Serious game self-regulation using human-like agents to visualize students engagement base on crowd

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ABSTRACT

Nowadays, the emergence of artificial intelligent (AI) technology for games has been advancely developed. A serious game is a technology employing AI to create a virtual environment in a serious gamification strategy. This research describes AI based virtual classrooms to adopt proper strategies and focusing on maintaining and increasing student engagement by encouraging self-regulation behavior at the learning process. The self-regulation behavior describes student's ability to direct their own learning to achieve learning targets on a path full of obstacles. By employing a human-like agent to visualize student engagement, this visualization aims to provide human-like experiences for users to comprehend student behavior. A reciprocal velocity obstacles (RVO)-based crowd behavior is employed to visualize student engagement. RVO is an autonomous navigation approach for directing the achievement of agents target. The human-like agents behave in various ways to reach the goal points depending on the performances and the obstacles before them. We employ our method in an investigation of students' learning activities in a pedagogically-centered learning environment at Universitas Islam Negeri (UIN) Walisongo, Semarang, Indonesia. The results demonstrate the best scenario changes along with the performances and obstacles faced to reach the goal points as well as the learning target.

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1. INTRODUCTION

The COVID-19 pandemic spreads globally forcing the world communities to realize that the world has changed [1]. The government's policy in the context of handling the massive spread of COVID-19 is the reason for the implementation of home education [2]. With the use of ubiquitous technology [3] which is suddenly employed, leads to the confusion of both educators and students, as well as their parents and even everyone in the house [4]. Information technology-based learning or known as e-learning or ubiquitous learning has long apply in various educational institutions [5], but online learning seems to have surprised almost all lines, both in the villages and even the world [6].

On the other hand, long before the pandemic, independence in student learning has become an increasing concern [7], various studies are competing to understand and facilitate this behavior [8]-[11], this is because it driven by empirical evidence that shows the role of independent behavior and self-regulation in having a positive impact on academic success quite significant [12], [13]. Self-regulation define as the process of students controlling their behavior in their learning so that they actively monitor [14] and maintain cognition towards learning goals appropriately [15].

As a result, substantial efforts in several studies on online intelligent guidance systems made to support and identify self-regulation strategies [16]. Most of this research has looked at self-regulation in highly structured problem solving and learning situations [17]. However, in an open learning environment where goals are poorly defined and students do not always have clear signals of their progress [18], understanding and supporting students' self-regulation behaviors becomes very important [19]. Students must actively develop and set their own goals, as well as evaluate their progress, to succeed in this learning environment. Unfortunately, during interactions with these settings children do not consistently display appropriate self-regulatory behaviors, which may limit the teaching potential of this system [20]. As a result, further research on the role of self-regulation in open-ended learning settings requires fully comprehending how these environments might be employ as effective learning tools.

Regarding the condition, with the emergence of artificial intelligent (AI) technology for games it is possible to employ it to simulate or visualize the self-regulation behavior of students. Serious games is a technology that uses AI to create a virtual environment in a game style in a serious way [21]. In some studies serious games can help in providing proper guidance to children to develop self-regulation skills [22], in this research project, we describe an AI-based virtual classroom to adopt the right strategy and focus on maintaining and increasing student engagement by encouraging self-regulating behavior in the learning process. Self-regulation describe as students' navigational ability to direct their own learning to achieve learning targets on a global path full of obstacles [23]. Human-like agents are employed to visualize student engagement to maintain the consistency of self-regulation [24]. In addition, this visualization also aims to provide a human-like experience for users to understand student behavior. A reciprocal velocity obstacles-based (RVO-based) crowd behavior proposed to visualize student engagement. RVO is an autonomous navigation approach to direct the achievement of goals on a global path [25], [26]. Agents behave in various ways to reach a goal point depending on the performance and the obstacles before them. So that the self-regulation scenario will adjust along with the performance and obstacles faced to reach the goal point as well as the learning target.

Self-regulation is a concept used to characterize the behaviors of students who actively control their learning goals and outcomes. Self-regulation requires students to actively define objectives and make conscious choices to assess and evaluate their progress. Among other things; self-regulated students consciously reflect on their knowledge and learning processes, making modifications depending on previous success and failure [27]. While it appears that all students engage in self-regulatory actions while learning, the level of competency varies widely, even among students of the same age. Furthermore, the student's superiority at controlling their learning is more successful [28].

Identifying and scaffolding self-regulation methods has been a focus of considerable study in the intelligent tutoring systems sector as well [29], outside of the traditional classroom. Think-aloud procedures have been used to study the tactics students employ in MetaTutor, a hypermedia environment for learning biology, while analysis of students' navigation through the hypermedia environment helps to establish profiles of self-regulated learners [30]. In the Betty's Brain system, researchers have discovered patterns of behavior that indicate low and high degrees of self-regulation [31]. When these patterns of behavior arise, prompting students to apply self-regulation methods has demonstrated to be effective.

Previous research has mostly concentrated on recognizing self-regulation activities in highly organized problem-solving and learning environments, but there has also been work on identifying self-regulation behaviors in open-ended exploration environments. Rodrigues *et al*. [32] for example, looked at the early prediction of students' use of serious games in order to inform possible interventions and scaffolding. Understanding and supporting students' self-regulation behaviors is especially crucial in open-ended learning environments, where goals may be hazy and students may lack a clear indicator of their progress [33]. Students must actively develop and set their own goals, as well as evaluate their progress, in order to succeed in this sort of learning environment. While the nature of the learning task may have implicit general goals like "completing the assignment" or "learning a lot," students should create more precise, tangible, and measurable goals [34].

This research describes an AI-based virtual classroom with gamification style to adopt the right strategy and focus on maintaining and increasing student engagement by encouraging self-regulatory behavior in the learning process so we call this project serious game self-regulation (SG-SR). At SG-SR we employ human-like agents to visualize student engagement so that consistency of self-regulation will be maintained. Furthermore, this visualization also aims to provide a human-like experience for users to understand student behavior. This study proposes reciprocal velocity obstacles (RVO)-based crowd behavior to visualize student engagement. RVO is an autonomous navigation approach to direct the achievement of goals on a global path [35]. Agents behave in various ways to reach a goal point depending on the performance and the obstacles before them. So that the self-regulation scenario will adjust along with the performance and obstacles faced to reach the goal point. And the destination point is the target.

2. METHOD

We designed a serious game to represent student capability at certain pedagogical aspects in a gamification manner. In our serious game, the student represents as non-playable character (NPC) known as mobile agents. The students' pedagogical aspect will represent as a parameter for mobile agents' navigation. These mobile agents are tasked to navigate toward their points of destination. This navigation task represents the study process with the point of destination as the study goal. With this serious game that we proposed, student capability to fulfill their learning objective can visualized in the form mobile agents trying to reach their destination.

Mobile agents in our serious games are informed with the general direction of their destination. Figure 1 shown diagram of out proposed method to visualize student capability in learning environment represented as mobile agents. In an ideal situation, these mobile agents simply need to navigate straight to reach their destination. This ideal situation in our serious game represents an ideal situation in the learning process. Of course, in real-world conditions, students will face many setbacks and hurdles in their learning process, either from student interaction against each other and from their learning environment. By acknowledging the existence of this condition, we create a navigation environment that fill with many obstacles. These obstacles act as hindrances in agents' navigation thus the mobile agents are required to overcome this challenge to achieve their objective.

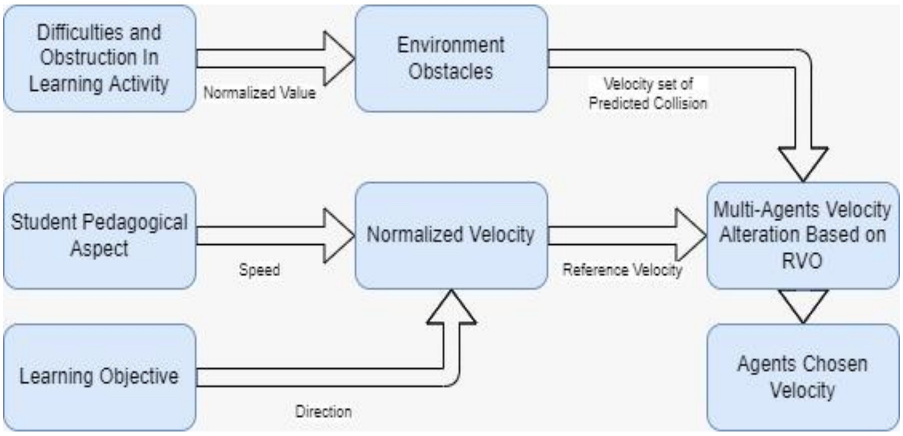

Figure 1. Diagram of out proposed method to visualize student capability in learning environment represented as mobile agents

Since the mobile agents' navigation occurs simultaneously in the same environment, the avoidance process against obstacles may cause confusion between agents. Thus, we employ a multi-agents navigation method known as reciprocal velocity obstacles (RVO). RVO designed to deal with local reactive collision avoidance that can produce collision and oscillation-free avoidance in multi-agents situations [35]. RVO avoidance works by selecting the closest velocity to the agent's preferred velocity that is outside the collision cone of that agent. The collision cone is a representation of the velocity set that predict by the RVO to produce collision if taken by a certain agent. In our proposed method, the preferred velocity for an agent derives from the straight direction to their point of destination with speed parameter taken from a certain value of pedagogical aspect

In (1) shows the speed parameter conversion from pedagogical aspect value. That equation takes a pedagogical aspect value from a set of students in the same learning environment and normalizes that value based on the min-max range in that set of students. This normalized value converts to the speed parameter of certain agents based on the determined min-max range in speed value. This speed value combined with the preferred direction, produces preferred velocity for an agent. This preferred velocity is the optimal velocity for an agent to take to fulfil their task.

$$S_{agent} = S_{min} + \frac{PA_{Student}}{PA_{Max}} x S_{add} \tag{1}$$

Where:
S_{agent} = Agent speed
S_{min} = Minimum determined speed value
S_{add} = Maximum speed addition value
$PA_{student}$ = Pedagogical aspect value for certain student
PA_{max} = Maximum pedagogical aspect value from set of observed students

As we already mentioned, mobile agents can simply navigate straight forward to their destination in an ideal situation. This ideal situation also enables the mobile agents to take their assigned speed parameter that take from pedagogical aspect value. Since the presence of obstacles denotes avoidance process against those obstacles as well as other mobile agents that exist in the navigation space, the preferred velocity of the agents will substitute by RVO if that preferred velocity predict to produce collisions. Since RVO adjusts the velocity of the agents for avoidance, this process implies the learning process situation in our serious game. We signify that preferred velocity represents the potential of the student in the learning process in certain pedagogical aspects. This potential may be hindered by certain difficulties and obstructions that exist in the learning environment. Student interaction with each other may affect the learning process. This represents by the RVO process to avoid obstacles and other agents. Due to variance in agents' potential speed and velocity alteration caused by the avoidance process, each mobile agent will reach their destination at varying times.

3. RESULTS AND DISCUSSION

We employ our method in an investigation of two of the virtual classes contained in an e-learning at the Walisongo State Islamic University, Semarang, Indonesia. This investigation intends to explore the data recorded in the virtual class system log. The data successfully explored were data from reading activities on written materials such as PDF files, viewing video tutorials, discussions with classmates and listening to music activities. Data was collected from 92 students from 2 classes, while the distribution of the data is shown in a graph in Figure 2.

The total log of the 4 variables collected is 3456 logs with varying Min and Max values for each variable as shown in Table 1. Based on the range of min-max values, the student set data is normalized, this normalized value convert to the speed parameter of certain agents based on the determined min-max range in speed value. This speed value combined with the preferred direction, produces preferred velocity for an agent. This preferred velocity is the optimal velocity for an agent to take to fulfil their task.

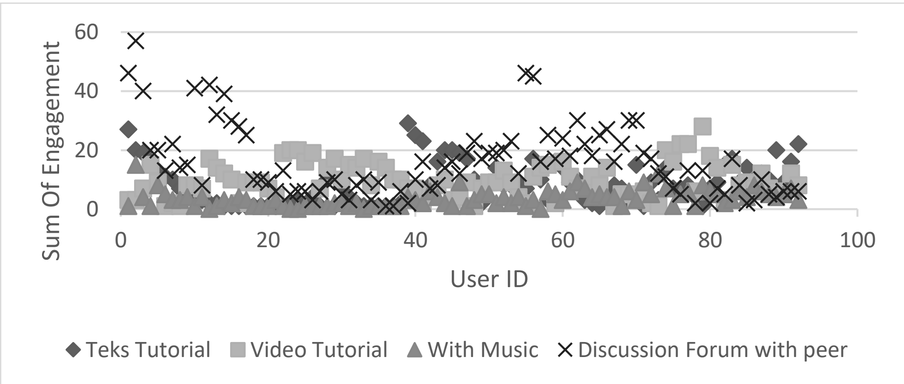

Figure 2. Engagement data distribution

Table 1. Min-max value of pedagogical aspect

	Teks tutorial	Video tutorial	Discussion forum with peer	With music
Total Log	781	889	327	1459
Max Value	29	28	15	57
Min Value	1	1	0	1

3.1. Observing self-regulation behavior

This research describes AI based virtual classrooms to adopt proper strategies and focusing on maintaining and increasing student engagement by encouraging self-regulation behavior at the learning process. Figure 3 shows a graph of a sample chosen randomly from the data set of students in the same class. The graph shows how students behave based on their self-regulation tendencies in first identification, significant differences showed between several students in the class. this proves ability of self-regulation among students in the class is different. Several factor showed in Figure 3 including learning factor from text-based, video-based and peer discussion, along with music accompanied learning.

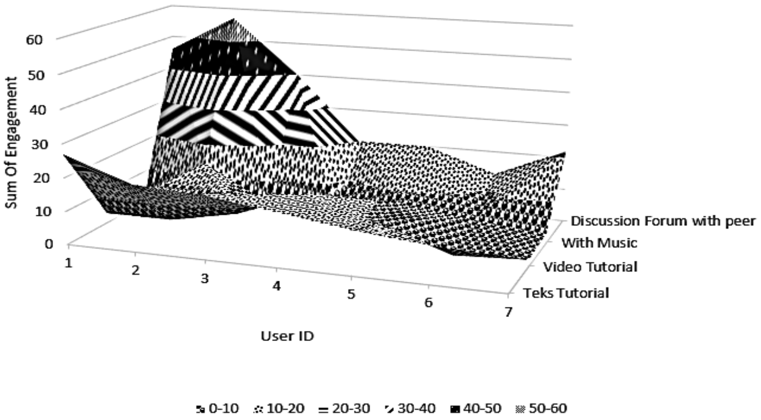

Figure 3. Student engagement at virtual class with self-regulation perform

3.2. Experiences of self-regulation

These findings point to a number of crucial aspects of self-regulation, the self-regulation behavior describes a student's navigational ability to direct their own learning to achieve learning targets on a global path full of obstacles. By employing a human-like agent to visualize student engagement, this visualization aims to provide human-like experiences for users to comprehend student behavior. A RVO-based crowd behavior is employed to visualize student engagement. RVO is an autonomous navigation approach for directing the achievement of goals on a global path. The human-like agents behave in various ways to reach the goal points depending on the performances and the obstacles before them.

This scenario, namely avoidance of obstacles with RVO will provide an experience to understand student behavior in self-regulation independently, we tested 10 times to discover changes in the scenario that occurred in each agent. Figures 4-6 depict the agent's time consumption throughout the course of ten tests. Every graph shows multiple changes in the time required for each test, this result indicating a existence of changing scenario, and the scenario chosen by each agent is the best scenario in each test. As visualized in Figure 7 with label F, all agents will arrive at predetermined points, namely learning targets, what distinguishes between agents is the travel time required, this is due to several factors, including poor initial resources, quite large obstacles. However, some agents also show the opposite, meaning that poor resources sometimes do not cause delays in reaching learning points or targets.

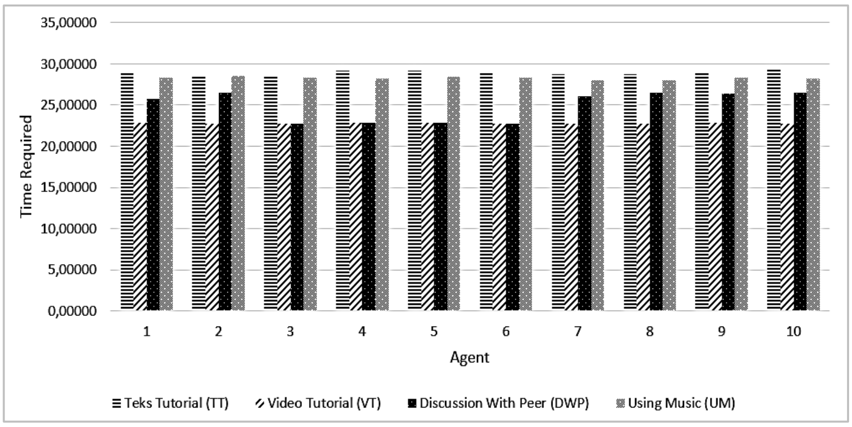

Figure 4. Sample result of the experiment for mobile agent in 10 trial

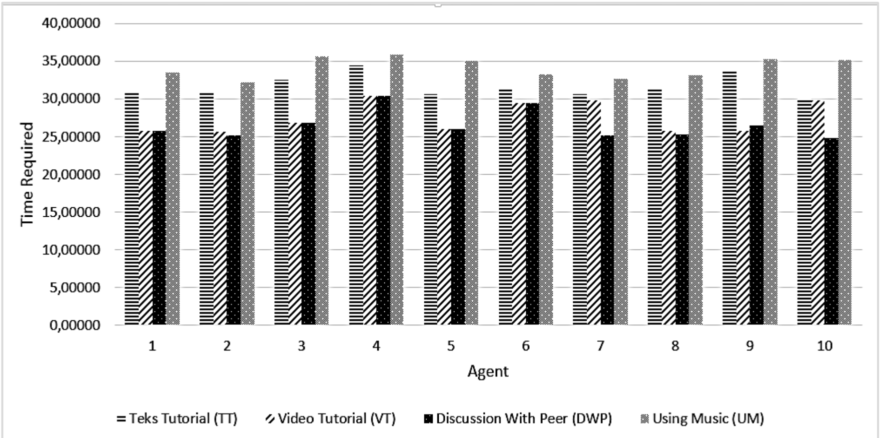

Figure 5. Average result of the experiment for mobile agent in 10 trial

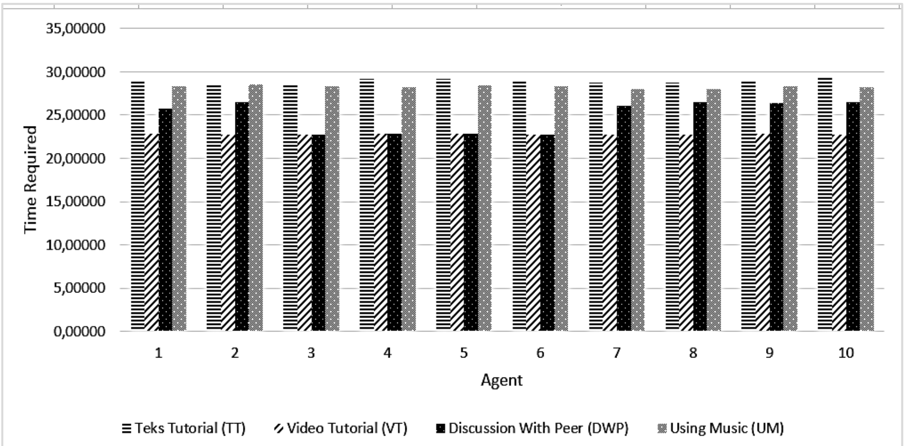

Figure 6. Another sample of the experiment result

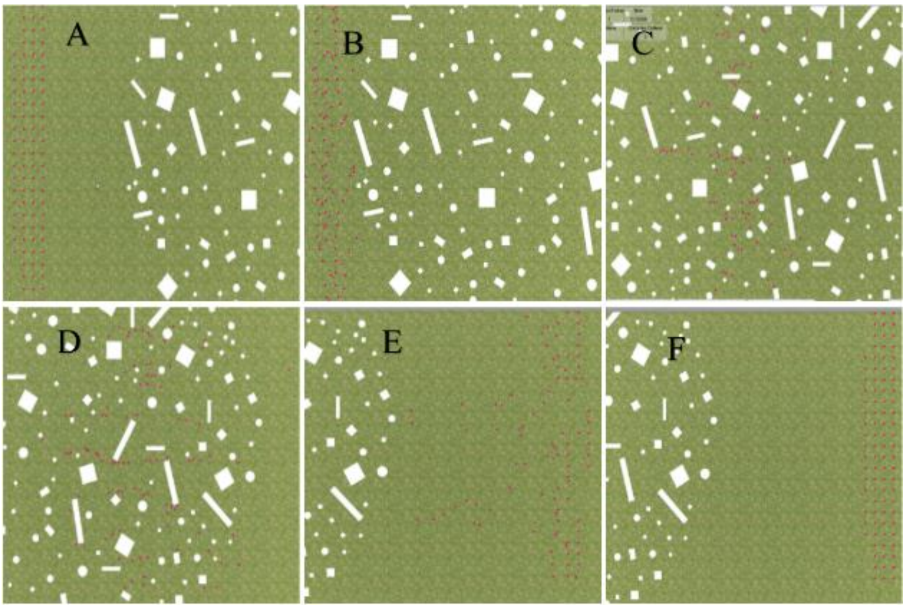

Figure 7. 92 mobile agents moving through various obstacles

Finally, Figures 8 and 9 exhibit the findings of the final experiment in this paper, demonstrating that each user has about comparable abilities and that no pupils have major discrepancies or are late. These findings demonstrate that RVO can depict students' learning self-regulation to deliver a meaningful experience for users. Dynamic obstacle will employ in future research to see if the RVO method is still viable for this project.

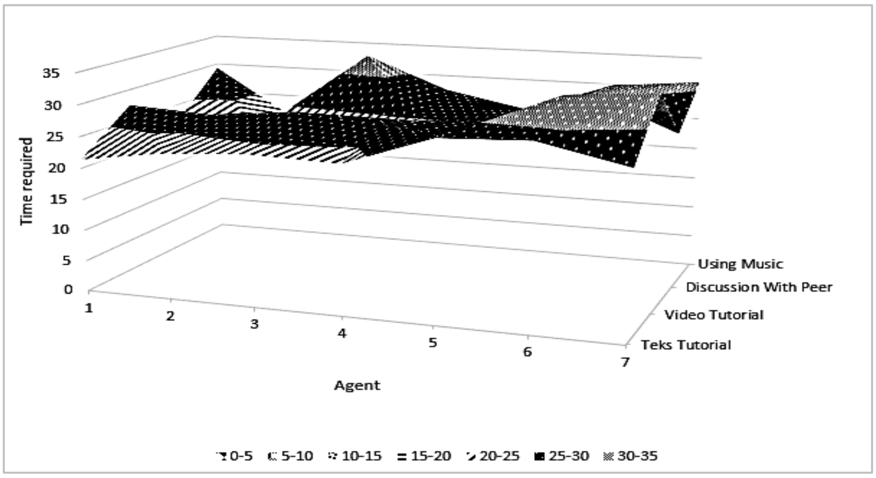

Figure 8. Graphic of mobile agents speed with seven random sample, y axis is time require and x axis is number of mobile agent

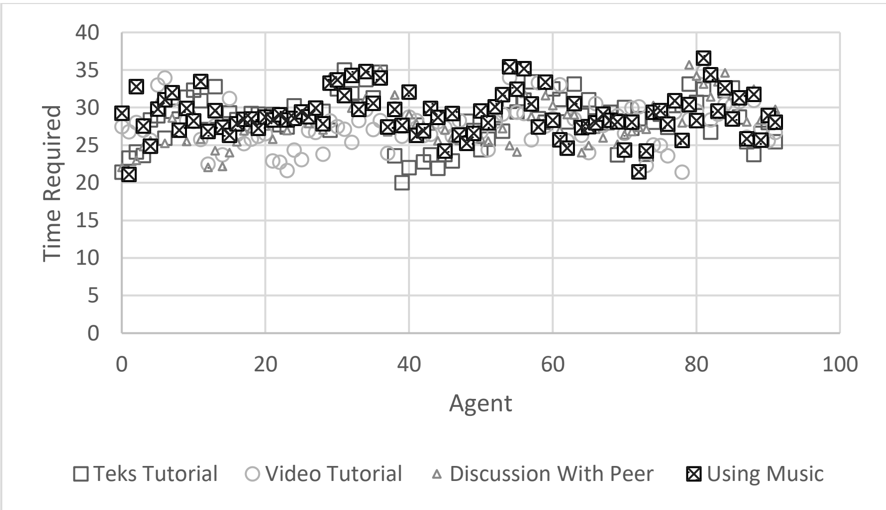

Figure 9. Engagement student distribution using self-regulation perform

4. CONCLUSION

In this work, we employ our method in an investigation of students' natural independent learning activities in a pedagogical-centered learning environment, in a virtual e-learning class at UIN Walisongo Semarang. In the initial investigation, not all learners have the potential to demonstrate their ability to self-regulate their learning. Even for those who can make superior to use of resources, it has not identified whether this ability is the success of their self-regulation. These findings highlight the necessity of able to identify learners who have low self-regulation tendencies so that appropriate scaffolding can provided. The machine learning algorithms mentioned in this work have much potential for providing experience in student's self-regulation abilities from early in their engagement.

This finding shows to several idea for future work. The most important of this is developing mechanisms of intervention for assist student self-regulation. Students with a low capacity to self-regulate may benefit from additional assistance when using these resources. Alternatively, it's possible that these students have difficulty recognizing and setting appropriate goals. The Serious game self-regulation could use to make this goal-setting behavior more obvious. Future research should focus on figuring out how to properly integrate these tactics into a pedagogy-centered learning environment. Exploration of a range of potential approaches to further strengthen students' self-regulation skills can aided by drawing on ongoing empirical investigations of learning and student engagement. An important following step in this line of investigation is to investigate individual instruction strategies and build self-regulatory features for components of pedagogy that consider individual differences and obstacle disparities (dynamic obstacle).

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REFERENCES

[1] G. Gao and L. Sai, “Towards a ‘virtual’ world: Social isolation and struggles during the COVID-19 pandemic as single women living alone,” *Gender, Work & Organization*, vol. 27, no. 5, pp. 754–762, 2020, doi: 10.1111/gwao.12468.

[2] P. Putra, F. Y. Liriwati, T. Tahrim, S. Syafrudin, and A. Aslan, “The students learning from home experiences during COVID-19 school closures policy in Indonesia,” *Jurnal Iqra*, vol. 5, no. 2, pp. 30–42, 2020, doi: 10.25217/ji.v5i2.1019.

[3] K. Umam, S. N. S. Mardi, and M. Hariadi, “Internet messenger based smart virtual class learning using ubiquitous computing,” *Journal of Physics: Conference Series*, vol. 855, no. 1, p. 012056, 2017, doi: 10.1088/1742-6596/855/1/012056.

[4] H. Zhuo, “Learning from global education arrangement during COVID-19 pandemic period,” *International Journal of Management and Education in Human Development*. vol. 01, no. 02, pp. 80–85, 2021, [Online]. Available: https://www.ijmehd.com/index.php/OJSJournal/article/view/34.

[5] K. Umam, S. N. S. Mardi, and M. Hariadi, “Ubiquitous learning model using interactive internet messenger group to improve engagement and behaviour for smart campus,” *Journal of Physics: Conference Series*, vol. 801, no. 1, p. 012083, 2017, doi: 10.1088/1742-6596/801/1/012083.

[6] R. Arundhati, “Arundhati Roy: ‘The pandemic is a portal’ | Free to read,” *Financial Times*, vol. 45, no. 2, pp. 1–6, 2020.

[7] F. S. Arista and H. Kuswanto, “Virtual physics laboratory application based on the android smartphone to improve learning independence and conceptual understanding,” *International Journal of Instruction*, vol. 11, no. 1, pp. 1–16, 2018, doi: 10.12973/iji.2018.1111a.

[8] D. Lee, S. L. Watson, and W. R. Watson, “Systematic literature review on self-regulated learning in massive open online courses,” *Australasian Journal of Educational Technology*, vol. 35, no. 1, pp. 28–41, 2019, doi: 10.14742/ajet.3749.

[9] I. Q. Utami, M. N. Fakhruzzaman, I. Fahmiyah, A. N. Masduki, and I. A. Kamil, “Customized moodle-based learning management system for socially disadvantaged schools,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3325–3332, Dec. 2021, doi: 10.11591/eei.v10i6.3202.

[10] A. H. Muhammad and D. Ariatmanto, “Understanding the role of individual learner in adaptive and personalized e-learning system,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3313–3324, Dec. 2021, doi: 10.11591/eei.v10i6.3192.

[11] R. Ramadiani, A. Azainil, A. N. Hidayanto, D. M. Khairina, and M. L. Jundillah, “Teacher and student readiness using e-learning and m-learning,” *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 3, pp. 1176–1182, Jun. 2020, doi: 10.11591/eei.v9i3.2006.

[12] M. Guilmette, K. Mulvihill, R. Villemaire-Krajden, and E. T. Barker, “Past and present participation in extracurricular activities is associated with adaptive self-regulation of goals, academic success, and emotional wellbeing among university students,” *Learning and Individual Differences*, vol. 73, pp. 8–15, Jul. 2019, doi: 10.1016/j.lindif.2019.04.006.

[13] A. F. Taylor and C. Butts-Wilmsmeyer, “Self-regulation gains in kindergarten related to frequency of green schoolyard use,” *Journal of environmental psychology*, vol. 70, pp. 0–29, 2020, doi: 10.1016/j.jenvp.2020.101440.

[14] Y. Xiao and M. Yang, “Formative assessment and self-regulated learning: How formative assessment supports students’ self-regulation in English language learning,” *System*, vol. 81, pp. 39–49, 2019, doi: 10.1016/j.system.2019.01.004.

[15] A. Melissa Ng Lee Yen, “The influence of self-regulation processes on metacognition in a virtual learning environment,” *Educational Studies*, vol. 46, no. 1, pp. 1–17, 2020, doi: 10.1080/03055698.2018.1516628.

[16] J. H. Eggers, R. Oostdam, and J. Voogt, “Self-regulation strategies in blended learning environments in higher education: A systematic review,” *Australasian Journal of Educational Technology*, vol. 37, no. 6, pp. 175–192, Aug. 2021, doi: 10.14742/ajet.6453.

[17] D. A. Robson, M. S. Allen, and S. J. Howard, “Self-regulation in childhood as a predictor of future outcomes: a meta-analytic review,” *Psychological bulletin*, vol. 146, no. 4, p. 324, 2020, doi: 10.1037/bul0000227.

[18] M. H. Cho, J. Cheon, and S. Lim, “Preservice teachers’ motivation profiles, self-regulation, and affective outcomes in online learning,” *Distance education*, vol. 42, no. 1, pp. 37–54, 2021, doi: 10.1080/01587919.2020.1869528.

[19] M. C. S. Manzanares, S. R. Arribas, C. P. Aguilar, and M. Á. Queiruga-Dios, “Effectiveness of self-regulation and serious games for learning stem knowledge in primary education,” *Psicothema*, vol. 32, no. 4, pp. 516–524, 2020, doi: 10.7334/psicothema2020.30.

[20] S. Van Laer and J. Elen, "Adults’ self-regulatory behaviour profiles in blended learning environments and their implications for design," *Technology, Knowledge and Learning*, vol. 25, no. 3, pp. 509–539, Sep. 2020, doi: 10.1007/s10758-017-9351-y.

[21] M. Severengiz, G. Seliger, and J. Krüger, “Serious game on factory planning for higher education,” *Procedia Manufacturing*, vol. 43, pp. 239–246, 2020, doi: 10.1016/j.promfg.2020.02.148.

[22] N. Hocine, “Personalized Serious games for self-regulated attention training,” *A Adjunct Publication of the 27th Conference on User Modeling, Adaptation and Personalization*, pp. 251–255, 2019, doi: 10.1145/3314183.3323458.

[23] J. Zheng, W. Xing, G. Zhu, G. Chen, H. Zhao, and C. Xie, "Profiling self-regulation behaviors in STEM learning of engineering design," *Computers & Education*, vol. 143, p. 103669, Jan. 2020, doi: 10.1016/j.compedu.2019.103669.

[24] S. Ariyurek, A. Betin-Can, and E. Surer, "Automated video game testing using synthetic and humanlike agents," in *IEEE Transactions on Games*, vol. 13, no. 1, pp. 50–67, 2021, doi: 10.1109/TG.2019.2947597.

[25] A. Turnwald and D. Wollherr, "Human-like motion planning based on game theoretic decision making," *International Journal of Social Robotics*, vol. 11, no. 1, pp. 151–170, 2019, doi: 10.1007/s12369-018-0487-2.

[26] V. Rahmani and N. Pelechano, "Towards a human-like approach to path finding," *Computers & Graphics*, vol. 102, pp. 2021, doi: 10.1016/j.cag.2021.08.020.

[27] N. Senovska and O. Pryshliak, "Developing professional self-regulation of students during pedagogical practice," *International Journal of Research in Education and Science*, vol. 6, no. 4, pp. 679–691, 2020, doi: 10.46328/ijres.v6i4.1147.

[28] C. Reparaz, M. Aznárez-Sanado, and G. Mendoza, "Self-regulation of learning and MOOC retention," *Computers in Human Behavior*, vol. 111, p. 106423, May 2020, doi: 10.1016/j.chb.2020.106423.

[29] J. W. Kooken, R. Zaini, and I. Arroyo, "Simulating the dynamics of self-regulation, emotion, grit, and student performance in cyber-learning environments," *Metacognition and Learning volume*, vol. 16, no. 2, pp. 367–405, Feb. 2021, doi: 10.1007/s11409-020-09252-6.

[30] E. B. Cloude, F. Wortha, D. A. Dever, and R. Azevedo, "How do Emotions Change during Learning with an Intelligent Tutoring System? Metacognitive Monitoring and Performance with MetaTutor," *Cognitive Science a Multidiscip. Journal*, vol. 1, no. 2, pp. 423–429, 2020.

[31] Y. Zhang *et al.*, "The relationship between confusion and metacognitive strategies in Betty's Brain," in *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, pp. 276–284, Mar. 2020, doi: 10.1145/3375462.3375518.

[32] R. Rodrigues, P. da C. Ferreira, R. Prada, P. Paulino, and A. M. V. Simao, "Developing children's regulation of learning in problem-solving with a serious game," *IEEE computer graphics and applications*, vol. 40, no. 5, pp. 26–40, 2020, doi: 10.1109/MCG.2020.3011616.

[33] K. Beckman, T. Apps, S. Bennett, B. Dalgarno, G. Kennedy, and L. Lockyer, "Self-regulation in open-ended online assignment tasks: the importance of initial task interpretation and goal setting," *Studies in Higher Education*, vol. 46, no. 4, pp. 821–835, 2021, doi: 10.1080/03075079.2019.1654450.

[34] A. M. Grant, "An integrated model of goal-focused coaching: framework for teaching and practice," *Coaching Researched: A Coaching Psychology Reader*, vol. 7, no. 2, pp. 146–165, 2020, doi: 10.1002/9781119656913.ch7.

[35] J. Den Van Berg, M. Lin, and D. Manocha, "Reciprocal velocity obstacles for real-time multi-agent navigation," im *2008 IEEE international conference on robotics and automation*, pp. 1928–1935, May 2008, doi: 10.1109/ROBOT.2008.4543489.

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