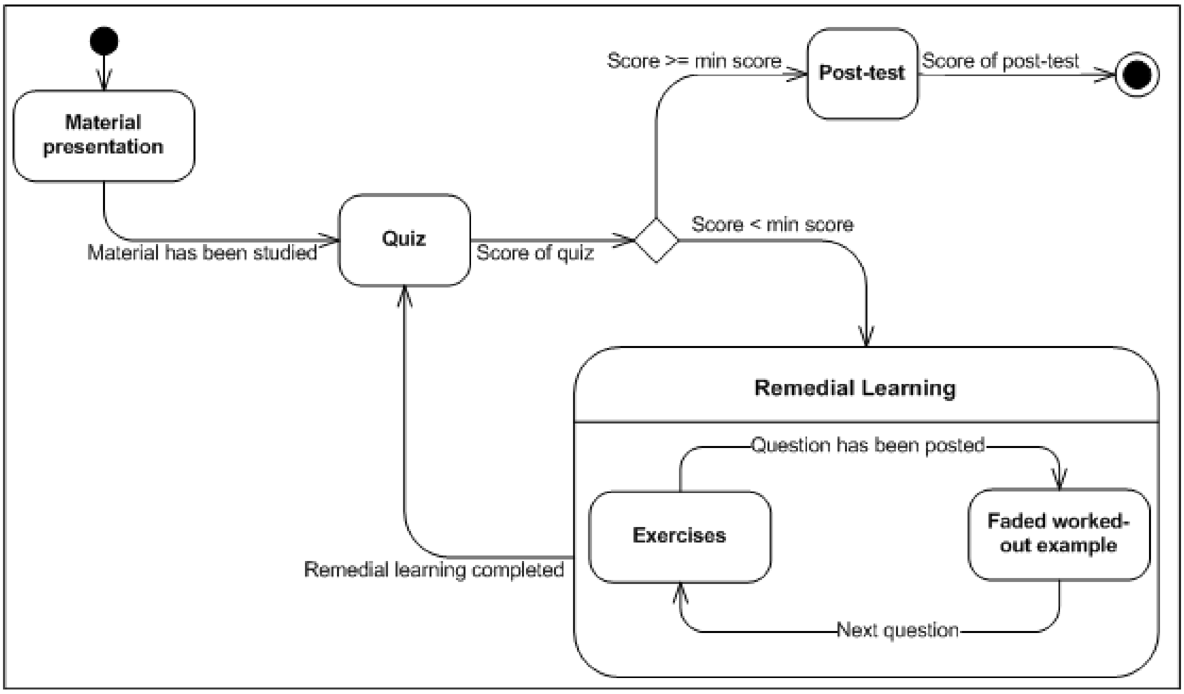

Figure 5. Personal remedial learning.

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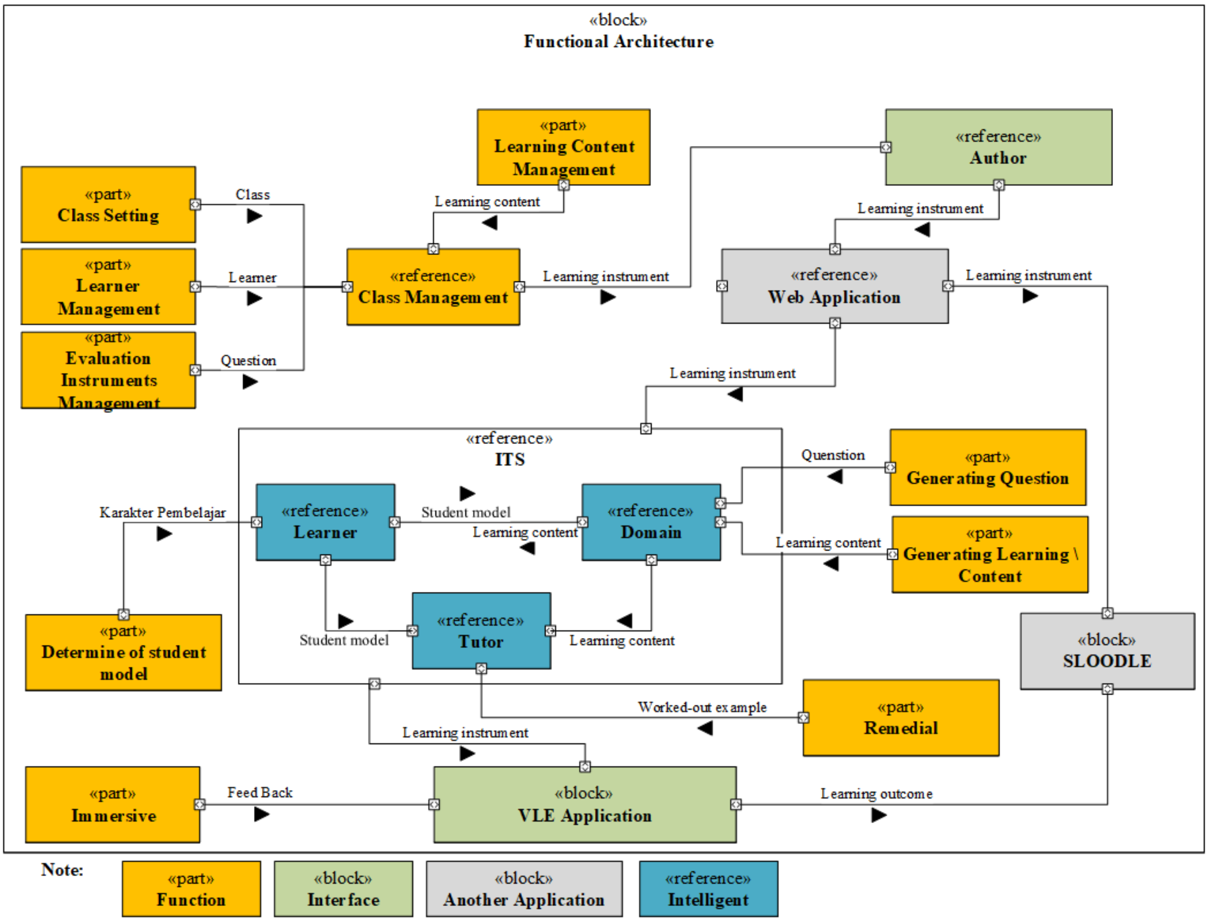

Figure 6. The model of IIT.

This module also contains intelligent agents to diagnose the learner's learning in order to determine their characteristics. Domain modules contain learning materials and question banks for the assessment. Meanwhile, the student modules consist of student characteristics in the form of static characteristics and dynamic characteristics. Static characteristics consist of personal data such as ID, name, password, while dynamic characteristics consist of the learner's performance.

The author module functions to capture the learning instruments in the form of instructional content and questions as evaluation material. Besides, this module also aims to capture the learning participants. Meanwhile, the ITS module aims to capture everything in the learning process, such as the learning character, and which teaching content is appropriate for the character. This module also provides personal learning. The remedial module aims to catch learners who are experiencing difficulties so it needs a special process in handling it. The immersive module aims to increase instinctive motivation through the interface and learning feedback

Figure 7 shows the 3DMUVLE for remedial learning. Learning arena is in the form of buildings or open parks. Learners must move from one location to another according to the instructions. The flow of learning in this study is as follows: 1) the learners register at the enrolment booth, 2) the learners do pre-test in the arena of the pre-test park, 3) the learners learn teaching material in the learning classroom building. The learning process is done by reading the teaching material, answering the quizzes, or practice the questions and discussions (remedial), 4) the learners do a post-test in the post-test building.

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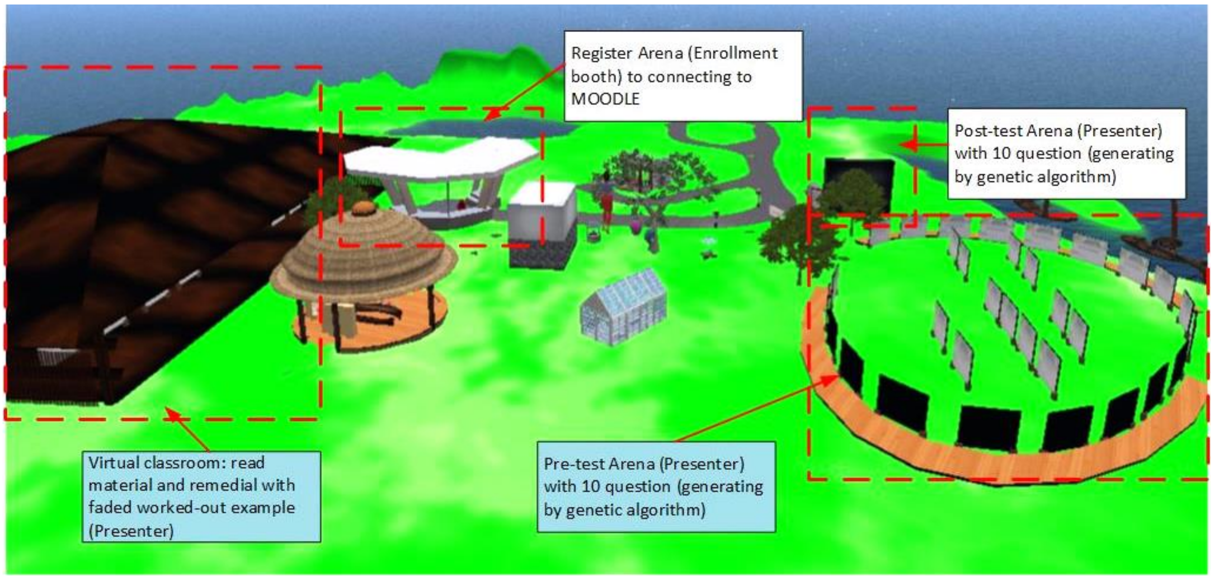

Figure 7. IIT remedial in 3DMUVLE.

Table 3 shows the results of the questionnaire using a Likert scale from scale 1 = not very good, 2 = not good, 3 = Normal, 4 = good, 5 = very good. These results indicate an average value of 4.15 on a scale of 5.

Testing is done by confirming the user's acceptance of the media used. The testing model is shown in **Figure 8**. The picture shows that Learning Outcomes (LO) are influenced by Immersion (IMR) and IMR is influenced by Enjoyment (ENJ).

The testing for improved learning is conducted by the Mann-Whitney test that shows in **Table 4** (Fagerland, 2012; Klotz, 1998; Ruxton, 2006). It can be seen in table IV that the value of Asym. Sig. (2-tailed) is 0.049 which indicates that the value is <5%. In other words, there are significant differences in the post-test values of the two classes. This shows that using personal remedial learning in the experimental class has a positive impact in improving cognitive learners. This is also indicated by the average difference between the control class and the experimental class as shown in **Table 5** which shows that the average experimental class is greater than the average of the control class.

Testing for the average difference is also done by comparing several methods as shown in **Figure 9**. The figure shows that the use of the proposed method has the highest average value.

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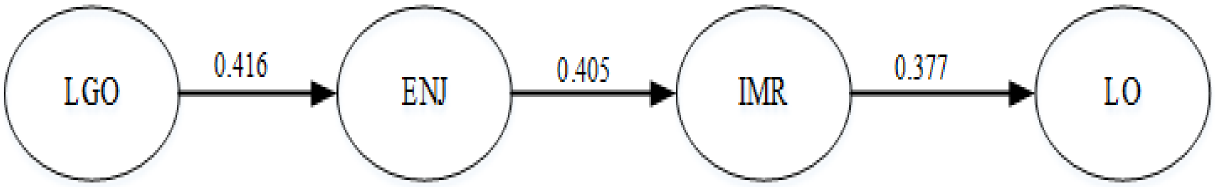

Figure 8. Final testing model.

Table 3. Questionnaire value.

Attribute	Average Questionnaire Value	Average Value per Category
Learning goal orientation (LGO)	4.3	4.40
	4.5	
Enjoyment (ENJ)	4.4	4.40
	4.4	
Perceived Ease-of-Use (PEU)	4.1	3.90
	3.7	
	3.9	
Perceived Usefulness (PU)	4.0	4.13
	4.2	
	4.2	
Behavioral Intention to Use (BIU)	4.1	3.97
	3.7	
	4.1	
Immersion (IMR)	4.5	4.10
	3.6	
	4.2	
Control (CTRL)	3.8	4.00
	4.2	
Learning Outcome (LO)	4.5	4.35
	4.2	
	Average	**4,15 (Good)**

Table 4. Mann-Whitney test.

Test Statistics[a]	
	Result
Mann-Whitney U	285.000
Wilcoxon W	585.000
Z	-1.967
Asymp. Sig. (2-tailed)	.049
a. Grouping Variable: Class	

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Table 5. Differences in mean control and experiment class.

	Ranks			
	Class	N	Mean Rank	Sum of Ranks
Result	Control	24	24.38	585.00
	Experiment	34	33.12	1126.00
	Sum	58		

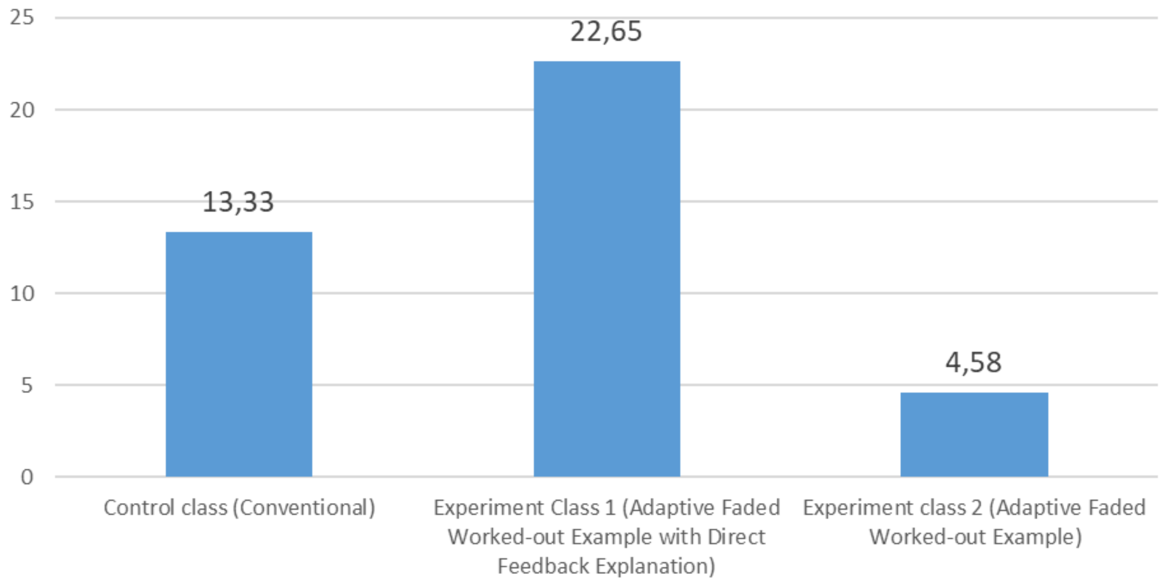

Figure 9. Comparison of mean values between methods.

5. CONCLUSION

The adaptive remedial learning model contains components such as interface modules, pedagogical modules, domain modules, and student modules that adopt ITS which is based on layering. An adaptive remedial learning model leads to remedial personal learning that provides remedial learning which is in accordance with the learner's abilities. Adaptive remedial learning models can be integrated with virtual learning environments to provide fun learning and lead to the learners' intrinsic motivation. Adaptive remedial learning models have been shown to provide significant cognitive improvement compared to traditional models.

However, this study still has some disadvantages, leaving a gap to be followed up with further research, for example: 1) this study still uses the cognitive value of learners as an instrument for determining student models. In the virtual learning environment, there are many other attributes that can be used as parameters for determining student models such as learner's behavior in learning, the length of time the learner performs activities in a learning activity or the frequency of learners visiting his favorite activity site; 2) the determination algorithm of student model in this study uses BKT considering that there are still many machine learning or artificial intelligence algorithms that can be used; and 3) the application of learning in a virtual environment in this study uses two servers and databases so that it requires better hardware specifications. Further research can streamline the use of resources.

6. AUTHOR'S NOTE

The author(s) declare(s) that there is no conflict of interest regarding the publication of this article. Authors confirmed that the data and the paper are free of plagiarism.

7. REFERENCES

Alam, A., Ullah, S., and Ali, N. (2017). The effect of learning-based adaptivity on students' performance in 3D-virtual learning environments. *Institute of Electrical and Electronics Engineers* (*IEEE) Access*, *6*(2017), 3400-3407.

Brusilovsky, P. and Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education*, *13*(2–4), 159–172.

Choquet, C., and Iksal, S. (2007). Modélisation et construction de traces d'utilisation d'une activité d'apprentissage: Une approche langage pour la réingénierie d'un EIAH. *Sciences et Technologies de l'Information et de la Communication pour l'Éducation et la Formation*, *14*(2007), 1-24.

Dai, C. Y., and Huang, D. H. (2015). Causal complexities to evaluate the effectiveness of remedial instruction. *Journal of Business Research*, *68*(4), 894-899.

Das, B. K., and Pal, S. (2011). A framework of intelligent tutorial system to incorporate adaptive learning and assess the relative performance of adaptive learning system over general classroom learning. *International Journal of Multimedia and Ubiquitous Engineering*, *6*(1), 43-54.

Fagerland, M. W. (2012). T-tests, non-parametric tests, and large studies—a paradox of statistical practice?. *BMC Medical Research Methodology*, *12*(1), 1-7.

Feng, M., Heffernan, N. T., Heffernan, C., and Mani, M. (2009). Using mixed-effects modeling to analyze different grain-sized skill models in an intelligent tutoring system. *IEEE Transactions on Learning Technologies*, *2*(2), 79-92.

Gong, Y., Beck, J. E., and Heffernan, N. T. (2011). How to construct more accurate student models: Comparing and optimizing knowledge tracing and performance factor analysis. *International Journal of Artificial Intelligence in Education*, *21*(1-2), 27-46.

Humanante-Ramos, P. R., García-Peñalvo, F. J., and Conde-González, M. Á. (2015). Personal learning environments and online classrooms: An experience with university students. *IEEE Revista Iberoamericana De Tecnologías Del Aprendizaje*, *10*(1), 26-32.

Juárez-Ramírez, R., Navarro-Almanza, R., Gomez-Tagle, Y., Licea, G., Huertas, C., and Quinto, G. (2013). Orchestrating an adaptive intelligent tutoring system: Towards integrating the user profile for learning improvement. *Procedia-Social and Behavioral Sciences*, *106*(2013), 1986-1999.

DOI: https://doi.org/10.17509/ijost.v6i3.38954
p- ISSN 2528-1410 e- ISSN 2527-8045

Kavitha, R., Vijaya, A., and Saraswathi, D. (2012). Intelligent item assigning for classified learners in ITS using item response theory and point biserial correlation. *2012 International Conference on Computer Communication and Informatics* (pp. 1-5). IEEE.

Khlaisang, J., and Songkram, N. (2019). Designing a virtual learning environment system for teaching twenty-first century skills to higher education students in ASEAN. *Technology, Knowledge and Learning*, *24*(1), 41-63.

Klotz, J. (1998). A linked list for the Wilcoxon signed rank test. *Journal of Nonparametric Statistics*, *9*(1), 87-93.

Kozhevnikov, M., Gurlitt, J., and Kozhevnikov, M. (2013). Learning relative motion concepts in immersive and non-immersive virtual environments. *Journal of Science Education and Technology*, *22*(6), 952-962.

Lavigne, G., Ruiz, G. G., McAnally-Salas, L., and Sandoval, J. O. (2015). Log analysis in a virtual learning environment for engineering students. *International Journal of Educational Technology in Higher Education*, *12*(3), 113-128.

Lin, C. C., Liu, Z. C., Chang, C. L., and Lin, Y. W. (2018). A genetic algorithm-based personalized remedial learning system for learning object-oriented concepts of Java. *IEEE Transactions on Education*, *62*(4), 237-245.

Lin, H. C. K., Wu, C. H., and Hsueh, Y. P. (2014). The influence of using affective tutoring system in accounting remedial instruction on learning performance and usability. *Computers in Human Behavior*, *41*(2014), 514-522.

Nkambou, R., Mizoguchi, R., and Bourdeau, J. (Eds.). (2010). Advances in intelligent tutoring systems. *Springer Science and Business Media,308*, 1-408.

Reisslein, J., Reisslein, M., and Seeling, P. (2006). Comparing static fading with adaptive fading to independent problem solving: The impact on the achievement and attitudes of high school students learning electrical circuit analysis. *Journal of Engineering Education*, *95*(3), 217-226.

Rosmansyah, Y., Achiruzaman, M., and Hardi, A. B. (2019). A 3D multiuser virtual learning environment for online training of agriculture surveyors. *Journal of Information Technology Education: Research*, *18*(2019), 481-507.

Ruxton, G. D. (2006). The unequal variance t-test is an underused alternative to Student's t-test and the Mann–Whitney U test. *Behavioral Ecology*, *17*(4), 688-690.

Salden, R. J., Aleven, V. A., Renkl, A., and Schwonke, R. (2009). Worked examples and tutored problem solving: redundant or synergistic forms of support?. *Topics in Cognitive Science*, *1*(1), 203-213.

Samuelis, L. (2007). Notes on the components for intelligent tutoring systems. *Acta Polytechnica Hungarica*, *4*(2), 77-85.

Scott, E., Soria, A., and Campo, M. (2016). Adaptive 3D virtual learning environments—A review of the literature. *IEEE Transactions on Learning Technologies*, *10*(3), 262-276.

Settouti, L. S., Prié, Y., Marty, J. C., and Mille, A. (2007). Vers des Systèmes à Base de Traces modélisées pour les EIAH. *Rapport de Recherche RR-LIRIS-2007*, *16*(2007), 1-30.

DOI: https://doi.org/10.17509/ijost.v6i3.38954
p- ISSN 2528-1410 e- ISSN 2527-8045

Skudder, B., and Luxton-Reilly, A. (2014). Worked examples in computer science. *Proceedings of the Sixteenth Australasian Computing Education Conference-Volume, 148*(2014), 59-64.

Van De Sande, B. (2013). Properties of the Bayesian knowledge tracing model. *Journal of Educational Data Mining*, *5*(2), 1-10.

DOI: https://doi.org/10.17509/ijost.v6i3.38954
p- ISSN 2528-1410 e- ISSN 2527-8045