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ADAPTIVE GAMIFICATION FRAMEWORK FOR IMPROVING MOTIVATION AND ACHIEVEMENT OF STUDENTS IN LEARNING PROCESS

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Abstract. *The usual problem in the learning process is the loss of learning motivation, which may be caused by the learning media and less-personalized learning materials. It leads to the need for adaptive gamification. This paper presents a novel adaptive gamification framework for the education support system. By using the developed framework from this study, it is expected that learning motivation and achievement should be improved significantly. The proposed framework has been tested using 50 samples from the university. The experiment had tried to figure the effect of adaptive gamification application for learner's motivation and achievement. The results concluded that adaptive gamification significantly improves learner's motivation and achievement compared to the use of the textbook for self-study. An interesting finding is that the learner's motivation could only be significantly improved among learners who finished the required learning process.*
Keywords: Adaptive gamification, Gamification framework, Motivation improvement, Achievement improvement, Fuzzy logic

1. **Introduction.** One of the usual problems faced by anyone while involved in the learning activity is the loss of motivation to learn. This problem could be traced from media used [1]. To motivate them, game elements could be adapted into learning activities which are known as gamification [2]. Sometimes gamification could not keep the learner motivated as the contents and difficulties of learning activities have not been personalized [3], which might be unsuitable for the learner. There is a need for adaptive gamification [4].

Despite several adaptive gamification frameworks that have been proposed such as [4-6], most of these proposed frameworks are typically less supported by experiment results to show its effectiveness. Therefore, the novelty of this study is the effectiveness evaluation of the framework proposed by [5] using some experimentations.

The rest of this paper is organized as follows. Section 2 will describe literature reviews related to the gamification framework. Next, our research framework is described in Section 3 and followed by our experiment result in Section 4. Finally, it will be concluded by a conclusion in Section 5.

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2. Literature Review.

2.1. Gamification. Deterding et al. [2] defined gamification as an act of applying game elements in non-game activities. Typical gamification adopts several game elements such as avatar, environment, storyline, feedback, status, economy, social interaction, and limitation [7]. The study by Kapp et al. [8] has proven that gamification in the learning process could create interactive learning sessions, sustain learning motivation, give learners time to solve the problem, make positive changes to learners, and simulate the situation of learning materials.

2.2. Adaptive gamification. Adaptive gamification is a term that refers to the ability of a gamification application to customize itself to various types of users to a certain extent [4,9]. In the past decade, adaptive gamification has raised attention from researchers in the education domain to improve learner's performance, increase learner's attention, better knowledge transfer, and keep the learner progress continuously in the learning process. According to a study reported by [8], the main areas of an adaptive feature of adaptive gamification are mainly content adaptation and difficulty adjustment to player performance, failure, and attention. Some prominent studies on content adaptation in adaptive gamification have been reported by [6,9] which show the similarity of content adaptation with the concept of gameplay reported by [5]. Whilst, studies on difficulty adjustment in adaptive gamification have been reported by [5,9].

2.3. Learner motivation. According to [7], motivation is a combination of the biological, emotional, social, and cognitive aspects of a person that would influence the person's actions in any situation to reach the objectives. According to [11] learning motivation can be categorized in general into four factors namely: (i) attention (learner's focus while doing the learning activity), (ii) relevance (the usefulness of the learning materials to solve real-world problems), (iii) confidence (the balance between learning material and activity's difficulty), and (iv) satisfaction (learner's expectation when the learning process ended completely).

2.4. Learner achievement. Achievement is a positive performance that happened in oneself [12]. While using the gamification system, someone's achievement could be seen from the user level, high score, cleared tasks, or cleared level [12,13]. When the learner felt the rise of difficulty level in gamification activity, the learner's performance might be dropped but the learner will be more focused on the goal, therefore the learner can achieve the goal [14].

3. Methodology.

The research framework in this study can be summarized in Figure 1.

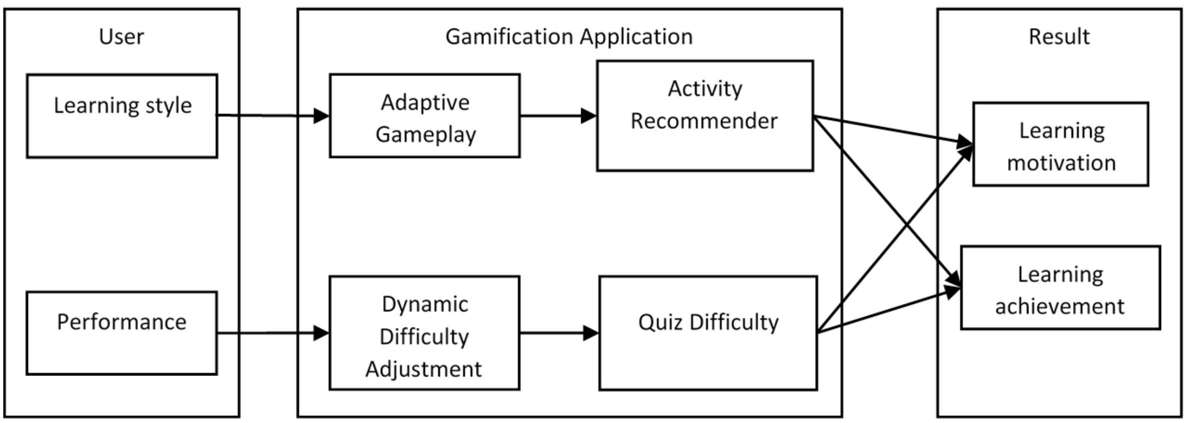

FIGURE 1. Adaptive gamification framework

Learners as the proposed adaptive gamification user will have two components which are learning style and performance. Learning style will be used by adaptive gameplay to regulate activity recommender, while performance will be used by dynamic difficulty adjustment to regulate quiz difficulty. Both activity recommender and quiz difficulty will improve learner's motivation and achievements as well.

For activity recommender, fuzzy rules were developed by simplifying the map made by [10] which paired various learning activities with the Felder-Silverman Index of Learning Style. The classification was made by mapping various learning activities with the Felder-Silverman Index of Learning Style, which assumed each person have four sets of paired learning styles, such as Active-Reflective, Sequential-Global, Visual-Verbal, and Sensing-Intuitive [10]. The classification could be seen in Figure 2.

Learning Activity

Learning Style		Exercise-concept	Exercise-fact	Exercise-detail	Exercise-overview	Practices	Lesson Outline/Summary/Objective	Case study	Slideshow	Web Page (few links)	Web Page (lots links)	Examples	Explanation
	Active	X	X	X	X	X							
	Reflective						X	X	X	X	X	X	X
	Sequential			X		X				X			
	Global				X		X				X		
	Visual								X			X	
	Verbal						X						X
	Sensing		X	X	X	X		X	X			X	
	Intuitive	X								X	X		X

Figure 2. Mapping of learning activity with learning style

Those learning styles will be scored based on the result of the questionnaire filled by the learner at the beginning of the application. The score for each learning style will be categorized as Mild (5.5 to 7), Moderate (7 to 9), and Strong (9 to 11); which symbolize the compatibility of the learner to the respective learning style. All learning style scores will be updated anytime the learner has completed a learning activity using Equation (1).

$$\mathrm{LS}_{new} = \mathrm{LS}_{prev} + \alpha\left(e^{\frac{-n}{t}}\right) \tag{1}$$

In Equation (1), LS_{new} is the latest condition of user's learning style, LS_{prev} is the previous condition of user's learning style, α is the learning rate, n is the current amount of learning activities that have been taken, and t is the total amount of expected amount of learning activities taken.

There are three categories of learning activity distribution. Each category represents the probability of its appearance compared to the other learning activities. When a learning activity is considered by fuzzy rules to seldomly appear on screen ("Low") then the other activities will often appear on screen ("High"); and vice-versa. However, when a learning activity is considered as "Mid" then all activities have a similar chance to appear on the screen. Therefore, we could formulate the fuzzy rules for learning activity recommendations in Figure 3. These rules will be called anytime an update to learner's learning style scores happened.

The activity recommender will take eight parameters as input to be processed by the rules in Figure 3 to get the weight of learning activities. The weight of learning activities

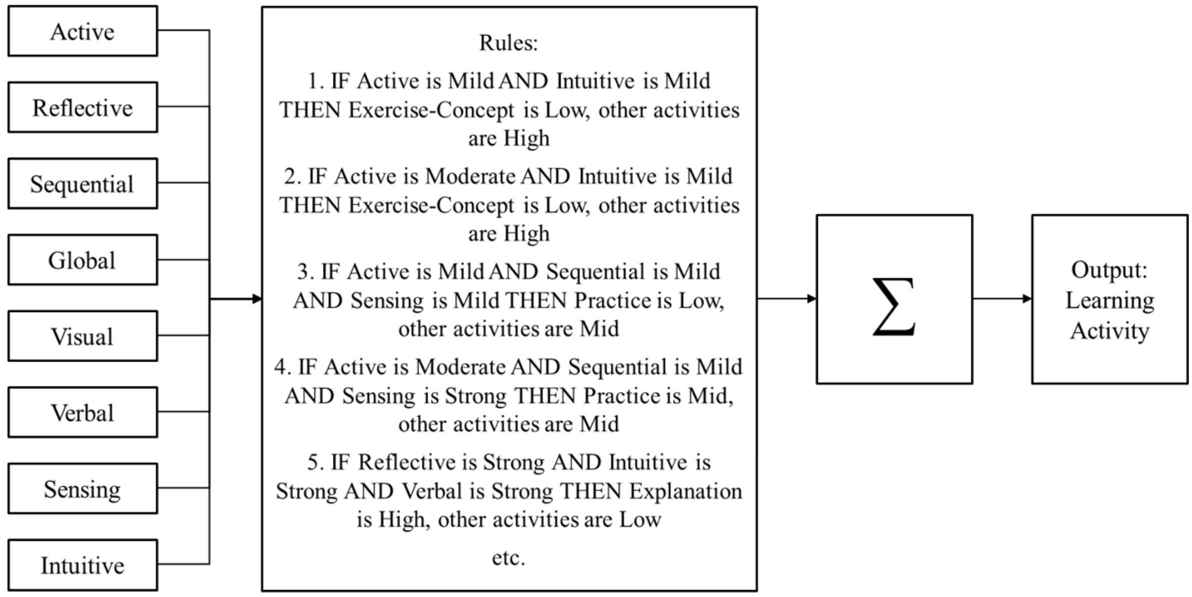

FIGURE 3. Fuzzy rules for learning activity recommender

will be used as the determiner of displayed learning activity on the screen. Since there is a looping process to check the eight parameters and assign the weight of learning activities, the computational complexity for learning activity recommender is $O(n)$.

The quiz difficulty level will be adjusted dynamically according to the learner's test score [11]. Each chapter's quiz will have several difficulty levels such as B1, B2, I1, I2, A1, and A2. Each difficulty level will have randomized questions with various time limits. B1/B2 has the highest time limit and A1/A2 has the lowest time limit, while the time limit of I1/I2 is between them. In each chapter, the learner will always start from B1. The learner must reach point NC which is after difficulty level A2 to move into the next chapter.

There are three quiz score categories that affect the difficulty level, such as Low (score $<= 60$), Mid ($60 <$ score $<= 80$), and High ($80 <$ score $<= 100$). When the learner had finished any difficulty level, the next starting point will be decided by the score from the currently finished level. The fuzzy rules for quiz difficulty adjustment could be seen in Figure 4. These rules will be called anytime an update to learner's quiz scores happened.

The quiz difficulty adjustment will take two parameters as input to be processed by the rules in Figure 4 to get the next difficulty level. The latest difficulty level and the latest

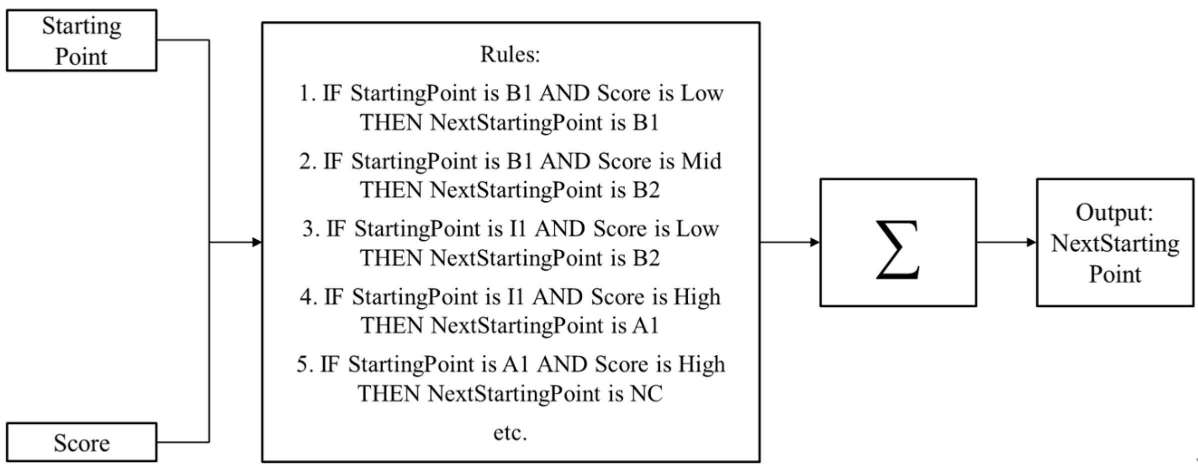

FIGURE 4. Fuzzy rules for quiz difficulty adjustment

quiz score will be used as the determiner of displayed learning activity on the screen. The two parameters will not influence the processing time of the difficulty adjustment; therefore the computational complexity for quiz difficulty adjustment is $O(1)$.

The experiment started with a brief explanation of the procedure to respondents. After finished with the briefing session, respondents took a pre-test about their expected motivation while hearing the explanation and knowledge test about learning materials provided in the application. When the pre-test session is finished, respondents will be separated randomly into two groups. Each group will be determined to use a certain media for each person in a 1-hour self-study session, either the gamification application or textbook. As the self-study session is over, respondents would take motivation and knowledge post-test in which the questions are the same as the pre-test.

4. **Result.** In this study, the framework of [5] has been implemented into a gamification application that could be operated using an Internet browser. At the beginning of the application, the learner should input the name and choose their avatar. After that, the learner should answer several questions regarding their learning style, which was adapted from the Felder-Silverman Index of Learning Style. Finishing the questions, the learner will enter the main page of the application as seen in Figure 5. All text in this application was written using the Indonesian language.

FIGURE 5. Application's main page

On the main page, the learner can read the current chapter title on the top-middle of the screen. Several actions could be done, such as see their profile (top-left button), choose the suitable learning activities (top-middle button), take the quiz and move to the next chapter after finishing several learning activities (top-right button), save their progress (bottom-left button), set text speed preference (bottom-middle button), and read the complete learning material as the bonus after completing several learning activities (bottom-right button). There is also a button on the top-right screen to read how to use the application.

From the top-middle button, the learner could choose one from two learning activities provided on the screen as seen in Figure 6. The provided learning activities in this screen were done based on the fuzzy rule in Figure 3. The learner should choose one activity so the learner could continue their learning progress.

From the top-right button, the learner could take the quiz as seen in Figure 7. The quiz must be done so the learner could move to the next chapter. The quiz will start at the difficulty level B1 (Mudah 1) and has ten questions that should be answered before the

FIGURE 6. Learning activity screen, with the learning activity options that could be chosen by user in the middle of the screen

FIGURE 7. Quiz screen, with the difficulty level and question in the top-left; score, number of question given, and time to answer in the top-right; and answers that could be chosen by user in the middle of the screen

time (Waktu) runs out. Each right answer will add the score (Nilai), while each wrong answer will reduce the score. When the learner is done with the quiz, the application will notify the learner to move to the next chapter.

In the experiment, 50 university students were involved. They would face motivation and knowledge tests in each of the pre-test and post-test sessions. The pre-test was conducted after a briefing session, while the post-test was conducted after the self-study session. A reliability test was conducted to find the reliability of pre-test and post-test questions. For the motivation test, Cronbach's alpha for the pre-test was 0.862 and the post-test was 0.784. Meanwhile, for the knowledge test, Cronbach's alpha for the pre-test was 0.828 and the post-test was 0.950. It can be said that the questionnaires used in the experiment had high reliability.

It can be seen in Table 1 that the respondents who got briefed to use the gamification app at the pre-test felt more motivated compared to the textbook users. Despite that, the knowledge level of the textbook users was higher. After the end of the self-study session,

Table 1. Pre-test and post-test result

Test phase	Complete/incomplete learning	Test type	Mean (Gamification app)	Mean (Textbook)
Pre-test	Complete	Motivation	**3.6881**	3.5536
		Achievement	38.3325	**43.1827**
	Incomplete	Motivation	**3.698**	3.6215
		Achievement	21.999	**37.5654**
Post-test	Complete	Motivation	**4.1263**	3.5082
		Achievement	**92.0825**	62.2736
	Incomplete	Motivation	**3.735**	3.7
		Achievement	**62.501**	52.1808

Table 2. Significance of paired t-test result

Complete/incomplete learning	Test type	Significance (Gamification app)	Significance (Textbook)
Complete	Motivation	0.0	0.717
	Achievement	0.0	0.001
Incomplete	Motivation	0.824	0.418
	Achievement	0.0	0.012

it could be seen that the gamification app users felt more motivated and have a better knowledge level compared to the textbook users.

Since the data are considered normal from the Shapiro-Wilk test, paired t-test could be used to compare pre-test and post-test results. The result from the paired t-test could be seen in Table 2.

From Table 2, it is found that both the gamification app and textbook could improve learners' achievement ($p < .05$). Despite that, respondents who complete the learning process using the provided application have a significant difference for motivation change ($p = .0$) while respondents who did not complete the learning process have insignificant differences ($p = .824$). Meanwhile, for the textbook learners, the motivation change for both finished and unfinished learners are insignificant ($p > .05$). Therefore, it can be said that the usage of the adaptive gamification framework throughout the learning process will improve learning motivation and achievement significantly compared to the textbook.

5. **Conclusions.** This paper tries to evaluate the effectiveness of the adaptive gamification framework in terms of improving learner motivation and achievement. The experiment findings showed that the adaptive gamification application improves the learners' motivation and achievement, yet the significantly improved motivation only happened to the learners that complete the learning process. For future works, the experiment will be broadened by comparing the effectiveness of the adaptive gamification framework and the traditional learning methods.

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