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Representing Learning Progression of Unguided Exercise Solving: A Generalization of Wheel-Spinning Detection

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Abstract: This study aims at modeling and visualizing students' behavior in a self-regulated and unguided learning environment with a focus on learning progression. Since the modeling approach is process-oriented and does not depend on specific mastery learning criteria, this paper provides a novel way to identify wheel-spinning in self-regulated learning solely based on activity monitoring. The study investigates the free and unsupervised engagement of junior high school students in solving mathematics exercises during summer vacation. During this period, a pool of exercises was provided on the LEAF online learning platform. Additionally, the students receive adaptive exercise recommendations as an add-on. Guided by the basic idea of wheel-spinning as persistent engagement without learning progression, we have designed a mathematical model and a graphical representation to capture and gauge the individual learning progression. Based on an expert questionnaire survey, we considered how this novel representation can serve as a basis to analytically characterize learning progression and specifically to identify wheel-spinning.

Keywords: Behavior modeling, self-regulated learning, learning progression, wheel-spinning, visualization

1. Introduction

The term "wheel-spinning" has been introduced to characterize a situation in which a learner spends excessive time and effort in a learning environment without mastering the intended learning goals (Beck & Gong, 2013). Wheel-spinning as a form of unproductive persistence has been discussed and studied in the context of intelligent tutoring systems (Wang et al., 2020; Zhang et al., 2019) as well as in game-based learning (Owen et al., 2019). Most of these studies rely on specific mastery learning criteria (Pelánek, 2018). In contrast, we plead for characterizing learning progression on the basis of behavioral data in the form of action logs. This a both a more general approach (not only targeting wheel-spinning) and it can be more flexibly applied to many real learning settings.

In our study, we conceive wheel-spinning as ongoing engagement and activity without positive progression, not necessarily only related to repeated failure. As a first step, we have tackled the issue of capturing learning progress in a way that allows for comparing and interpreting individual learning trajectories. This brought us to generating "learning progress graphs" (LPGs) from the action logs. Although useful for many different purposes, the graphs can also be used specifically to identify wheel-spinning.

In the investigated scenario, junior high school students use an online platform for self-regulated learning (SRL) with mathematics exercises during their summer vacation. The data are from students in three different grades from the same school with an overall of 345 participants. The system environment provides a pool of exercises selected by the teachers in combination with an adaptive recommendation mechanism for additional exercises and links to textbook pages.

The studied learning setting can be characterized as an extreme form of SRL (Owen et al., 2019) in which the students' engagement is based on free choice without any kind of supervision or instruction during the learning period. Analyzing and measuring SRL has been identified as an important research challenge (Sacks & Leijen, 2014; Winne, 2010). We see the work reported here as a contribution to meeting this challenge.

In our approach, we have targeted two aspects to evaluate the quality of LPGs for characterizing learning progression and specifically for identifying wheel-spinning. The first one is "expressiveness" as the information-richness of the model representation. I.e., does the LPG representation transmit the information that is relevant for characterizing the corresponding learning sequence? Secondly, "adequacy" addresses the question in how far the model-based interpretation corresponds to human expert judgement of the cases. To **evaluate the properties of LPG in terms of expressiveness and adequacy**, we have conducted an expert study with example LPGs based on real student data.

2. Background and Related Work

Our aim in this research is to find a way of interpreting "wheel-spinning" in the context of unguided self-regulated learning (SRL).

SRL is typically defined as self-generated thoughts, feelings, and behaviors that are planned and cyclically adapted to achieve personal learning goals (Zimmerman, 2000). Self-regulation involves the capacity to cultivate knowledge, skills, and attitudes that are applicable across various learning environments and can be adapted from contexts in which they were learned to both leisure and professional settings (Boekaerts, 1999). The field of learning analytics, which focuses on interventions and learning processes, provides good opportunities to analyze SRL and bring good insights (Roll & Winne, 2015). SRL activity consists of the sequence which has (1) activation of perceptions through goal setting, (2) metacognitive awareness through monitoring SRL processes, (3) control of the various aspects of the self, and (4) reflections on the self (Pintrich, 2000).

Interdisciplinary cooperation between the fields of learning science, learning analytics, and AI is essential to solving the combination of data-driven approaches and theory-driven verification metrics (Molenaar et al., 2023). The context that we focus on in this study is the ultimate form of self-regulated learning, compared to self-directed learning, in that students work on the teacher-prescribed tasks and additional problems given to them during their school's summer holidays in a completely free environment (Sacks & Leijen, 2014). In this study, we used self-regulated learning context that is assessed in terms of whether the goals set are too high or too low, based on activity monitoring that assess students' self-reports of the problems they solve. We do not distinguish internal elements of the SRL process but rely on analyzing the dynamics of student activity.

The notion of wheel-spinning refers to a situation in which learners spend considerable time learning a topic without actually achieving mastery (Beck & Gong, 2013) or substantial progression. This concept has been applied to the studying-learning interaction with intelligent tutoring systems where students may be stuck in the mastery learning cycle without achieving mastery criteria (Beck & Rodrigo, 2014). In the educational context, we have a number of prior definitions and thresholds of mastery and wheel-spinning. Previous studies define mastery prior to wheel-spinning (Beck & Gong, 2013; Beck & Rodrigo, 2014; Kai et al., 2018; Owen et al, 2019; Palalog et al., 2016; Park, 2023). Beck & Gong (2013) and Park (2023) set the wheel-spinning threshold as the status of that student who practiced the same skill set over 10 times but failed to mastery. Beck & Rodrigo declared wheel-spinning as students who fail to master a skill in a computer tutor promptly. Kai et al. (2018) watched the number of students solving the exercises in the border of wheel-spinning, which is defined as those who tried to 10 or more problems and on either following status while not reaching the mastery status or on the mastery status but not accomplished the test. In a game-based learning environment, Palalog et al. (2016) set a different definition of mastery as the situation in which students clear the level at each of two considered levels, and defined wheel-spinning as not clear the lower level even for 15-minute attempt or the attempt of not reaching the higher level after achieving the lower level. Owen et al. (2015) aimed to detect whether students are on productive persistence or wheel-spinning, and the border of them is determined by a model created concerning the number of activities, the ratio of skills mastered, rate of mastery, student age, average activity duration, and more. Most studies focused on wheel-spinning as the attempts/effort without mastery, while no other papers research wheel-spinning in the environment of no instructional guidance that does not have a specific mastery. In this research, first, we defined progression based on each exercise's difficulty and wheel-spinning as no positive change of progression. Our approach aims to putting wheel-spinning in the broader context of identifying and quantifying learning progression through monitoring behavioral dynamics (see Figure 1). Combined with a specific visualizing method, this provides a new way to characterize wheel-spinning.

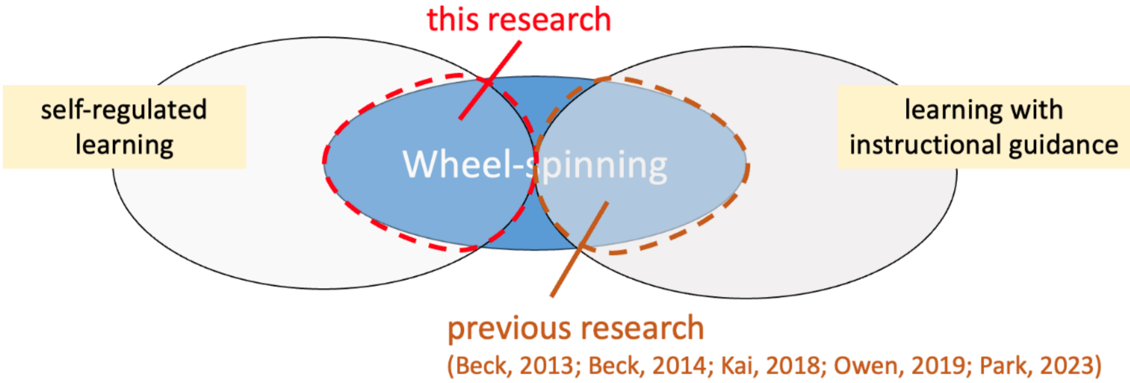


Figure 1. *Comparison of research on wheel-spinning*

3. Method

3.1 System environment and context

The experimental setting for our empirical research makes use of the digital learning platform LEAF (Flanagan & Ogata, 2018). System users first enter the environment by logging in to the Moodle LMS, and then proceed to the BookRoll platform which includes an analysis tool called LogPalette. All logs both at BookRoll and at LogPalette are collected in a learning record store (LRS), and the systems can also use these logs for analysis. The BookRoll system gives access to pooled exercises. Regarding the exercise materials, there are three types of pooled materials. One type consists of the exercises prescribed by teachers, another type comprises the exercises that students take on as additional exercises, and the other consists of the textbook pages that help to solve these exercises. Each learning material page was labeled one unit by publishers or mathematical teachers in advance based on the Japanese mathematical curriculum declared by MEXT (Ministry of Education, Culture, Sports, Science and Technology).

We took some logs to trace each student's behavior related to the recommendation system in the LEAF platform. The system recommended exercises with applied explanations according to their solving log. There are three types of explanations as follows:

- Because the student solved the exercise incorrectly, they should try it again.
- Because the recommended exercise was related to the one that the students solved incorrectly, they should understand the unit well through the recommended exercise.
- Because the students incorrectly solved exercises in the same unit successively, they should understand the basis on the unit through the textbook page related to the unit rather than solving the other exercises.

The recommender system considered the order of the displayed exercise based on the collected log data as well. There are two specific logs related to the system: "Displayed" and

“Clicked”. “Displayed” is recorded when the student accesses the recommender system and recommended materials are displayed automatically. The log contains what and when recommended materials were displayed to the student with what explanations. “Clicked” is recorded when the student access clicks on the link of recommended materials. The log contains what and when recommended materials were clicked by the student. The recommendation system also showed the list of assignments with the link to each exercise, and the students could see how many people in the same grade had taken on each exercise and how many students had reached the correct answer.

3.2 Provision of exercises and recommendations

This research was conducted in a Japanese junior high school with 358 participants from grades 7-9 (12-15 years old). They were all on summer vacation during the research (from July 21 to August 23, 2023). They were provided with teacher’s customized exercises through BookRoll as an assignment and the results were recorded in the LRS. This activity can be categorized as self-regulated learning, since the students’ activity was based on free initiative, and they did not receive any additional instructions during the respective period (Sacks & Leijen, 2014).

For the general exercise activity, students reported the result of solved exercises by entering whether their answers were correct or incorrect on the selective form, referred to Figure 2.

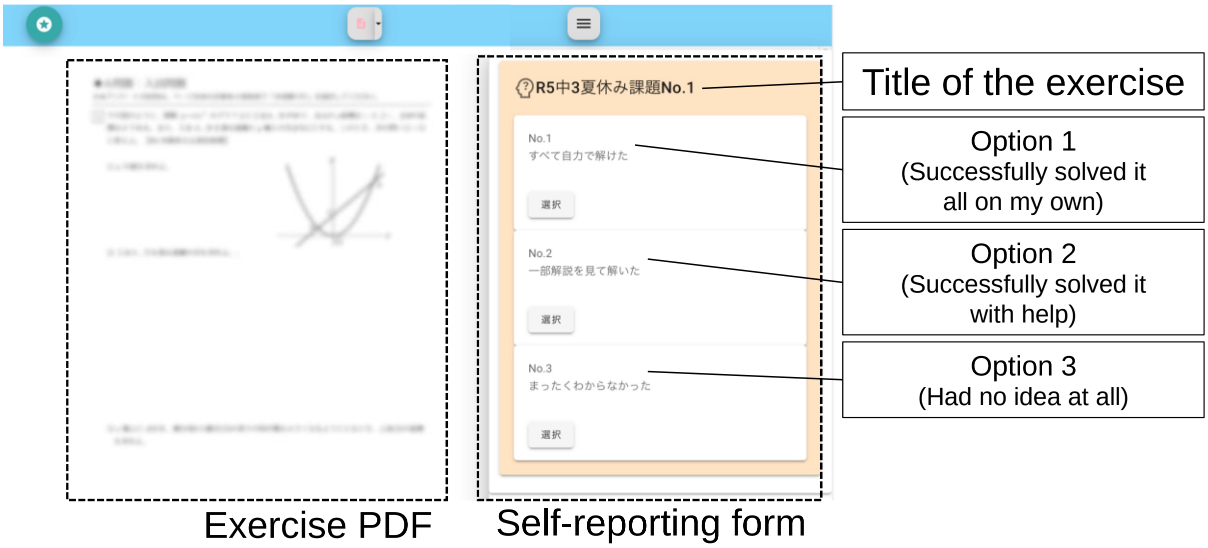


Figure 2. *User interface for viewing and answering exercises on BookRoll*

Students are not forced to work on the prescribed exercises, i.e., whether they are taken up and completed or not depends on the free choice of the students. Exercises are also recommended by the system, either drawing from the pool of additional exercises or as new attempts with exercises that were not completed correctly and without using help information previously. In addition, the system also recommends textbook pages to the students in case of repeated failure. They could solve other exercises by themselves as self-regulated learning on the system, or even without the system. They all could use the recommendation system when they want to do so, and they use the system as a self-regulated learning, for example, to reflect on an assignment or to solve additional exercises with an exercise book. We show the information of material context and how students and the system treat them in Figure 3.

When a student reports the exercise result through BookRoll, the recommendation system updates recommendations based on input and displays a new set of materials, each of which is with the explanation to describe the reason of recommendation of the materials. The materials on the display had a link to the material page on the BookRoll, and the student could continue solving additional exercises.

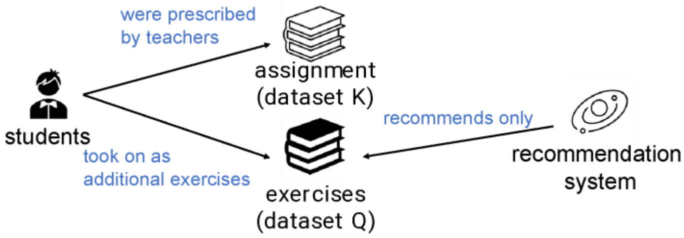


Figure 3. *Student access to exercise material in the learning setting*

3.3 Operationalizing, quantifying, and visualizing learning progression

Following our aim to describe learning progression conforming to the free SRL context, we have defined "engagement" as a basic term, and specified two formulae for the "difficulty" of exercises and for quantifying "learning progression".

To trace the student behavior through the activity, we took the activity logs of each student. In this research, the attribute "engaged" means the corresponding student has delivered (i.e., viewed and reported on) at least one exercise.

For each exercise Q_i in the exercises, we defined the *difficulty* D_{Q_i} as follows:

$$D_{Q_i} = \frac{N_{\bar{C}} + 1}{(N_C + 1) + (N_{\bar{C}} + 1)}$$

where N_C or $N_{\bar{C}}$ represents the number of people whose initial answer of the Q_i is correct or incorrect, respectively. As the more people give the incorrect to the exercise, the more difficult the exercise is. This definition derives from the number of correct or incorrect students plus 1; this is the smoothing whose value will be calculated as 0.5 when nobody is trying to answer the exercise.

For each user's nth answering result R_n (which equals 1 if the answer is a success, 0 otherwise) of the exercises with difficulty D_{Q_n}, we can calculate the progression status P_{n+1} with the previous progression status P_n as follows:

$$\Delta P_n = P_n - P_{n-1} = \begin{cases} 0 \text{ (if } Q_n \text{ is repeated with most recent} \\ \quad \text{occurence } Q_k \text{ and } R_n = R_k) \\ \quad \dfrac{(1 - P_{n-1}) D_{Q_n}}{2} \text{ (else if } R_n = 1) \\ \quad -\dfrac{P_{n-1}(1 - D_{Q_n})}{2} \text{ (else if } R_n = 0) \end{cases}$$

Based on this stepwise calculation of differences, an LPG is constructed as a graph (or plot) with linear segments that accumulate the ΔP_n successively. Note that $P_0 = 0$ and P_1 is defined as D_{Q_1}, the difficulty of the first exercise Q_1 that the student reported its success.

The formula meets two important basic requirements: All P_n would be between 0 and 1, and failure on a more difficult exercise should be less negative than failure on easier exercise. LPGs can be easily interpreted as indicators of learning progression based on the line gradients increasing, decreasing, or stable. As to be expected, the gradient is affected more by the result of a newer exercise, and a more difficult exercise generates less decrease (proportional to $(1 - D)$) in the negative case but higher increase (proportional to D) in the positive case than an easier one.

Visual methods in education are gaining popularity, yet additional research is required to evaluate their enhanced contributions in terms of effectiveness, efficiency, and other learning-related criteria (Klerkx et al., 2014). Although we are not interested in content visualization, one study suggests the visualization of a timeline with learning events, which can organize the complicated multiple classroom events more easily (Dillenbourg et al., 2018). Applying visualization in the SRL context is also conducted by previous research, which makes the process clearer with the graph path (Zheng et al., 2021).

Our approach introduces a new graph visualization for grasping students' learning progression and possibly wheel-spinning behavior based on engagement sequences with the difficulty of the exercises using line diagrams with additional markers. Figure 4 shows one example of a student's engagement sequence graph. The x-axis of the graph represents incremental discrete steps of activity (such as self-reporting the results by working on learning materials and clicking the link to the recommended materials or the exercises on the assignment list) that we call "engagement steps." The y-axis of the graph represents the difficulty of each exercise as explained above. The markers represent the engagement on the exercise. The number attached to the marker represents the ID of the learning material. The color of the marker represents whether the student reported success (green) or failure (red). Green curves across the graph represents the connection of the points of P_n at each step of the solution of each exercise. The gradient of the curve represents learning progression ΔP_n. As a linear plot is useful and good to represent a trend, it is also good to use a learning process that represents a student's "trend" (Kirk, 2019).

For the holiday scenario from which our data were harvested, proportional scaling of the events over a timeline is not adequate since there would be long phases of inactivity and very short and dense bursts of engagement with the exercises. Our choice focuses on the sequences of actions and their evolution for individual students. For classroom scenarios within the time limitations of a lesson, a proportional timeline could be used.

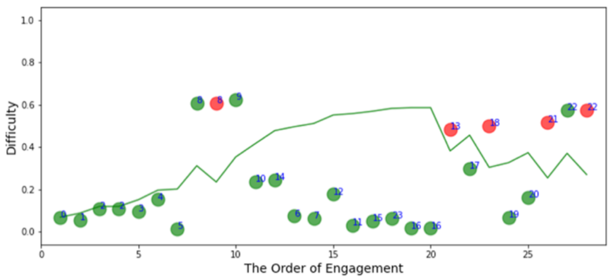


Figure 4. *Example of a graph that shows the sequence of a student's entire engagement*

4. Results and Discussion

4.1 Case-based analysis

There are a total of 191,003 logs in the subjective course during the experiment. For preprocessing the data, we omit the data that are created not by students or the data that show looking at one material page for less than 60 seconds without any other recorded logs on BookRoll. We observed any logs collected on the BookRoll and LogPalette, such as Open/Close the material pages, Correct/Incorrect the exercises' answers, and click on the star-drawn green recommend button in the BookRoll. We first collected the behavior of the student based on the log. There are a total of 12,153 taking-exercise logs and 4,168 exercise self-reporting logs by all students among the three grades. Table 1 shows the information on engagement, including the overall number of students, the number of engaged students during the summer vacation, the number of assignments the teacher compelled students to solve, the average of viewed exercises (this equals the total number of times the page of the educational material was viewed for more than 60 seconds), an average of answered exercises as "delivered exercises" with delivered correct/incorrect answers per student.

Table 1. *The result of student taking exercises during the summer vacation*

grade	num of engaged students (overall num of students)	num of assignments	num of viewed exercises per person (num of delivered exercises per person)
7th	120 (120)	24	38.74 (18.17)
8th	111 (120)	29	33.73 (10.90)
9th	114 (118)	27	32.98 (6.82)

We tried to see where the students weren't progressing in their learning behaviors, so we set red areas in the graph if there is three-successive 0 or less gain in P_n, which can work as one of the wheel-spinning criteria. One example in Figure 5 describes a student's learning progression with the green vertical dotted lines, which represents the student "Clicked" recommended exercises. In the figure, there are four red areas, and three clicks to the recommended exercises which are resulted both in a delivered exercise and in a non-delivered exercise. Here the recommended exercise number pointed out by the red arrow represents the ones that are delivered. As we see in the graph, there was a period of wheel-spinning just until the recommended exercises were delivered, and after taking on the recommended exercises, the student appeared to overcome the wheel-spinning. This result of the sequence is one result of the recommendations that were helpful for the student to overcome the wheel-spinning.

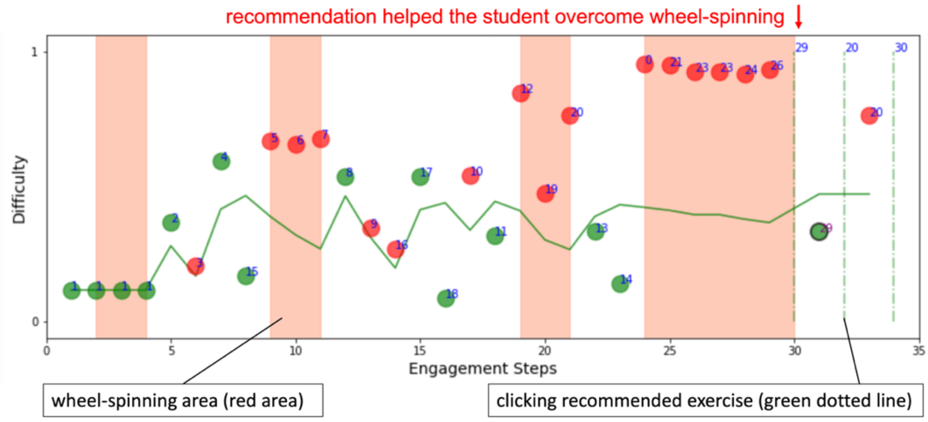


Figure 5. *Example of an LPG with red areas indicating possible wheel-spinning*

Through this research, we could explore the new SRL research field that assesses SRL with the behavioral data throughout students' activity (Molenaar et al., 2023). We overserved learning progression in SRL focusing on behavioral dynamics, which is the activities over time. The long-term learning analysis has different results according to the patterns of the students' time usage in the SRL (Rienties et al., 2019). This research would contribute to giving a new idea to analyze SRL activities in the long span. According to the idea of progression curves of the visualization we proposed, there is no instruction or intervention during the monitoring period. Another perspective of this research is that student's performance will be better if they do self-reporting even in the SRL context (Oudman et al., 2022).

4.2 Questionnaire-based expert evaluation

To test the adequacy and interpretability of the wheel-spinning visualization, we took a questionnaire survey. The context of the questionnaire survey is as follows:

- Ten researchers specializing in educational technology participated in, who are skillful researchers familiar with online learning educational technology and data analysis.
- We presented participants with randomly selected six examples including ones that have wheel-spinning area and the others don't have it.
- We first gave a definition of wheel-spinning and how to read the graph with randomly selected six examples using a wheel-spinning criteria above (it is treated as "working hypothesis"), and then they were asked to complete six questions about the wheel-spinning area of the graph with confidence of the answer.
- We also asked to describe adequacy and interpretability of the graph.

Table 2 shows all questions of the questionnaires with the answer of them. In the table, we show the quiz number, target area of example questions, the number of those who recognized the wheel-spinning area or non-wheel-spinning area with confidence, and the model’s answer (working hypothesis referred in section 4.1).

According to the survey results, adequacy is almost enough for participants because the correct answer is more than wrong answers for four questions, where Q3 and Q4-C is not. For Q3, there is no progression in that area, but half of the participants recognized it as non-wheel-spinning area. On the other hand, for Q4-C, there is positive ΔP_n and thus there is not wheel-spinning, but over the half of the participant recognized it differently. While this graph representation doesn’t have numerical problem, for visual interpretation it has a saturation effect, which is the ΔP_n is too small to see a change of it when the too easy problem was solved correctly, so we should reconsider about the problem to increase adequacy of the graph.

We can also discuss the interpretability of the graph through the confidence and description of the questionnaire. In the survey, low confidence indicates a “lack of interpretability”, which may be related to problems with the LPG but may also come from ambiguous situations. One of the participants stated that “*I agree, to assess repeating the same exercises again and again (whether green or red) can be categorized as wheel spinning. but failing exercises and needing several attempts, might be very helpful for learning - do you make such a distinction, or is all wheel spinning and negative? Might the duration of missing progress be important to judge something as problematic wheel spinning?*” and another stated “*In the annotated wheel-spinning domain, except for the challenge of extremely difficult problems, the problem seems to be solved in some stepwise manner, and in this respect, we felt that identification as wheel-spinning was not appropriate.*” Although the graph conveys wheel-spinning area well, we should reconsider the wheel-spinning phenomenon in the context of successive failure.

For the summary, we learned following from the questionnaire results:

- Adequacy: the survey indicates most answers are corresponding to that of hypothesis, but graph adequacy suffers from saturation in visual interpretation.
- Interpretability: Low interpretability derives from how to deal with student’s “failure” activity, which concludes that reconsidering of "wheel-spinning" is needed.

5. Conclusion

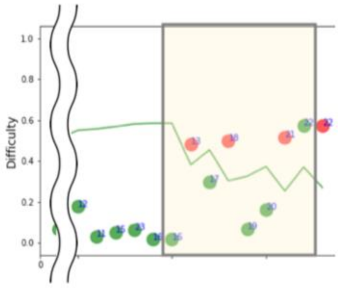
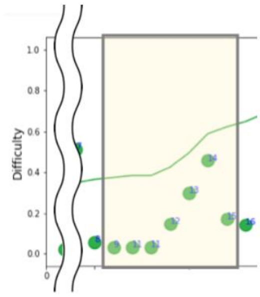
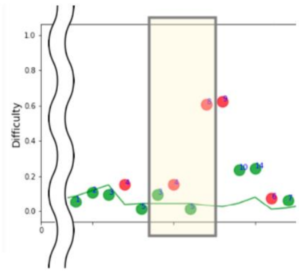
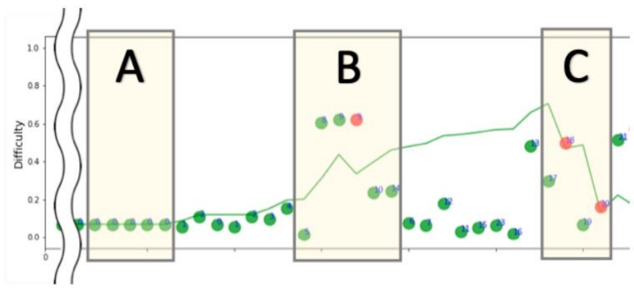
This research discusses the concept of “learning progression” in the context of no-instruction learning among junior high school students using an online math exercise platform during their summer holidays. To address the challenge of capturing learning progression, the study introduces “learning progression graphs” (LPGs) generated from action logs.

The literature on SRL introduces a “richer” context, with different phases, scaffolding and feedback (Edisherashvili et al., 2022; Pintrich, 2000). However, this research based on observational data was conducted under specific restrictions with an extremely free form of SRL in the absence of teacher intervention and feedback during the activity period. It might be argued that this was different for the system-generated additional recommendation however these were used only very rarely.

Regarding the learning outcomes, this experiment only relies on students’ self-assessment in terms of self-declared success or failure. The results of solving exercises had to be analyzed based on topics of the study materials that we use for the recommendations. However, we only see very scarce use of recommendations and there are not enough logs to verify the effectiveness of the recommendations. Still, a few examples indicate the effectiveness of the recommendations as observed through the LPG graphs. In addition, the survey results indicate that the current LPG graph layout should be revised to mitigate the "saturation effect". In general, we can re-consider the wheel-spinning definition for unguided learning under the aspect of interpretability, as suggested by the high correspondence of the answers to that of hypothesis could be seen.

For students, LPGs can be used as feedback on individual learning activities, allowing them to review their own learning activities. That is, if there are a series of errors in their answers, they may work on easier questions or go back to material such as textbooks. Teachers can monitor their students’ efforts with LPG; they can refer to difficulty to see which questions students are struggling with. They also can use this to plan what to teach and how to teach questions. In addition to educators, this visualization algorithm can also be integrated into educational recommendation systems and open learner models (Bull & Kay, 2010). By checking the difficulty of an exercise and the learning progression of a student, it will be possible to recommend easier or new exercises. In fact, in the current experiment, a system for detecting wheel spinning can be integrated into the recommender system to create learning progression for students by recommending questions according to the situation. In addition, as this visualization is created based on students' self-reporting, it can be introducing patterns of wheel-spinning in combination with self-reports.

Table 2. *Results of the questionnaire*

#	Target area	Num of people (average confidence)		Answer based on working hypothesis
		Yes	No	
Q1		3 (3.67)	7 (3.43)	No
Q2		3 (3.67)	7 (4.14)	No
Q3		5 (3.00)	5 (3.33)	Yes
Q4-A		6 (3.67)	4 (4.25)	Yes
Q4-B		0	10 (3.90)	No
Q4-C		6 (3.80)	4 (3.50)	No

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