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Social process awareness and its preliminary data analysis of regular assessment results

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Abstract

In formative assessment (FA), students' agency is increasingly emphasized, making it essential to provide feedback that is both actionable and reflective of their learning processes. However, existing learning analytics dashboards (LADs) often fall short in delivering such feedback. To address this gap, we proposed the concept of "social process awareness" (SPA), which encourages students to reflect on the learning process of their peers. This study explores the feasibility of implementing SPA by analyzing weekly test scores and unit exam performance of grade 8 students in a Japanese junior high school. Through clustering analysis, we identified four distinct learning process patterns and examined their distribution across performance groups. The results suggest that students could benefit from referencing the learning processes of peers who perform slightly better, enabling stepwise improvement. Additionally, the study reveals that common learning challenges can be identified across all groups, suggesting the value of visualizing shared difficulties. These findings demonstrate the feasibility of SPA and provide insights for designing LADs that support student-led FA in K-12 education.

Keywords: learning analytics, social process awareness, formative assessment, self-regulated learning

Introduction

In formative assessment (FA), the importance of shifting from traditional teacher-directed approaches to student-centered participation has been emphasized (Black & Wiliam, 2009; Harlen, 2012). While students' involvement in FA has been increasingly emphasized, it has also been pointed out that for feedback to effectively support students in improving their learning, it must be actionable (Gibson et al., 2017; D. Nicol, 2009; Sadler, 1998). Furthermore, the typical timing of feedback—provided after students complete a task—has been criticized for failing to support improvement during the learning process (Gamlem & Smith, 2013).

The increasing availability of one-to-one device learning environments has expanded the potential for educational use of various types of data (Ogata et al., 2023; Stanja et al., 2023). This has led to growing efforts to support students in their learning process using trace data. For example, from a self-regulated learning (SRL) perspective, many learning analytics dashboards (LADs) have been developed to support students by visualizing individual learning activities as a form of feedback (Matcha et al., 2020). However, this line of research also suggests that existing LADs may not meet key recommendations for effective feedback. It is pointed out that rather than simply presenting counts or frequencies, research should focus on identifying the kinds of information that can provide meaningful feedback to students (Matcha et al., 2020). In other words, merely allowing students to view the amount of learning in progress is insufficient for effective support. Therefore, this study addresses the limitations of actionable feedback in FA, emphasizing that merely visualizing the amount of learning is insufficient for effectively supporting students.

To address this issue, research has been conducted on providing students with actionable feedback—not only by visualizing the amount of learning, but also by delivering personalized feedback messages based on it (Pardo et al., 2019), as well as developing dashboards incorporating predictive analytics and alert mechanisms (Howell et al., 2018; Ramaswami et al., 2022). However, this may conflict with the view that students should be positioned as agents in the FA process (Wiliam, 2018). In contrast, systems have been developed to foster students' "knowledge awareness (KA) is defined as awareness of the use of knowledge" (Ogata et al., 1996; Ogata & Yano, 2004), without positioning them as passive recipients. This form of KA, which arises through comparison between one's own and others' learning states, has been shown to be effective in helping students identify suitable collaborators in computer supported collaborative learning (CSCL) environments (El-Bishouty et al., 2010).

Building on the concept of KA established in the field of CSCL, this study applies it to FA. We define "social process awareness" (SPA) as students gaining insights for improving their learning through comparing their own learning processes with those of others. In the context of SPA, "social" refers to familiar individuals such as classmates or senior students, while "process" denotes the process of learning activities. While we have investigated the feasibility of SPA from the perspective of learning engagement (Hamada et al., 2025), in the context of FA, it has been reported that students adjust their learning based on regular assessment such as weekly tests (Gholami & Moghaddam, 2013).

Therefore, we focused on weekly test score data stored in the learning and evidence analytics framework (LEAF) system (Ogata et al., 2022), a learning support system used in a Japanese junior high school to deliver learning materials and manage test results. Using this weekly test score data, we aimed to examine what patterns of social processes can be classified from the perspective of learning outcome. We also discuss what insights can be obtained from differences among the classified social processes. If this study shows that social processes can be extracted in the context of weekly tests and that these processes can be shared with students, it will clarify the need to implement system functions that support SPA.

The structure of this paper is as follows. Section 2 reviews related work and then describes the proposed SPA in detail, whose feasibility this paper aims to examine and which we plan to implement in a future system. Section 3 describes the regular assessment dataset used in the analysis and the analysis flow for classifying social processes. Section 4 reports the analysis results. Section 5 discusses what awareness can be obtained from the classified social processes and examines the feasibility of SPA in the context of regular assessment.

If the feasibility of SPA can be demonstrated in both learning engagement and regular assessment, it would enable the implementation of SPA using various types of educational data and contribute to the development of new approaches in FA. This study contributes to the development of effective designs for FA in school education through the use of educational data in the K-12 context.

Related Works

The importance of focusing the learning process in formative assessment

Traditionally, FA has been implemented in a teacher-led manner with the primary goal of improving instruction. However, with increasing emphasis on SRL—recognized as a key competency for tackling complex problems in the 21st century (OECD, 2021)—there is growing recognition of the importance of student-led FA, in which students actively monitor and adjust their own learning to achieve goals (Wiliam, 2018). To position students as active agents of assessment, recent efforts have focused on incorporating peer assessment into learning activities, such as evaluating each other's final products like reports, thereby developing students' assessment literacy (Alqassab et al., 2023; Wiliam & Thompson, 2017).

Despite these advances, many peer assessments still focus on evaluating final outcomes after the completion of learning, such as written assignment (Alqassab et al., 2023). As a result, such assessments often fail to support improvement during the learning process itself (Dann, 2014). In response to this issue, the increased availability of one-to-one digital devices in Japanese schools offers new opportunities to leverage trace data for formative purposes (Stanja et al., 2023). Moreover, research on effective feedback design in FA highlights that students generate internal feedback at various stages of task engagement to regulate their learning (D. J. Nicol & Macfarlane-Dick, 2006). It is therefore essential to establish environments where students can actively engage in FA in real time (Tay, 2015).

This implies that FA should not only focus on the final outcomes but also support students in directing their attention to the learning process itself. Indeed, influential models of feedback in FA—such as the "Where am I going? How am I going? Where to next?" framework—emphasize the importance of clarity across all three stages (Hattie & Timperley, 2007; Wiliam & Thompson, 2017). Enabling learners to monitor and adjust their ongoing learning process is thus critical for enhancing learning through FA.

The lack of actionable formative feedback in existing learning analytics dashboards

A growing body of research has explored how visualizing students' data can be used to support learning. In the context of LADs, a widely cited feedback stage model proposed outlines four sequential phases: (1) Awareness – visualization of data; (2) Reflection – evaluation of the visualized data; (3) Sensemaking – generation of insights based on the evaluation; and (4) Impact – behavioral change (Verbert et al., 2013). As indicated in this model, LADs are designed to first facilitate students' awareness through data visualization and then guide them in interpreting this information meaningfully. In addition to this model, the student-centered learning analytics-enhanced SRL methodology (Chatti et al., 2021) has been proposed as a framework for supporting SRL. It describes how learning analytics can provide necessary information at each phase of the student's SRL cycle: Goal, Plan, Specify, Perform, Perceive, Interpret, and Compare.

However, in research trends concerning LADs from the perspective of SRL, it has been pointed out that most indicators used as feedback still focus solely on individual learning activities. Existing dashboards may not meet key recommendations for effective feedback (Matcha et al., 2020). The research emphasizes the need to move beyond mere frequency counts and to focus instead on identifying information that can provide meaningful feedback to students. This suggests that even when various types of data are visualized, the absence of clear interpretive criteria makes it difficult for students to make sense of the data—creating a significant barrier. In fact, research investigating how students interpret dashboards has identified three key elements that influence the sensemaking process: (1) transparency of design – how indicators are calculated and how they relate to learning goals; (2) reference frames – standards for evaluating progress and performance; and (3) support action – recommendations for next steps (Jivet et al., 2020). From the perspective of feedback, one of the essential conditions for actionable feedback is that it must be understandable to students and actually utilized by them to improve their own learning (Gibson et al., 2017; D. Nicol, 2009). In this study, we define actionable feedback as feedback that promotes student awareness for improving their learning, rather than encouraging competition through ranking. It is increasingly recognized that simply providing visualizations is insufficient (Jivet et al., 2017); instead, LADs must also support students in interpreting the data and turning it into actionable feedback.

Effectiveness and challenges of incorporating social comparison into learning analytics dashboards

Traditional LADs have primarily focused on visualizing individual learning data to encourage students' self-reflection and behavioral change. Recently, however, research has begun to expand beyond individual data, exploring group-based visualizations grounded in theories incorporating a social perspective such as social comparison (Festinger, 1954), as a means to support students in interpreting data. For example, in the context of CSCL, Social Awareness has been defined as self-presence and co-presence, that is, the sense that the self and others are real and simultaneously present in the learning environment (Lambropoulos et al., 2012). Furthermore, in the context of learners' engagement with others in CSCL, it has been suggested that effective collaboration can be promoted when students differ slightly in their knowledge levels (Dillenbourg, 1999). In line with this, studies such as knowledge awareness maps (Ogata & Yano, 2004) and open social learner modeling (Hsiao et al., 2013; Somyürek et al., 2020) have visualized students' and peers' knowledge states, enabling students to gain awareness of their own knowledge improvement by observing others. These approaches have advanced the application of social dimensions in knowledge visualization by incorporating interpersonal relationships (El-Bishouty et al., 2010). In contrast, within the context of SRL and FA, three distinct types of Social Comparison-based approaches have been explored.

First is the ranking-based comparison within a group. For instance, leaderboards visualizing students' rankings based on the number of badges earned in gamified environments (Hanus & Fox, 2015), or dashboards displaying progress rankings during long vacation assignments (Kuromiya et al., 2024), apply social comparison to ongoing learning activities. These systems are designed to foster SRL and learning engagement. While some studies report increased student engagement, others caution that direct competition among peers may undermine motivation and negatively affect learning outcomes (Hanus & Fox, 2015).

Second is the cumulative action-based comparison within a group. For example, dashboards have been developed to allow students to compare their reading paths, page markers, and other behavioral traces with those of classmates (Chen et al., 2020). These systems have been found to support students' metacognitive processes.

Although both of the above approaches promote social comparison within the same cohort, a third approach involves comparison with past students from different cohorts. For example, in massive open online courses (MOOCs), dashboards have been developed to compare a current student's activities with the successful learning patterns of past course completers, thereby enhancing completion rates (Davis et al., 2017). These studies take advantage of the stable context of MOOCs—where students are geographically dispersed, and video-based content remains relatively unchanged over time. This approach significantly improved completion rates in MOOCs. However, its applicability is limited in primary and secondary school contexts, where students' characteristics and learning environments change from year to year.

Our proposal: Social process awareness (SPA)

Based on the reviewed literature, three key insights can be drawn: (1) the importance of focusing on the learning process rather than just final outcomes in FA; (2) the need for LADs to provide actionable feedback that promotes awareness in students; and (3) the effectiveness of incorporating social elements that use others as a reference point. Among the studies reviewed in 2.3, those that incorporated social perspectives into LADs are summarized in Table 1. Table 1 categorizes each study from three perspectives: the learning context in which the LADs are implemented, the way social comparison is incorporated into the LADs, and the granularity of the process visualized in the LADs.

These findings suggest the potential effectiveness of integrating these elements into a unified concept, which we defined as "social process awareness" (SPA)—the awareness of one's own areas for improvement through comparison with the learning processes of others (Hamada et al., 2025). SPA differs from the existing studies in three main ways.

First, it incorporates two types of social references within the K-12 context: the peer group to which the student belongs, and a more advanced group of students who have already completed the relevant content. Here, we use the term "social" to refer to peers in the reference frame of LADs (Jivet et al., 2017; Wise, 2014).

Second, it emphasizes the use of finer-grained process data. In the classification of learning analytics data based on granularity, outcome measures such as the number of badges earned or problems attempted are categorized as coarse-grained data, whereas finer-grained data can be obtained from learning management system logs that capture students' engagement and behavioral patterns (Tamura, 2020).

Third, our approach introduces a new element of peer comparison by combining information about peers with process data. Although prior studies have already explored social features such as ranking systems, many existing student dashboards mainly visualize cognitive conditions (e.g., test results) and operational metrics (e.g., number of logins) using bar charts. As reported by Matcha (2020), such numerical information often does not provide students with actionable feedback. In contrast, the "social" component in our study still refers to peers (e.g., classmates), as in previous research, but differs in that it aims not to promote competition. Instead, it encourages students to gain insights for improving their own learning by visualizing peers' learning behaviors—such as changes in their review or re-solving activities—rather than simply showing performance rankings.

In Table 1, prior studies on LADs are categorized by labeling the visualization of students' learning processes as "how," and elements such as activity levels, number of badges earned, and test results as "result." In addition, the emergence of open player modeling (Maram et al., 2024), which includes students' actions and in-system behaviors—not just static indicators like test scores or submissions used in traditional open learner models—demonstrates a growing recognition of the importance of process-level data. Nevertheless, the incorporation of social elements into the visualization of learning processes in existing research remains largely limited to coarse-grained data. In contrast, this study proposes to visualize fine-grained process information and to derive SPA by enabling students to compare their own processes with those of a group. This distinguishes our work from previous studies. The aim of this study is to explore the feasibility of implementing dashboards that support SPA in K-12 education by examining how social processes can be extracted and what kinds of awareness might potentially emerge from them. Therefore, we set the following two research questions:

- RQ1: Can students' score patterns of regular assessment be classified into different groups?
- RQ2: Can the extracted score pattern be shared as social process across different student groups?

Table 1

Positioning of this study within LADs incorporating social perspective

Research		Ranking Based LADs (Hanus & Fox, 2015; Kuromiya et al., 2024)	Action Based LADs (Chen et al., 2020)	Action Based LADs (Davis et al., 2017)	Our proposal (SPA)
Learning context		K-12, Higher education	Higher education	MOOCs	K-12
Social	Comparison with current peer	✔	✔	-	✔
	Comparison with past senior	-	-	✔	✔
Process	"How" (e.g., learning engagement)	-	✔	-	✔
	"Results" (e.g., weekly tests, the total amount of learning activity)	✔	-	✔	✔

Method

Learning context and dataset

It is important to consider not only students' learning engagement but also the results of regular assessments. These regular assessment results can influence students' learning process and final outcomes (Gholami & Moghaddam, 2013), suggesting that SPA should also be examined in relation to regular assessment results such as weekly tests. Therefore, this study focuses on weekly mathematics test scores from grade 8 students in a Japanese junior high school supported by the LEAF system. The LEAF system, widely used in Japanese secondary schools, consists of a learning management system, BookRoll for distributing digital materials, a learning record store that stores learning logs, and LogPalette for analyzing them (Ogata et al., 2022). The LEAF system enables the capture of student learning behaviors—such as page-turning and quiz answering—making learning processes visible. Previous studies using LEAF logs have classified learning engagement patterns and linked them to performance trends (Hamada et al., 2025; Kuromiya et al., 2024).

In this study, we focused on weekly and unit exam are administered during each unit (see Figure 1). Weekly tests are based on a workbook and designed so that well-prepared students can score perfectly. Students are free to choose how they study within teacher-defined limits. LEAF was used to collect test scores and log data. For example, student S06 studied consistently throughout the unit, while S04 and S07 studied intensively at specific times (see Figure 2). Such differences reflect learning engagement patterns observed in previous studies, which have shown connections to academic performance (Hamada et al., 2025). The dataset used in this study includes four weekly tests and one unit exam on "expansion and factorization of expressions," with a final sample size of 87 students. Scores were normalized to percentages for analysis.

Figure 1

The flow of test preparation, weekly tests and unit exam

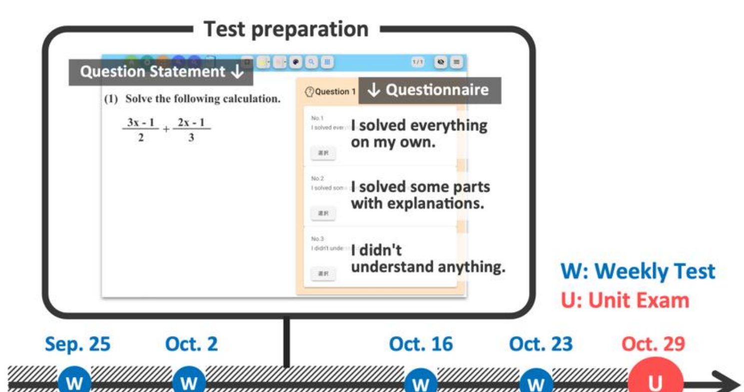
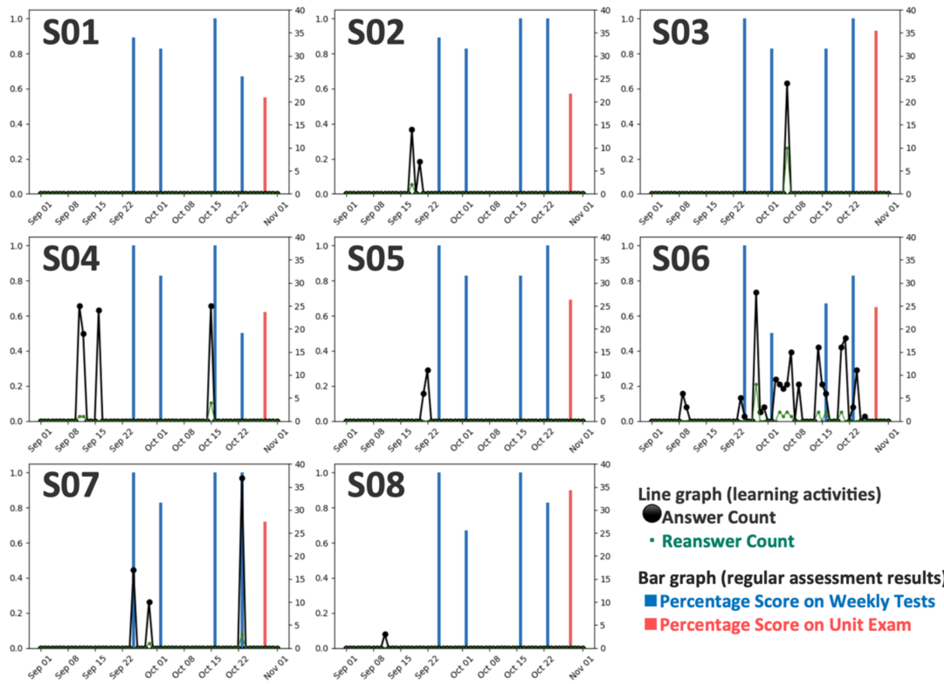


Figure 2

Process of student learning activities and regular assessment results



Analysis items

Based on the FA cycle (Wiliam, 2018), we defined two analysis components to answer the research questions (RQ1: Can students' score patterns of regular assessment be classified into different groups?; RQ2: Can the extracted score pattern be shared as social process across different student groups?). The FA cycle is structured around three levels—long, medium, and short—corresponding to term-level, unit-level, and lesson-level activities, respectively (see Table 2). As described in 3.1, this study focuses on weekly and unit exams within a single unit. Therefore, our analysis centers on the medium cycle, which corresponds to unit-level assessment. In line with the research questions, the present study conducts the following two analyses. Analysis 1 investigates students' weekly tests' score trajectories and their relationship to unit exam performance. Analysis 2 examines weekly tests' score patterns across student groups stratified by performance levels on the unit exam.

Results

Analysis 1: Clustering weekly test score patterns and corresponding unit exam score

First, we conducted clustering analysis on students' weekly test score trajectories. Since there were four weekly tests and all students took them on the same schedule, we applied

Table 2

Perspectives on formative assessment adapted from Wiliam, 2018, p.51

Cycle	Long Cycle	Medium Cycle	Short Cycle
Curriculum levels	Term-level	Unit-level (our target)	Lesson-level
Span	Across terms or teaching units	Within and between teaching units	Within and between lessons
Length	Four weeks to a year (or more)	One to four weeks	Minutes-by-minutes and day-by-day
Impact	Monitoring, curriculum alignment	Student-involved classroom assessment, teacher cognition improvement	Student engagement, teacher responsiveness improvement

time-series k-means clustering with Euclidean distance. The number of clusters was determined to be four based on the elbow method. The clustering results are shown in Figure 3 (1). Based on the clustering results of the weekly test scores, students were classified into four groups: the high score-kept group consistently achieved high scores; the recovered group experienced a drop in scores midway but successfully recovered; the un-recovered group partially recovered after a decline but ultimately showed a decrease in scores; and the declined group showed a continuous decline in scores toward the end of the unit.

Next, we plotted boxplots of unit exam scores for each cluster of weekly score trajectories and confirmed normality with the Shapiro-Wilk test (all clusters showed $p > 0.05$). We also found that the variances were homogeneous according to Levene's test ($p = 0.30$). Therefore, we applied a parametric method, a one-way ANOVA, to the unit exam scores (see Table 3). The ANOVA revealed a statistically significant difference among the clusters ($F = 11.7$, $p < 0.01$), so we performed a Tukey post-hoc test for pairwise comparisons (see Table 4). The distribution of unit exam scores by weekly score trajectory cluster is presented in Figure 3 (2). The findings from the above analyses—namely, the patterns of weekly test score trajectories and their corresponding trends in unit exam score—can be summarized as Table 5. The results of the Tukey post-hoc test for pairwise comparisons showed that the high score-kept group scored significantly higher on the unit exam than both the un-recovered group and the declined group. Additionally, the recovered group scored significantly higher than the declined group.

Figure 3

Analysis 1: Clusters of weekly test scores and corresponding unit exam score

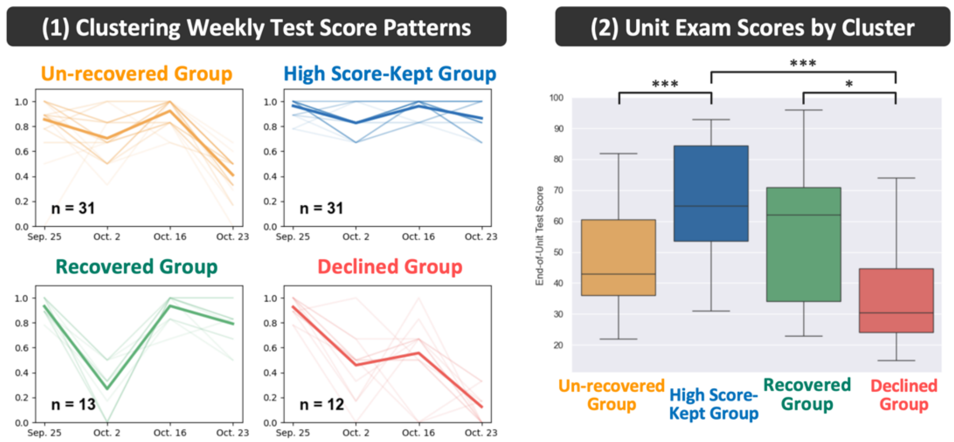


Table 3

ANOVA tests of unit exam score between weekly test score patterns

	Weekly test score patterns	n	Mean (SD)	F
Unit exam score	High Score-Kept Group	31	67.00 (17.66)	11.71***
	Recovered Group	13	57.85 (23.77)	
	Un-Recovered Group	31	47.68 (14.28)	
	Declined Group	12	35.58 (16.76)	

***p < .001

Table 4

Tukey's post-hoc comparisons between weekly test score patterns

	Weekly test score patterns	Mean difference	Adjusted p-value
Unit exam score	High Score-Kept Group – Recovered Group	9.15	0.39
	High Score-Kept Group – Un-Recovered Group	19.32	< . 001***
	High Score-Kept Group – Declined Group	31.42	< . 001***
	Recovered Group – Un-Recovered Group	10.17	0.30
	Recovered Group – Declined Group	22.26	< . 05*
	Un-Recovered Group – Declined Group	12.09	0.18

Analysis 2: Analyzing weekly test score patterns by unit exam performance level

The results described in Analysis 1 suggest that students' weekly test score patterns may differ by final achievement level. To address RQ2 (Can the extracted score pattern be shared as social process across different student groups?), we calculated the distribution of weekly test score trajectory patterns across different unit exam performance groups, based on the clustering results presented in Section 4.1.

Table 5

Summary of cluster characteristics in Analysis 1

Group name	Description
High Score-Kept Group	Consistently high weekly test scores; highest unit exam score
Recovered Group	Mid-unit dip in weekly test scores followed by recovery; second-highest unit exam score
Un-Recovered Group	Fluctuating weekly test scores with partial recovery; third-highest unit exam score
Declined Group	Gradual decline in weekly test scores; lowest unit exam score

The classification of performance levels was based on prior research on learning patterns by achievement level (Geng et al., 2023) and was used to clearly examine whether high- and low-scoring students on the unit exam showed different weekly test score processes. Specifically, students scoring within one standard deviation below the highest score were categorized as high performers, those within one standard deviation above the lowest score were categorized as low performers, and the remaining students were classified as middle performers.

Table 6 presents the distribution of weekly score patterns by performance level. We focused on identifying the main volume segment within each distribution. As a result, we found that 71% of the students who achieved high scores on the final unit exam belonged to the high score-kept group, who consistently performed well on the weekly tests. Among those who scored in the middle range on the unit exam, 45% were classified as the un-recovered group, who showed recovery during the process but ultimately experienced a decline. In contrast, 55% of the students who scored low on the unit exam belonged to the declined group, who showed a continuous decline in scores toward the end of the unit. These differences in the distribution patterns of weekly test performance across the final achievement levels are summarized in Figure 4, which highlights that the divergence in performance trajectories emerges during the process, even before the final outcome becomes apparent.

To examine at which stage differences began to appear before the final outcomes became clear, we conducted ANOVA for each weekly test by unit exam performance group: high, middle, and low. The results showed no significant differences in the first two weekly tests, but statistically significant differences began to emerge from the third test onward (the third weekly test: $F = 11.4$, $p < 0.01$; the fourth weekly test: $F = 11.7$, $p < 0.01$). This suggests that there were no major distinctions between performance groups until the third weekly test.

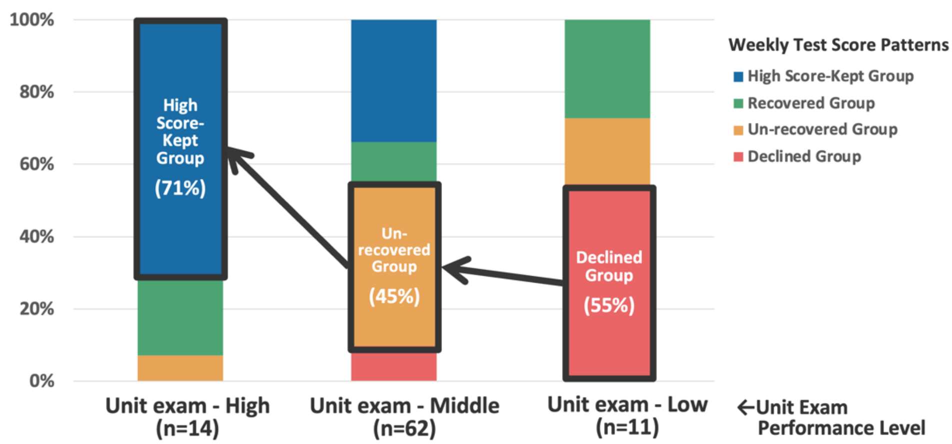
Table 6

Analysis 2: Proportions of weekly test score patterns by unit exam performance level

Unit exam performance level	Weekly test score patterns								Full sample	
	High Score-Kept Group		Recovered Group		Un-Recovered Group		Declined Group			
	n	%	n	%	n	%	n	%	n	%
High	10	71	3	21	1	7	0	0	14	16
Middle	21	34	7	11	28	45	6	10	62	71
Low	0	0	3	27	2	18	6	55	11	13

Figure 4

Differences in main weekly test score patterns by unit exam performance level



Discussion

This study investigates the feasibility of SPA by focusing on weekly test scores used in FA in junior high school in Japan. In this section, based on the findings from analyses 1 and 2, we explore what types of social processes can be extracted from weekly test results and what kinds of awareness may emerge from them, in order to examine the feasibility of implementing SPA.

Key findings

In Analysis 1, through clustering of weekly test score trajectories, we identified four distinct score patterns: the high score-kept group, the recovered group, the un-recovered group, and the declined group. Among these patterns, the high score-kept group, who consistently achieved high scores on weekly tests, scored significantly higher on the unit exam compared to all other groups except for the recovered group, whose scores initially declined but recovered toward the end. The recovered group also scored significantly higher on the unit exam compared the declined group, whose scores declined steadily throughout the unit. These findings suggest that students who either demonstrate consistent understanding from the outset or recover their understanding by the end are more likely to achieve higher final outcomes. This analysis demonstrates the feasibility of discovering social processes by classifying weekly test score patterns and identifying significant differences in final outcomes among the clusters.

In Analysis 2, when weekly test score patterns were analyzed by unit exam performance level, distinct distribution trends emerged. In the low-performance group, 55% of students belonged to the declined group. In the middle-performance group, 45% fell into the un-recovered group, characterized by an initial recovery followed by a final score decline. In the high-performance group, 71% were the high score-kept group, who consistently performed well on weekly tests. These results not only confirm the presence of distinct social processes but also show that these processes differ by performance level. This suggests the potential for identifying optimal others for students to reference when engaging in awareness-building activities. Rather than presenting the same social process to all students, it may be more effective to tailor the reference examples to each student's performance level. Some researches have emphasized the importance of students comparing themselves to peers who perform slightly better, as such comparisons can facilitate learning improvement (Huguet et al., 1999; Vygotsky, 1962). The following section further described the SPA feasibility by showing how to get awareness of their learning improvement with the observed variation in social process distributions across performance levels.

Implications: Potential types of awareness emerging from sharing the social process

Case 1: Reference the "social process (as weekly tests)" of students who perform slightly better

Presenting the social process may encourage students to engage in stepwise improvement rather than striving for overly ambitious goals. For example, Analysis 2 suggests that for students in the low-performance group on the unit exam, aiming to consistently achieve high scores on weekly tests is likely unrealistic. Previous research has emphasized the importance of enabling students to identify achievable steps tailored to their own progress, rather than imposing uniform goals (Nordengren, 2019). On the other hand, the zone between what a learner can do independently and what they can achieve with the assistance of others is defined as the zone of proximal development (ZPD) (Vygotsky, 1962). This concept has continued to inform the design of effective learning strategies up to the present day (Erbil, 2020).

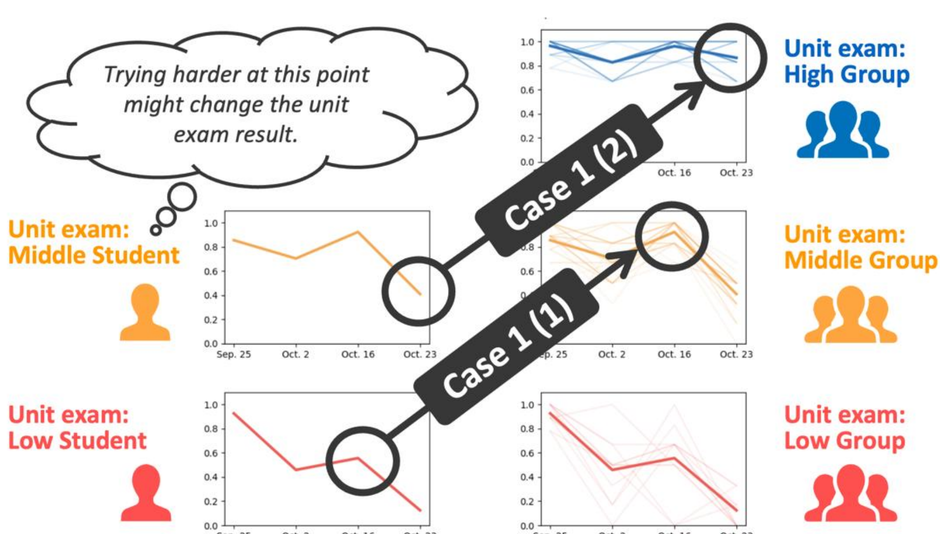
As this theory suggests, setting uniformly high goals for all learners is not appropriate; instead, goals should be tailored to each individual. In terms of FA, this implies that the learning goals should be ones that students are likely to achieve next — in other words, feedback should be actionable from the students' perspective. Considering SPA from the perspective of the ZPD, what is deemed actionable can be interpreted as a behavior that students can realistically adopt for improvement. This suggests that ZPD-informed strategies may be effective not only from the perspective of learning strategies but also within the context of FA. We presented two examples of actionable feedback for students learning improvement as follows.

Case 1 (1), illustrated in Figure 5, provides the first example. The key difference between low- and middle-performing students was whether they were able to recover during the learning process. While both groups eventually experienced a drop in their scores on the final weekly test, the behaviors exhibited earlier in the unit were crucial. Therefore, an appropriate goal for low-performing students could be framed as: "Try to make a recovery on at least one weekly test during the unit."

Case 1 (2), also presented in Figure 5, shows the second example. The main distinction between middle- and high-performing students was whether they were able to achieve a high score on the final weekly test. Although middle-performing students were able to recover after score declines in earlier weekly tests, they ultimately showed a decrease in performance at the end. Consequently, a suitable goal for middle-performing students could be: "Even if you recover midway through the unit, maintain your efforts through to the end." These examples demonstrate how SPA could offer students a framework for identifying and acting on incremental strategies for improvement.

Figure 5

Awareness emerging from the social process of slightly better-performing students



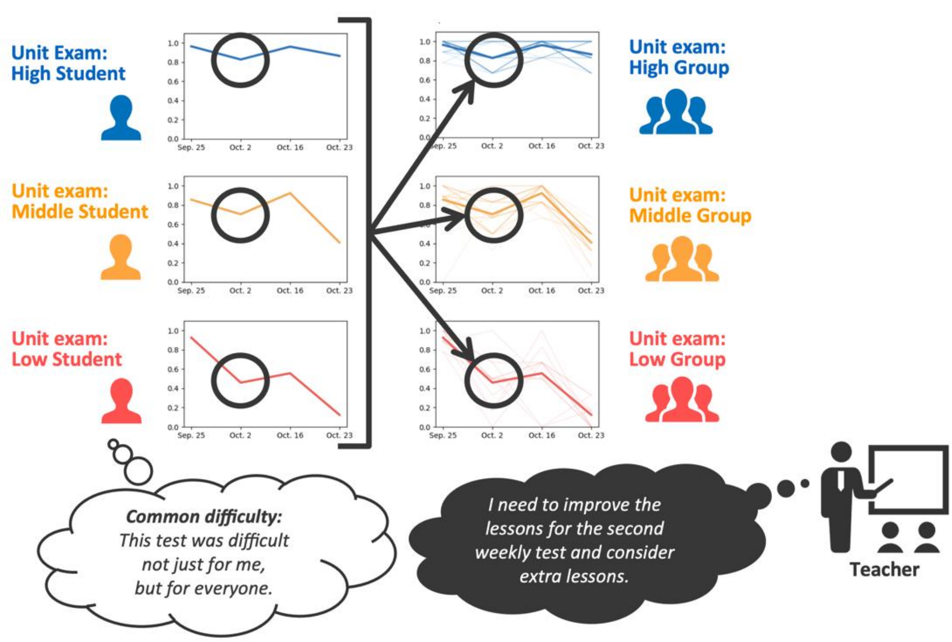
Case 2: Reference the common difficulties students face

FA in K-12 education is widely supported as an effective approach for identifying students' learning gaps and promoting better learning outcomes (Sortwell et al., 2024). However, the nature of the feedback received as part of FA can sometimes induce confusion or anxiety, especially when the feedback is perceived as overly critical (Van der Kleij & Lipnevich, 2021). In this regard, providing social process information—beyond individual student data—may help dispel the sense of isolation that students feel when they perceive their lack of understanding (e.g., low scores on weekly tests) as a personal failure.

An example is shown in Figure 6. The Analysis 2 revealed that learning patterns differ by performance group and that there are identifiable stepwise paths toward improvement. Among the findings, the clustering of weekly test score trajectories showed a common drop in scores on the second test across all clusters. This indicates that the drop in scores on the second test may reflect a broader, shared issue among all students—possibly related to instruction or content, rather than individual shortcomings. These findings imply that, for students, the second test score drop should not be interpreted too harshly as a personal failure. At the same time, teachers should recognize the possibility that the issue lies in their instructional approach or the content design, and take steps to improve their teaching or provide timely interventions to support students.

Figure 6

Awareness emerging from the social process of all groups

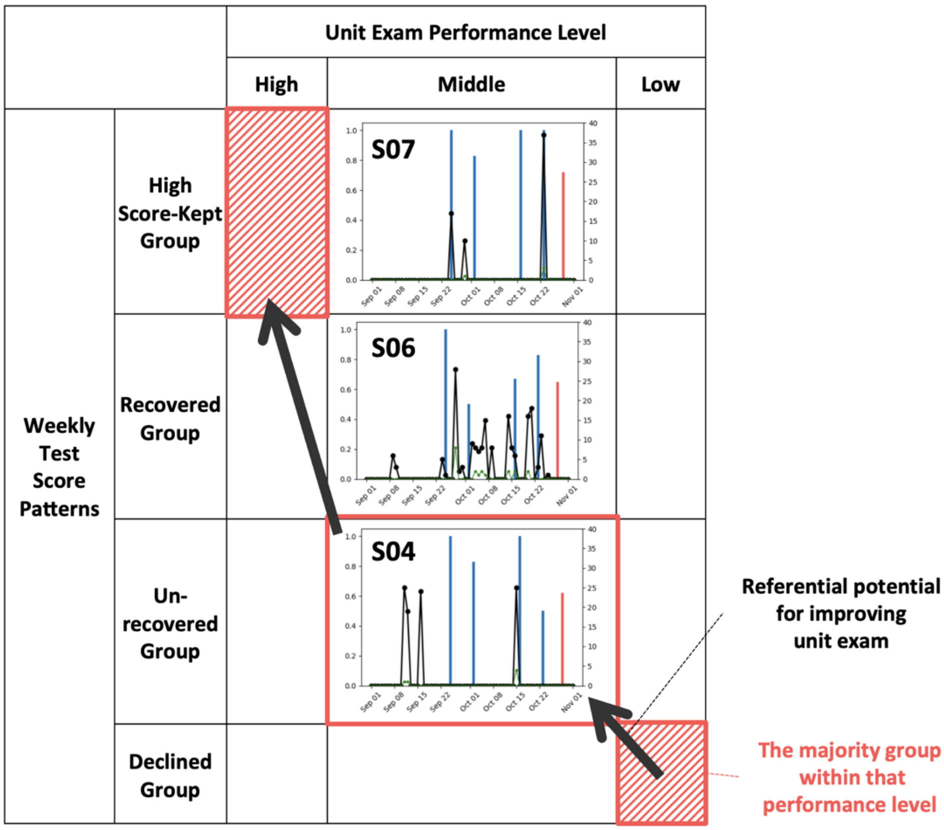


Case 3: Reference the "social process (as weekly tests and learning activities)" of students who perform slightly better

In this study, we extracted weekly test score patterns and examined the feasibility of SPA by showing that these patterns differed by achievement level. In addition to this main result on weekly test score patterns, it is also necessary to investigate SPA based on actual learning behaviors. Therefore, although the sample size was small, we conducted an additional analysis using learning behavior data. For the preparation of these tests, students were able to use both printed materials and BookRoll, a digital content delivery system. Some students used BookRoll and reported their performance by responding to embedded surveys after each practice question (Figure 1: Test Preparation). The number of students for whom such interaction data were accumulated was n = 8 (Figure 2). Among them, only three students (n = 3) had consistent records throughout the unit, and although the sample size is very small, we used their cases to illustrate an example of SPA. Based on the distribution patterns of weekly test scores shown in Analysis 1 and the patterns stratified by unit exam performance shown in Analysis 2, we examined the positioning of these three students (Figure 7). In this figure, the three students, who ultimately achieved middle-level scores on the unit exam despite differing patterns of weekly test performance, are presented. The data show distinct learning behaviors: S07 solved a large number of problems on the day of the test, S06 engaged consistently from the beginning to the end of the unit, and S04 worked in a more irregular manner. Although we were unable to collect learning behavior data from students in the high and low achievement groups, the examples in Figure 7, indicated by arrows, suggest that insights (awareness) can potentially be gained by examining the learning approaches of students who performed slightly better. In the field of CSCL, it has been shown that when learners have almost the same level of knowledge but differ slightly, these small differences can create conflicting interactions, such as differences in opinions and the need to explain ideas, which are effective for collaborative learning (Dillenbourg, 1999). Therefore, in our study, students may also benefit from referring to peers whose achievement is slightly higher than their own, because the differences between them can have a similar positive effect.

Figure 7

Awareness emerging from the social process of slightly better-performing students with learning activities



Limitations

This study investigated the feasibility of SPA, which encourages students to gain insights by reflecting on the learning processes of others. The investigation was based on an analysis of weekly and unit exam results. This study has three primary limitations.

First, the study is limited by its reliance on data from a single grade level at one school, with a relatively small sample size. In fact, our prior studies have identified different process patterns across other grade levels and instructional units, indicating that learning processes may vary depending on context. In addition, with the current sample size, some groups in the classification of unit exam performance levels and weekly test score patterns contain very few students, which further reduces the generalizability of the findings. Therefore, further investigation is necessary to determine whether similar findings can be replicated across different schools, grade levels, units, and student populations. As a limitation related to the current sample size, we also included examples from eight students (n = 8) to illustrate learning behaviors. In future work, it will be necessary to increase the sample size and reanalyze students' learning behaviors.

Second, this study used weekly test results as a proxy for learning processes. These tests were designed so that any student could achieve full marks if they had sufficiently engaged with supplementary materials. From this perspective, weekly test scores may not only be interpreted as test results but also as an indicator of students' preparedness within the learning process. Nevertheless, they remain assessments, and their inherent nature as tests cannot be entirely dismissed. Future studies should incorporate actual learning behaviors that lead up to the weekly tests. This study represents a first step in demonstrating the feasibility of SPA. Moving forward, it will be essential to enhance both the quality and quantity of data used in the analysis in order to further develop and evaluate the SPA.

Third, there is a limitation in our analysis methods. For the clustering of weekly test score patterns, we converted each score into a percentage of the maximum possible score and then ran the clustering. This showed that we could extract group-level patterns of score change over time. However, because test difficulty can affect these patterns, we need to consider methods based on item response theory in future work. For the classification of achievement levels, we defined high-achievement students as those within 1 SD of the maximum unit test score, and low-achievement students as those within 1 SD of the minimum score. Using this definition, we examined how weekly test score patterns differ between achievement levels. However, this is not the only possible approach; for example, percentile-based methods can also be used. The choice of classification method is important because it changes which peers are shown in the SPA. Therefore, in future implementations of the SPA, we need to consider which classification method is most appropriate.

Conclusion

To address the challenge of lack of actionable formative feedback in LADs, this study investigates the feasibility of future implementation of SPA, which encourages students to reflect on the learning processes of others. In this paper, to examine the feasibility of SPA, we analyzed weekly test scores and unit exam performance collected from grade 8 students in a Japanese middle school. The analysis explored whether student learning trajectories could be categorized as social processes and whether these processes could offer opportunities for improvement-oriented awareness depending on students' performance levels. The results revealed that learning processes varied by performance group, suggesting that students may benefit from comparing their own processes with those of others. Rather than simply imitating the behavior of high-performing students, the findings imply that students could adopt stepwise improvement strategies by referencing peers slightly above their own level—e.g., low-performing students learning from middle performers, and middle performers learning from high performers. Moreover, the visualization of social processes allowed for the identification of common challenges across all performance groups. For instance, the second weekly test showed a score decline across all groups, indicating shared difficulties that are not limited to any single performance tier.

Looking ahead, expanding the social process component of SPA beyond test results to include more detailed learning behaviors will be critical for generating actionable feedback. This study demonstrates the feasibility of SPA in the context of student-led FA in K-12 and provides foundational insights for its future implementation.

Abbreviations

FA: Formative Assessment; SRL: Self-Regulated Learning; LADs: Learning Analytics Dashboards; KA: Knowledge Awareness; CSCL: Computer Supported Collaborative Learning, SPA: Social Process Awareness; LEAF: Learning and Evidence Analytics Framework; MOOCs: Massive Open Online Courses; ZPD: Zone of Proximal Development.

Author's contributions

SH performed the data analysis and drafted the manuscript. CH, IH and HO provided insights and reviewed the manuscript. SH and HO acquired funding for the research. All authors read and approved the final manuscript.

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Availability of data and materials

Not applicable.

Declarations

Competing interests

The authors declare that they have no competing interests.

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