Exploring the Relationship Between System Operation Behaviors and Learning Achievement in Agricultural Education

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Abstract: With the growing integration of digital technologies into agricultural education, learning support systems play a pivotal role in enhancing students' understanding of environmental and field-based concepts. While previous studies have shown their effectiveness, less attention is given to the specific student behaviors that contribute to improvements. This study investigates which system operation behaviors are strongly associated with learning achievements in a high school agricultural context. Behavioral log data are collected from a class using the Field Environment Digest System, a web-based platform visualizing real-time field data from sensor networks. Students are grouped into quartiles based on test performance, and their usage behaviors are analyzed comparatively. Results show that high-performing students engage more in interactive operations such as switching chart views, exploring legends, and adjusting sensor variables. These patterns suggest that deliberate, exploratory interactions are linked to better outcomes and can inform instructional strategies and system designs that promote deeper understanding.

Keywords: Agricultural education, Learning support system, System interaction behavior, Student engagement, Educational technology

1. Introduction

With the rapid advancement of digital technologies in education, learning support systems are increasingly used across disciplines, including agricultural education. These systems often integrate real-time environmental monitoring, data visualization, and mobile interfaces to provide contextualized, interactive learning experiences (Subbarao et al., 2024). In agricultural high schools, they help bridge the gap between theory and practice, enabling students to develop a concrete understanding of environmental and farming concepts (Lin et al., 2017).

Despite their growing adoption, many studies focus on overall learning effectiveness without examining how students interact with specific system features (Cao, 2021). Understanding not only whether a system improves performance, but also how it is used to achieve better outcomes, remains a key gap. Identifying behaviors that contribute most to learning can guide pedagogy and system design.

In our previous study, we introduced the Field Environment Digest System in high school agricultural classes, finding that students who used it achieved higher test scores. However, the mechanisms behind this impact remain unclear. This study analyzes students' log-recorded actions in the system—such as switching sensors, adjusting chart views, and interacting with visualizations—to determine which operations are significantly associated with learning achievement. By correlating behavioral logs with test performance, we aim to identify effective patterns of use. The findings can inform technology design and provide actionable feedback for instructors. Therefore, this study seeks to answer the following research question:1. Does the use of the agricultural learning system lead to improved student academic performance?2. Which system operation behaviors contribute most to differences in student academic performance?

2. Related Work

Learning analytics and educational data mining are widely used to analyze students' interaction behaviors in digital learning environments, aiming to uncover patterns that improve outcomes and guide instruction (Kaur & Dahiya, 2023). Research shows that behavioral features such as content access frequency, revisiting materials, and engagement in assessments often correlate positively with grades or test performance (Liu et al., 2022). Machine learning models predict success from interaction logs (Zeng, 2023), while temporal analyses examine how action sequences influence outcomes (Prasertisirikul et al., 2022).

However, most studies are in higher education or large-scale online systems such as MOOCs and LMS courses (Sun et al., 2018), limiting applicability to secondary agricultural education. Fine-grained behavioral analysis is particularly important here because tasks involve multi-step decision-making, real-time interpretation of environmental data, and integration of theory with practice (Zachariou et al., 2025). Such analysis can reveal behaviors missed in overall usage counts and help teachers provide targeted support (Klerkx, 2022).

Agricultural education often occurs in authentic field settings, where students manage both conceptual understanding and hands-on practice (Nur Dinie & Enio, 2023). These contexts create unique interaction patterns, such as interpreting sensor data to adjust cultivation parameters (Wan Jusoh et al., 2023). Yet, research on high school agricultural education rarely examines detailed usage behaviors and their impact on achievement (Baideldinova et al., 2022). This study analyzes system operation logs from high school students using a mobile-based field environment monitoring system. By linking specific interactive operations with test performance, it aims to identify behavior patterns that influence learning outcomes and inform the design of agricultural learning technologies.

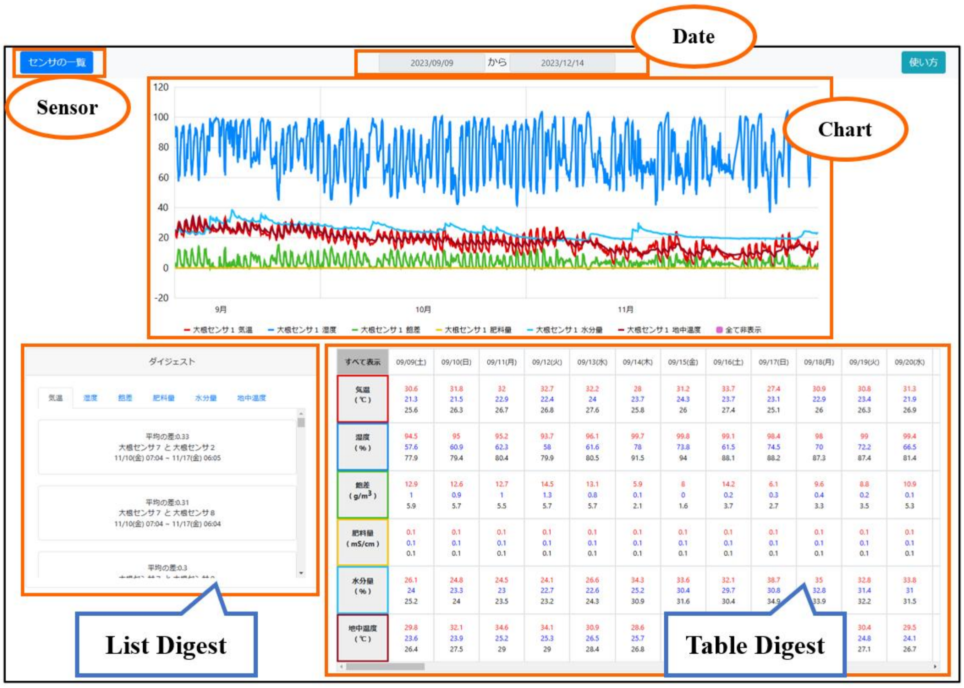

Figure 1. Field Environment Digest System Interface

3. System Description

In our research, we introduce the "Field Environment Digest System" to enhance student learning. The system aggregates sensor-derived agricultural field data and presents it in a simplified format (Shiga et al., 2023), providing time-series data from sensors such as temperature and humidity. Students explore this data through interactive line graphs and statistical summaries, helping them connect theoretical knowledge with real-world conditions. A core function is the logging module, which records all user operations in real time. This study analyzes specific log events to identify behavioral patterns linked to learning performance, counting each user action once per occurrence to calculate frequency.

The stored log data is shown in Table 1. The id column indicates the ID of each log entry; user_id assigns a unique ID to each student; created_at records the timestamp; action identifies the type of operation performed; time_from and time_to record the period viewed; sensor specifies the sensor involved; and category shows the type of data explored. For example, in the first and second rows, user 235 adjusts the displayed time range of sensor xx-yy and maintains it for a certain duration; in the second row, the user examines the period of change related to moisture content. In the third row, the user checks moisture content via the aggregate summary, with the viewed period indicated by time_from and time_to. In the fourth row, the user operates the saturation content chart, with the viewed period similarly derived from the same columns.

Table 1*. Data to Manage Operation Logs*

id	user_id	created_at	action	time_from	time_to	sensor	category
1	235	1697761492	chart_change	1694703600	1697727600	xx-yy	temp
2	235	1697761503	chart_legend	1696724399	1696724419	xx-yy	humidity
3	235	1697761506	date_from	1697284929	1697306428	xx-yy	moisture
4	235	1697761509	date_to	1695131013	1695134613	xx-yy	saturation
5	235	1697761529	sensor_select	1695975878	1696001721	xx-yy	electric

4. Method

This study is conducted at an agricultural high school in Japan with 34 first-year students from the same intact class enrolled in an agricultural experiment course. The same teacher delivers all lessons to ensure identical classroom conditions. To minimize confounding variables, all students follow the same curriculum before the experiment, report no prior experience with the system in a pre-test survey, and use identical iPads after a short orientation session.

During the experimental phase, students use the Field Environment Digest System in the last 20 minutes of class to explore sensor-derived data (e.g., humidity, temperature, soil moisture) from their managed plots. A post-test, based on validated items from previous examinations, assesses factual recall, conceptual understanding, and application, with emphasis on conceptual understanding. System logs record six types of operations—Chart_change, Chart_legend, Date_from, Date_to, Digest_table, and Sensor_select—representing distinct forms of data exploration and visualization.

Data analysis uses Pearson correlation and linear regression to examine the relationship between operation frequency and test scores, with regression slope and coefficient of determination indicating predictive strength. Correlations between each behavior type and scores identify high-impact interactions. Students are grouped into quartiles by performance, and the Kruskal–Wallis H test detects group differences, followed by Bonferroni-adjusted Mann–Whitney U tests for post hoc comparisons.

5. Results

5.1 Analysis of the Relationship Between System Operations and Learning Outcomes

Analysis for RQ1 shows a strong positive relationship between overall system use and academic performance. Figure 2 plots test scores against the number of system operations, showing a clear upward trend: students performing more than 30 operations often score above 90, while those with fewer than 20 rarely exceed 80. Operation frequency correlates highly with test scores (r = 0.89, $p < 0.001$), with a regression slope of 1.03 and R^2 of 0.79, indicating that 79% of score variance is explained by usage. Frequent interaction is linked to higher scores, indicating that consistent engagement enhances understanding of agricultural concepts (Salama & Aly, 2024; Lin, 2025).

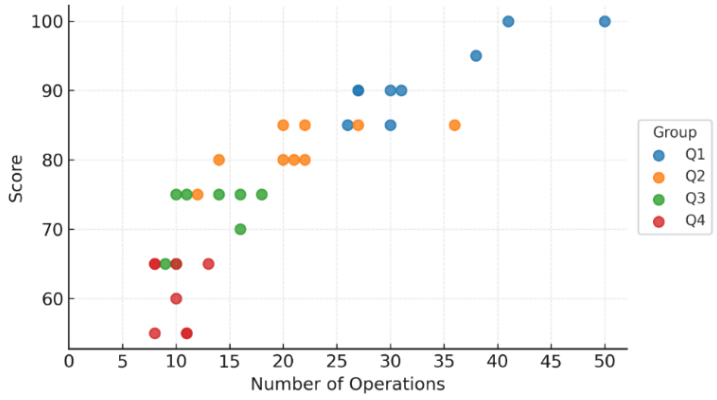

Figure 2. Relationship Between Score and Number of Operations

Table 2. *Correlation Analysis Between Test Score and System Operation Count*

Metric	Pearson r	p	Slope	*R^2*
Value	0.89	0.001***	+1.03	0.79

***p < .001

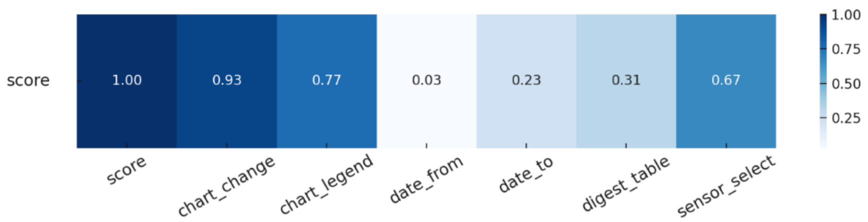

Figure 3. Pearson correlation coefficients between six types of system operations and students' test scores.

Further analysis (Figure 3) identifies chart_change (r = 0.93), chart_legend (r = 0.77), and sensor_select (r = 0.67) as the behaviors most associated with performance, while date_from (r = 0.03), date_to (r = 0.23), and digest_table (r = 0.31) show weaker associations. These findings suggest that active exploration and comparison of environmental data are more strongly linked to higher performance than procedural actions, underscoring the importance of meaningful interaction in digital learning tools (Klerkx, 2022). Teachers can integrate short, targeted system-based tasks into coursework to encourage these behaviors, while designers should ensure easy access to high-value features, such as chart comparisons and multi-sensor views, to promote sustained, high-quality engagement (Salama & Aly, 2024; Lin, 2025).

5.2 Differences in System Operation Behaviors

Students are divided into four quartiles by test scores (Figure 2) to compare behavior frequencies. A Kruskal–Wallis H test reveals significant differences for chart_change (H = 31.016, $p < .001$), chart_legend (H = 20.459, $p < .001$), and sensor_select (H = 13.342, p = .004), while date_from, date_to, and digest_table show no differences (Table 3).

Post-hoc Bonferroni-adjusted Mann–Whitney U tests (Table 4) show chart_change differs in nearly all pairwise comparisons ($p < .001$), making it a robust performance indicator. For chart_legend, differences appear between Q1 and Q3/Q4 (p = .003), suggesting it distinguishes top performers. Sensor_select differs only between Q1 and Q4 (p = .015), indicating its variation is most evident when contrasting the highest- and lowest-performing groups.

Table 3. *Kruskal–Wallis Test Results for Operation Behavior Differences Among Performance Groups*

Behavior	chart_ change	chart_ legend	date_ from	date_ to	digest_ table	sensor_ select
H	31.016	20.459	1.979	2.631	3.223	13.342
p	0.001***	0.001***	0.577	0.452	0.358	0.004**

** p <.01, *** p < .001

Table 4. *Bonferroni-Adjusted Pairwise Comparisons of Operation Behaviors Between Quartile Groups*

Behavior	Q1 vs Q2	Q1 vs Q3	Q1 vs Q4	Q2 vs Q3	Q2 vs Q4	Q3 vs Q4
chart_change	0.002**	0.003**	0.003**	0.003**	0.003**	0.006**
chart_legend	0.076	0.003**	0.003 **	0.383	0.131	1.000
sensor_select	1.000	0.130	0.015 *	0.871	0.078	1.000

* p <.05, ** p < .01

For RQ2, correlations identify chart_change (r = 0.93), chart_legend (r = 0.77), and sensor_select (r = 0.67) as the most performance-related behaviors. Non-parametric tests confirm chart_change as a consistent differentiator, chart_legend as moderately distinctive for top performers, and sensor_select as significant only between the highest- and lowest-performing groups. High achievers engage more in exploratory actions—switching chart views, toggling variables, and comparing sensor outputs—that integrate theoretical concepts with real-time field data (Reddy & Chandu, 2025).

6. Discussion and Conclusion

This study relates system-operation logs to test performance in high school agricultural learning. Grouping students by scores shows that *chart_change* and *chart_legend* are most strongly linked to higher achievement, indicating that visually guided exploration supports deeper understanding. For design, prioritizing features that elicit meaningful comparisons rather than simply increasing clicks can enhance learning value. For instruction, behavior logs can serve as early indicators of engagement, enabling timely support for students who underuse core visualization tools; encouraging low-performing students to practice these features may help close performance gaps.

Across analyses, data-comparison and visualization behaviors show greater learning value than procedural operations. Actions such as chart_change and chart_legend—which prompt students to juxtapose variables and interpret trends—align strongly with achievement, whereas date_from, date_to, and digest_table display weak correlations and little variation across groups. Unlike LMS contexts where navigation often dominates, impactful actions here require synthesizing multiple environmental factors in real time (Issa et al., 2024). This domain-specific demand supports designs and teaching strategies that foreground cognitively rich, exploratory visual features.

Limitations include analysis of a single session within one subject context, which may constrain generalizability. Future work should analyze longer deployments across varied settings and experimentally manipulate interaction types to test causality. Overall, the type—not merely the amount—of system interaction matters for learning in agricultural education.

Acknowledgments

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