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# The Effect of the MURDER Learning Model on Primary Students' Data Literacy and Mathematical Problem-Solving: A Quasi-Experimental Study

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***Abstract***

According to cognitive scripting theory, systematic learning phases can significantly optimize information processing and enhance cognitive retention. Based on this theoretical justification, the Mood-Understand-Recall-Detect-Elaborate-Review (MURDER) model was implemented to address students' low proficiency in data analysis and probability. This study aims to evaluate the influence of the MURDER model on the data literacy and mathematical problem-solving abilities of fourth-grade students. Using a non-equivalent pretest-posttest control group design, the research involved 74 students in Primary Schools Cluster 2, Slahung District. Through purposive sampling, SDN 5 Slahung was designated as the treatment class ($n$ =16) and SDN 3 Slahung as the control class ($n$ =18). The statistical analysis for data literacy revealed a t-value of 2.91, exceeding the t-table value, which indicates a significant difference between the experimental and control groups. In contrast, mathematical problem-solving abilities yielded a t-value of 1.63, falling below the significance threshold. The study concludes that the MURDER model has a significant influence on data literacy both within and between groups. However, its impact on mathematical problem-solving was limited to within-group improvements only. These findings suggest that while cognitive scripting effectively builds literacy, additional logical scaffolding is required to bridge the gap in complex mathematical problem-solving.

**Keywords:** Data Literacy, Mathematical Problem-solving Ability, MURDER Learning Model

**Abstrak**

Menurut teori skrip kognitif, fase pembelajaran sistematis dapat secara signifikan mengoptimalkan pemrosesan informasi dan meningkatkan retensi kognitif. Berdasarkan justifikasi teoritis ini, model *Mood-Understand-Recall-Detect-Elaborate-Review* (MURDER) diimplementasikan untuk mengatasi rendahnya kemampuan siswa dalam analisis data dan probabilitas. Studi ini bertujuan untuk mengevaluasi pengaruh model MURDER terhadap literasi data dan kemampuan pemecahan masalah matematika siswa kelas empat. Dengan menggunakan desain *non-equivalent pretest-posttest control group design,* penelitian ini melibatkan 74 siswa di Gugus 2 Sekolah Dasar, Kecamatan Slahung. Melalui pengambilan sampel bertujuan, SDN 5 Slahung ditetapkan sebagai kelas perlakuan ($n$ = 16) dan SDN 3 Slahung sebagai kelas kontrol ($n$ = 18). Analisis statistik untuk literasi data menunjukkan nilai t sebesar 2,91, melebihi nilai t tabel, yang menunjukkan perbedaan signifikan antara kelompok eksperimen dan kelompok kontrol. Sebaliknya, kemampuan pemecahan masalah matematika menghasilkan nilai t sebesar 1,63, yang berada di bawah ambang batas signifikansi. Studi ini menyimpulkan bahwa model MURDER memiliki pengaruh signifikan terhadap literasi data baik di dalam maupun antar kelompok. Namun, dampaknya terhadap pemecahan masalah matematika terbatas pada peningkatan di dalam kelompok saja. Temuan ini menunjukkan bahwa meskipun skrip kognitif efektif membangun literasi, diperlukan kerangka kerja logis tambahan untuk menjembatani kesenjangan dalam pemecahan masalah matematika yang kompleks.

**Kata kunci:** Literasi data, Kemampuan Pemecahan Masalah Matematis, Model Pembelajaran MURDER

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## Introduction

In the era of the "Merdeka" Curriculum, primary education must prepare students for a data-driven world where technological advances necessitate the use of big data for everyday decision-making

(Burbules et al., 2020). The Indonesian National Assessment (Asesmen Kompetisi Minimum/AKM) reflects this shift by emphasizing literacy and numeracy over rote memorization. However, students frequently struggle with data analysis and probability, specifically in describing data and writing complete answers (Mursyidah et al., 2023). This gap in data literacy, which refers to the ability to understand and utilize data as a basis for reasoning (Sampson et al., 2022), also directly hinders mathematical problem-solving. As noted by Moon et al. (2025), data literacy is foundational to problem-solving because it provides the analytical framework required to make informed decisions after comprehensive data analysis.

To address these cognitive hurdles, a learning model is required that specifically trains accuracy in reading and processing data. The MURDER (Mood-Understand-Recall-Detect-Elaborate-Review) model, grounded in Cognitive Scripting Theory, provides a systematic framework to enhance information encoding and long-term memory (Hythecker et al., 1988). By assigning roles such as "recaller" and "listener," the model facilitates the "Detection" of errors and the "Elaboration" of material, which are critical for processing complex datasets.

A theoretical gap remains because existing research often treats mathematical skills as a monolith (Faza & Wijayanti, 2023). Prior studies have not sufficiently explained why structured cognitive scripts produce differential effects on literacy (decoding) and problem-solving (application). The MURDER model likely optimizes data retrieval and interpretation, whereas the transition to abstract mathematical modeling demands additional cognitive scaffolding. Accordingly, this study examines the influence of the MURDER model on students' data literacy and on their mathematical problem-solving ability.

## Method

The study utilized a quasi-experimental study with a non-equivalent pretest-posttest design (Siswono, 2019). The researcher acknowledged the limitations of data sources and research time due to his full-time teaching role in an area with primary schools with a small number of students. However, researchers conduct research as well as answering research problems and objectives. Quasi-experiments are chosen to assess how independent variables influence other variables, without random assignment because classes or groups have already been formed in the population so there is no equivalence. The non-equivalent pretest-postest design is presented in Table 1.

Table 1. Research Design

| Class | Pretest | Treatment | Posttest |
|---|---|---|---|
| Treatment Class | $T1_X$ | X | $T2_X$ |
| Control Class | T1 | | T2 |

Source: Siswono (2019)

Table 1 shows that the research design with $T1_x$ is pretest for treatment class and $T2_x$ is posttest for treatment class. Next, T1 is pretest for control class and T2 is posttest for control class. Finaly, X is an intervention or treatment given specifically to the treatment class.

The population of this study took all 4th grade students in 5 primary schools in the cluster 2 area of Slahung Sub-district, totaling 74 students. Sampling was purposive, choosing schools with similar academic standings to ensure baseline comparability. Despite the small sample size (N=34), Shapiro-Wilk and Levene's tests confirmed data normality and homogeneity, justifying the use of parametric t-tests (Setyaedhi et al., 2025). Variables of this study consisted of two dependent variables, which were student's data literacy (Y1) and mathematical problem-solving ability (Y2), and one independent variable (X), which was MURDER learning model (X). Data collection in this study was carried out by tests and documentation. The test instrument in this study consists of 2 parts of the test instrument, namely the DL test for data literacy testing and the MPSA test for mathematical problem-solving ability testing. Meanwhile, the documentation was carried out through photos of test sheets and worksheets.

Data literacy (DL) indicators used in this study refer to data literacy indicators by Sampson and shared in Table 2.

Table 2. Data Literacy (DL) Test Instrument Grid

| No | Indicator | Sub-indicators |
|---|---|---|
| 1 | Data collection | The ability to know the data that want to obtain<br>The ability to know the right data source |
| 2 | Data management | The ability to process and handle the required data<br>The ability to apply data description |
| 3 | Data analysis | The ability to practice data analysis methods, and data modeling<br>The ability to apply data presentation methods |
| 4 | Data comprehension and interpretation | The ability to understand insights after data analysis<br>The ability to understand the implications of data analysis insights |
| 5. | Data application | The ability to make decisions from data analysis<br>The ability to evaluate decision making based on data |
| 6. | Data ethics | The ability to determine what personal data needs to be protected<br>The ability to know who is responsible and can utilize the data |

Source: Sampson et al. (2022)

Table 2 shows that data literacy has six indicators, each consisting of two sub-indicators. A total of twelve sub-indicators were used as guidelines for creating DL test items in this study. The indicators of mathematical problem-solving ability (MPSA) used in this study were adapted from indicators developed by Anggoro and shared in Table 3.

Table 3. Mathematical Problem-Solving Ability (MPSA) Test Instrument Grid

| No | Indicator | Sub-indicators |
|---|---|---|
| 1 | Understanding the Problem | The ability to mention known information<br>The ability to determine the questions that need to be known |
| 2 | Constructing a mathematical model | The ability to develop steps for a problem-solving plan<br>The ability to choose the right steps in solving problems |
| 3 | Applying mathematical models to solve problems | The ability to create problem-solving models<br>The ability to examine problem-solving steps. |
| 4 | Explain the results according to the original problem | The ability to check the suitability of the results of problem solving with the main problem |

Source: Anggoro et al. (2023)

Table 3 shows that mathematical problem-solving ability has four indicators, each consisting of one or two sub-indicators. A total of seven sub-indicators were used as guidelines for creating MPSA test items in this study. Initially, the test instrument consisted of 20 descriptive questions items for the data literacy (DL) test and 10 descriptive questions items for the mathematical problem-solving ability (MPSA) test. After validation by experts, 14 descriptive questions items of the DL test were declared in the valid category and 7 descriptive questions items of the MPSA test were declared in the valid category and were recommended for use for research purposes. Supported by the results of the construct validity test, 14 items of the DL test are included in the valid criteria, and have a reliability value of 0.867, which exceeds 0.60, making 14 items of the DL test declared reliable. Furthermore, the results of the construct validity test on 7 items of the MPSA test are included in the valid criteria and have a reliability value of 0.831 which exceeds 0.60, making 7 items of the MPSA test declared reliable. The instrument grid and research assessment guidelines after passing expert validation and the trial process for construct validation are shown in Table 4.

Table 4. Research Instruments Grid

| test | Indicator | Sub-indicators | Numbers |
|---|---|---|---|
| (DL) | Data collection | The ability to know the data that want to obtain | 4 |

| | | | |
|---|---|---|---|
| | | The ability to know the right data source | 3 |
| | Data management | The ability to process and handle the required data<br>The ability to apply data description | 8 and 9<br><br>7 |
| | Data analysis | The ability to practice data analysis methods, and data modeling<br>The ability to apply data presentation methods | 14<br>15 |
| | Data comprehension and interpretation | The ability to understand insights after data analysis<br>The ability to understand the implications of data analysis insights | 17<br><br>18 and 19 |
| | Data application | The ability to make decisions from data analysis<br>The ability to evaluate decision making based on data | 20<br>16 |
| | Data ethics | The ability to determine what personal data needs to be protected<br>The ability to know who is responsible and can utilize the data | 5<br>6 |
| (MPSA) | Understanding the Problem | The ability to mention known information<br>The ability to determine the questions that need to be known | 1<br>2 |
| | Constructing a mathematical model | The ability to develop steps for a problem-solving plan<br>The ability to choose the right steps in solving problems | 10<br>11 |
| | Applying mathematical models to solve problems | The ability to create problem-solving models<br>The ability to examine problem-solving steps. | 12<br>13 |
| | Explain the results according to the original problem | The ability to check the suitability of the results of problem solving with the main problem | 21 |

In this study, the data analysis consisted of prerequisite test analysis, including a normality test using the Shapiro-Wilk method, which is suitable for small samples usually ≤50, and the homogeneity test uses the Levene test which has the highest power for extreme situation with small size of sample (n smaller than 20) (Zhou et al., 2023). Finally, the hypothesis was tested using the paired sample t-test and the independent sample t-test, both can be tested on small samples (n<30) (Setyaedhi et al., 2025).

## Results and Discussion

This section several data analysis results are presented, consisting of tests on instruments, data descriptions, pre-analysis tests and hypothesis tests to examine the significant influence from the MURDER learning model is on data literacy and mathematical problem-solving ability.

*Instrumen Testing*

Validity and reliability tests for research instruments produced the values presented in tables 5 and 6.

Table. 5 Result of the Validity Test

| Test | Number | Pretest | | Posttest | |
|---|---|---|---|---|---|
| | | $r_{value}$ | $r_{table}$ (n=21, 0,05) | $r_{value}$ | $r_{table}$ (n=21, 0,05) |
| Data literacy (DL) | 3 | 0.700 | | 0.954 | |
| | 4 | 0.660 | | 0.692 | |
| | 5 | 0.660 | | 0.618 | |
| | 6 | 0.732 | | 0.680 | |
| | 7 | 0.645 | | 0.669 | |

| | | | | | |
|---|---|---|---|---|---|
| | 8 | 0.507 | | 0.460 | |
| | 9 | 0.754 | 0.456 | 0.653 | 0.456 |
| | 14 | 0.576 | | 0.529 | |
| | 15 | 0.536 | | 0.619 | |
| | 16 | 0.597 | | 0.670 | |
| | 17 | 0.498 | | 0.615 | |
| | 18 | 0.563 | | 0.823 | |
| | 19 | 0.628 | | 0.670 | |
| | 29 | 0.722 | | 0.544 | |
| Mathematical problem-solving ability (MPSA) | 1 | 0.933 | | 0.770 | |
| | 2 | 0.823 | | 0.661 | |
| | 17 | 0.581 | | 0.559 | |
| | 18 | 0.483 | 0.456 | 0.487 | 0.456 |
| | 19 | 0.626 | | 0.634 | |
| | 20 | 0.628 | | 0.716 | |
| | 21 | 0.799 | | 0.583 | |

The construct validity test on the pretest and posttest provided valid results on 14 items of the DL test with the smallest r-value of 0.460 and the largest r-count value of 0.954, which exceeded the r-table value of 0.456 sourced from the r-table distribution for a sample size of 21, indicating that all 14 items of the DL test were in the valid category. Meanwhile, on 7 items of the MPSA test with the smallest r-value of 0.483 and the largest r-count value of 0.933, which exceeded the r-table value of 0.456 sourced from the r-table distribution for a sample size of 21, indicating that all 7 items of the MPSA test were in the valid category.

Table 6. Result of the Reliability Test

| Test | Pretest | | | Postest | | |
|---|---|---|---|---|---|---|
| | Cronbach's Alpha | N of Items | acceptable threshold | Cronbach's Alpha | N of Items | acceptable threshold |
| Data literacy (DL) | .867 | 14 | .600 | .894 | 14 | .600 |
| Mathematical problem-solving ability (MPSA) | .831 | 7 | .600 | .734 | 7 | .600 |

The results of the reliability test for the DL test demonstrate that the reliability value of 0.867 in the pretest and 0.894 in the posttest, which exceeded the agreement limit of 0.6, providing evidence that the DL test instrument is reliable. A similar result was observed in the reliability test results for the MPSA test, which demonstrate the reliability value of 0.831 in the pretest and 0.734 in the posttest, providing evidence that the MPSA test instrument is reliable.

Both types of test instruments in this study were proven to have valid and reliable test items for data collection. Next, the researchers began preparing supporting instruments for the treatment, including teaching modules and student worksheets, which had been declared valid by expert validators.

*Descriptive Statistic Test*

The average value obtained for each indicator between classes is presented in table 7 below.

Table 7. Average Score for Each Indicator

| Test | Indicator | Treatment Class | | Control Class | |
|---|---|---|---|---|---|
| | | Average Value | | Average Value | |
| | | Pretest | Posttest | Pretest | Posttest |
| Data literacy (DL) | Data collection | 4.1 | 5.8 | 4.3 | 5.3 |
| | Data management | 7.1 | 9.1 | 7.4 | 7.9 |
| | Data analysis | 5.4 | 6.1 | 5.4 | 5.8 |

| | | | | | |
|---|---|---|---|---|---|
| | Data comprehension and interpretation | 7.3 | 7.9 | 7.5 | 7.9 |
| | Data application | 4.8 | 5.8 | 4.9 | 5.1 |
| | Data ethics | 5.3 | 6.0 | 4.8 | 4.8 |
| | Total | 34.0 | 40.6 | 34.1 | 36.3 |
| Mathematical problem-solving ability (MPSA) | Understanding the Problem | 5.4 | 6.3 | 4.8 | 5.1 |
| | Constructing a mathematical model | 4.5 | 5.1 | 5.3 | 5.3 |
| | Applying mathematical models to solve problems | 4.9 | 5.3 | 4.8 | 5.1 |
| | Explain the results according to the original problem | 2.1 | 2.1 | 2.0 | 2.2 |
| | Total | 17.0 | 18.9 | 16.4 | 17.6 |

The average scores of both classes are shown per indicator in Table 7 above. The average total score of the data literacy test in the treatment class increased, the result before the treatment was 34.0 and the average score became 40.6 after the post-test was conducted. Meanwhile, the control class also experienced some improvements with the average total score of the data literacy test from 34.1 to 36.3. Furthermore, the average total score of the MPSA test in the treatment class increased, the result before the treatment was 17.0 and the average score became 18.9 after the treatment was given, while in the control class it increased from 16.4 to 17.6. Finally, both classes experienced an increase in the average total score on both tests after being given the treatment.

*Pre-Analysis Test*

The test results, which determine the normality of the data distribution from the DL test, are presented in the display shown in Table 8. The significance value for the treatment class was obtained at 0.126 for the pretest and 0.977 for the posttest, where both results exceeded 0.05, which indicates that the distribution of data for the treatment class is in the normal category. Furthermore, the significance value for the control class at 0.117 for the pretest and 0.136 for the posttest, where both results exceeded 0.05, which shows that the distribution of class data is also in the normal category.

Table 8. Result of the Normality Test

| Test | Class | Shapiro-Wilk | | | | | |
|---|---|---|---|---|---|---|---|
| | | Pretest | | | Posttest | | |
| | | Statistic | df | Sig. | Statistic | df | Sig. |
| Data literacy (DL) | Treatment Class | .912 | 16 | .126 | .982 | 16 | .977 |
| | Control Class | .918 | 18 | .117 | .921 | 18 | .136 |
| Mathematical problem-solving ability (MPSA) | Treatment Class | .955 | 16 | .576 | .929 | 16 | .232 |
| | Control Class | .932 | 18 | .212 | .943 | 18 | .327 |

Furthermore, the results of the data normality test from MPSA test shown in Table 8, The p-value for the treatment class was obtained at 0.576 from the pretest and 0.232 from the posttest, where both results exceeded 0.05, which indicates the distribution of data for the treatment class in the normal category. Next, the p-value of control class is 0.212 for pretest and 0.327 for posttest, where both results exceeded 0.05, which shows that the distribution of class data is also in the normal category.

Table 9. Result of the Homogeneity Test

| Test | Class | Levene (Based on Mean) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Pretest | | | | Posttest | | | |
| | | Statistic | df1 | df2 | Sig. | Statistic | df1 | df2 | Sig. |
| Data Literacy (DL) | Treatment Class | | | | | | | | .121 |
| | Control Class | 1.039 | 1 | 32 | .316 | 2.535 | 1 | 32 | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Mathematical Problem-solving Ability (MPSA) | Treatment Class<br>Control Class | .512 | 1 | 32 | .480 | .836 | 1 | 32 | .367 |

The results of the Levene test are used to determine whether the data are homogeneous or not. The first test on the DL pretest of both classes showed p-value of 0.316, which is a significance level exceeding 0.05, providing evidence of the suitability of the sample for hypothesis testing because it was obtained from a homogeneous population. The Second test on the DL posttest of both classes showed p-value of 0.121, which is a significance level exceeding 0.05, providing evidence of the suitability of the sample for hypothesis testing because it was obtained from a homogeneous population.

Table 9 shows that the testing on the MPSA pretest for both classes obtained a p-value of 0.480, which is a significance level exceeding 0.05, providing evidence of the suitability of the sample for hypothesis testing because it was obtained from a homogeneous population. Furthermore, testing on the MPSA posttest of both classes obtained a p-value of 0.367, which is a significance level exceeding 0.05, providing evidence of the suitability of the sample for hypothesis testing because it was obtained from a homogeneous population.

Table 10. Result of Pretest Comparison

| Pretest | Independent sample T-test | | |
|---|---|---|---|
| | t | df | Sig |
| Data literacy (DL) | .287 | 32 | .776 |
| Mathematical problem-solving ability (MPSA) | .180 | 32 | .858 |

Table 10 shows that the testing on the DL pretest and MPSA pretest with Independent sample T-Test. Independent sample t test on the pretest was added to compare the pretest results of the two classes. The results of the DL pretest obtained a t-value of 0.287 less than the t-table (df = 32, $\alpha = 0.05$) which is 2.036, so there is no significant difference in the average DL pretest results between classes. Furthermore, the results of the MPSA pretest obtained a t-value of 0.180 less than the t-table (df = 32, $\alpha = 0.05$) which is 2.036, so there is no significant difference in the average MPSA pretest results between classes.

*Hypothesis Test*

Hypothesis testing in this study has two objectives: (1) to examine the significant influence of the MURDER learning model on data literacy of 4th grade students of primary school cluster 2, Slahung sub-district, (2) to examine the significant influence of the MURDER learning model on mathematical problem-solving abilities of of 4th grade students of primary school cluster 2, Slahung sub-district.

Hypothesis testing in this study has two functions: (1) to ensure whether or not there is a significant influence from the independent variable after being given treatment in the treatment class on the previous dependent variable, which is done through a paired sample t-test, and (2) how significant the influence is in the treatment class when the post-test results are compared with the results of the control class, which is done through an independent sample t-test.

Table 11. Result of Statistical Hypothesis's Test

| Posttest | Paired sample t-test | | | Independent sample T-test | | |
|---|---|---|---|---|---|---|
| | t | df | Sig. | t | df | Sig |
| Data literacy (DL) | 7.441 | 15 | .000 | 2.910 | 32 | .007 |
| Mathematical problem-solving ability (MPSA) | 2.877 | 15 | .012 | 1.625 | 32 | .114 |

The hypothesis test for data literacy generated through the paired t-test is arranged in Table 11, showing that the t-value of DL test is 7.441 exceeds the t table is 2.131 from degrees of freedom (df) = 15 in the t table distribution, and the p-value obtained was 0.000, that means it is less than 0.05 and shows that the average DL test scores before and after treatment in the treatment class reached a significant difference. Next, hypothesis test with independent sample t-test demonstrates the t-value of DL is 2.910 exceeds the t-table is 2.036 from degrees of freedom (df) = 32 in the t-table distribution, and the p-value obtained was 0.007, that means it is less than 0.05 and shows the average value of DL between classes is significantly different. Finally, the hypothesis testing criteria are met, suggesting that there is a significant influence from using the MURDER learning model on the data literacy of 4th grade students at primary school cluster 2, Slahung sub-district.

The hypothesis test for MPSA generated through the paired t-test is arranged in Table 11, demonstrates the t-value of MPSA test is 2.877 exceeds the t-table is 2.131 from degrees of freedom (df) = 15 in the t table distribution, and the p-value obtained is 0.012, that means it is less than 0.05 and shows that the average MPSA test scores before and after treatment in the treatment class reached a significant difference. Next, hypothesis test with independent sample t-test demonstrates the t-value of MPSA is 1.625, which less than the t-table is 2.036 from degrees of freedom (df) = 32 in the t table distribution, and the significance value (2-tailed) obtained is 0.114, which exceeds 0.05 and shows that the average value of MPSA between classes is not significantly different. The independent variables were proven to provide a significant difference in the average score on the dependent variable of mathematical problem-solving ability (MPSA) when tested using paired difference tests in the treatment class but were not significant to prove a difference in the average score when tested using independent difference tests with the control class.

This study involved two sample groups: a treatment class using the MURDER learning model, and a control class using conventional learning model. Analyzed through the results of the hypothesis test, the statistical value shows that students who use the MURDER learning model have better data literacy than students who use the conventional learning model. The average DL posttest score was 40.6 for students in the treatment class, compared to 36.3 for students in the other class. These results are in line with research conducted by Rahmadhani et al. (2019), which found that student literacy in mathematics lessons using the MURDER learning model was better than student literacy taught using conventional learning models. The MURDER model's structure aligns specifically with the fundamental stages of data literacy: recall, categorization, and representation. A stepwise approach through 'Understanding' and 'Recall': These stages encourage students to break down information into manageable chunks. By explicitly requiring students to identify key ideas (Understanding) and transform them into personal summaries (Recall), the model reduces intrinsic cognitive load. This was evident when students in the experimental class, during the recall activity, more actively corrected their peers' memories to better categorize and represent data without being overwhelmed by the complexity of the dataset.

In this study, Students in the treatment class showed significantly better results in answering DL test question items after treatment than students in the other class. This confirms that the MURDER learning model makes a significant contribution to students' data literacy. The comparative analysis of student data literacy has been expressed in percentages, which are arranged in Table 12.

Table 12. The Value Obtained for each Data Literacy Indicator in Percent

| Indicator | Treatment Class | Control Class |
|---|---|---|
| Data collection | 72.7% | 66.4% |
| Data management | 75.5% | 66.2% |
| Data analysis | 76.6% | 72.7% |

| | | |
|---|---|---|
| Data comprehension and interpretation | 65.6% | 66.2% |
| Data application | 71.9% | 64.1% |
| Data ethics | 75.0% | 60.2% |

The general analysis of student responses can be seen by comparing the percentages for each data literacy indicator above. Students in the treatment class showed good performance in answering questions on five of the six data literacy indicators, as reflected in the percentages for indicators one, two, three, five, and six. Meanwhile, the control class only had an advantage in the average value on the fourth indicator. A more detailed analysis of student responses across classes is presented in figure 2 below.

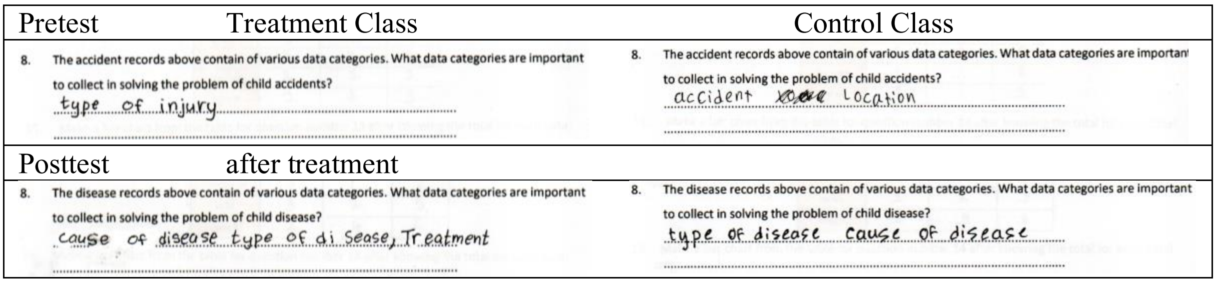



Figure 2. Answers from respondents across classes on Questions 8

The answers from students in the treatment class for question number eight with 'type of injury' in the pretest, then in the posttest answered with 'cause of disease', type of disease and treatment'. Meanwhile, the students in the control class answered with 'accident location' in the pretest, then in the posttest answered with 'type of disease, cause of disease'. Question number eight asks about the important categories of data to be collected from the accident records for the pretest and the disease records for the posttest. The question represents the second indicator of data literacy, namely data management. In this question, students are required to process and handle the required data from secondary data in the form of records. This shows that students in the treatment class were able to provide complete answers to the important categories to be collected, compared to students in the control class.

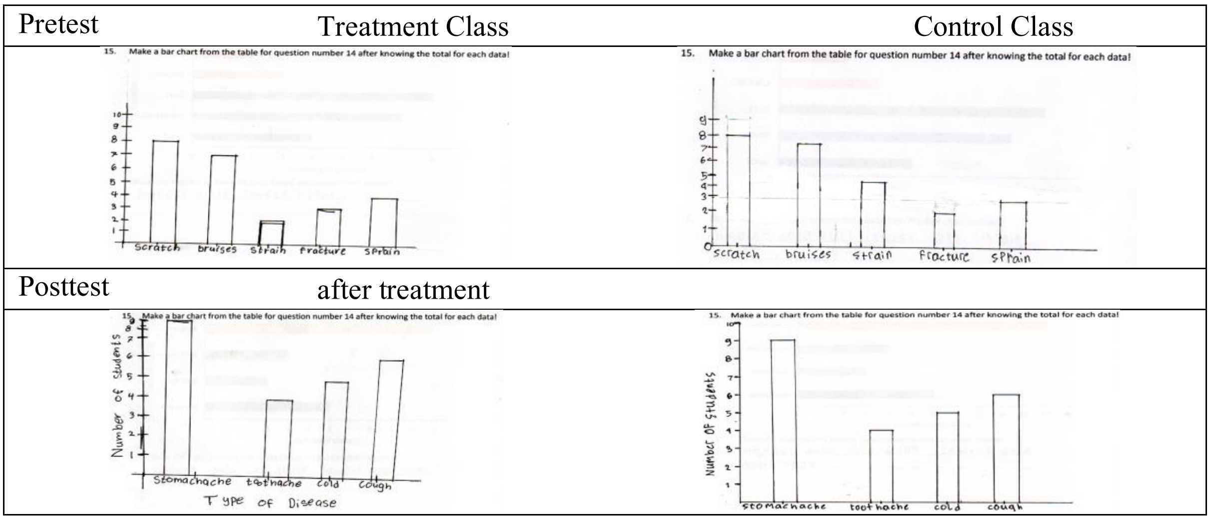



Figure 3. Answers from respondents across classes on Questions 15

The answers from students in the treatment class for question number fifteen with created an incomplete bar chart in the pretest, then in the posttest they answered with creating a complete bar chart with the required categories and number of students. Meanwhile, the students in the control class answered with creating an incomplete bar chart in the pretest, then in the posttest they answered with almost making a complete bar chart. Question number fifteen asks about the bar chart from the table.

The questions represent the third indicator of data literacy, namely data analysis. In this question, students are required to apply data presentation methods. This shows that students in the treatment class were able to create a complete data presentation method using a bar chart, compared to students in the control class.

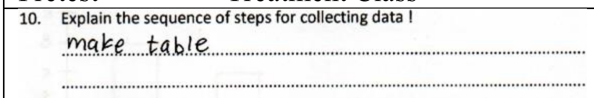
Next, students in the treatment class demonstrated better results on several indicators of MPSA compared to students in the control class. The comparative analysis of student MPSA has been expressed in percentages, which are arranged in Table 13.

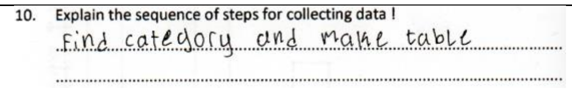
Table 13. The Value Obtained for each MPSA Indicator in Percent

| Indicator | Treatment Class | Control Class |
|---|---|---|
| Understanding the Problem | 78.3% | 63.3% |
| Constructing a mathematical model | 64.2% | 66.7% |
| Applying mathematical models to solve problems | 66.7% | 64.2% |
| Explain the results according to the original problem | 53.3% | 55.0% |

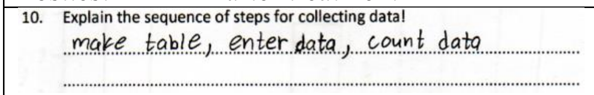
The general analysis of student responses can be seen by comparing the percentages for each indicator of mathematical problem-solving ability above. Students in the treatment class showed good results on two of the four indicators of MPSA, as reflected in the percentages for indicators one and three. Meanwhile, the average scores for indicators two and four are superior to students in the control class. A more detailed analysis of student responses in the treatment and control classes can be seen in Figure 3.

Pretest Treatment Class Control Class


10. Explain the sequence of steps for collecting data !
make table


10. Explain the sequence of steps for collecting data !
Find category and make table

Posttest after treatment


10. Explain the sequence of steps for collecting data!
make table, enter data, count data

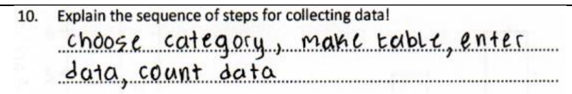
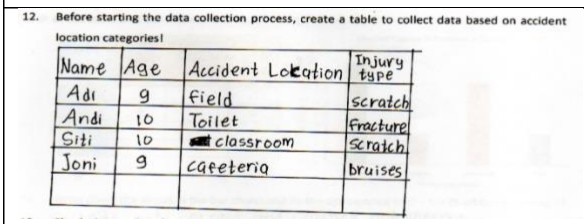

10. Explain the sequence of steps for collecting data!
choose category, make table, enter data, count data

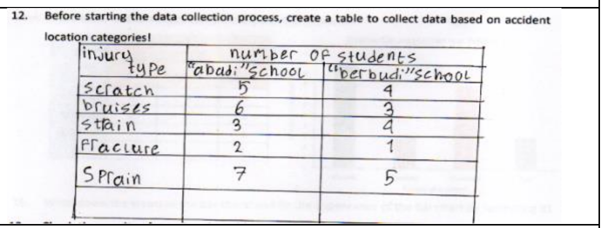
Figure 4. Answers from respondents across classes on Questions 10

The answers from students in the treatment class for question number ten with 'make table' in the pretest, then in the posttest answered with 'make table, enter data, count data'. Meanwhile, students in the control class answered with 'make table' in the pretest, then in the posttest answered with 'choose category, create a table, enter data, count data'. Question number ten asks about the sequence of steps for collecting data. This question represents the second indicator of mathematical problem-solving ability, namely constructing a mathematical model. In this question, students are required to develop steps for a problem-solving plan. This shows that students in the control class were able to provide complete answers for the sequence of steps for collecting data, compared to students in the treatment class.

Pretest Treatment Class Control Class

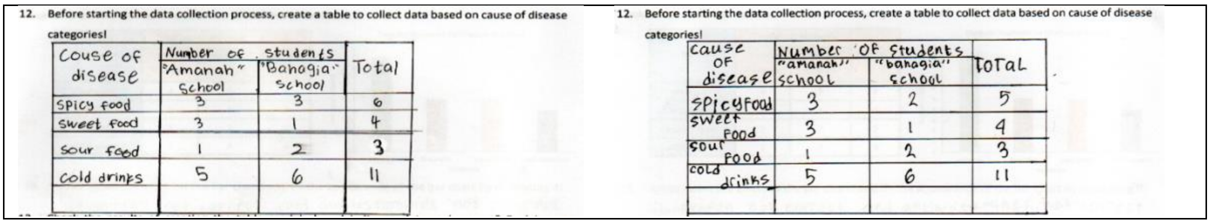

12. Before starting the data collection process, create a table to collect data based on accident location categories!

| Name | Age | Accident Location | Injury type |
|---|---|---|---|
| Adi | 9 | Field | scratch |
| Andi | 10 | Toilet | Fracture |
| Siti | 10 | classroom | Scratch |
| Joni | 9 | cafeteria | bruises |


12. Before starting the data collection process, create a table to collect data based on accident location categories!

| injury type | number of students "abadi" school | "berbudi" school |
|---|---|---|
| scratch | 5 | 4 |
| bruises | 6 | 3 |
| strain | 3 | 4 |
| Fracture | 2 | 1 |
| Sprain | 7 | 5 |

Posttest after treatment



12. Before starting the data collection process, create a table to collect data based on cause of disease categories!

| Couse of disease | Number of students "Amanah" School | "Bahagia" School | Total |
|---|---|---|---|
| Spicy food | 3 | 3 | 6 |
| Sweet food | 3 | 1 | 4 |
| Sour food | 1 | 2 | 3 |
| Cold drinks | 5 | 6 | 11 |

12. Before starting the data collection process, create a table to collect data based on cause of disease categories!

| Cause of disease | Number of students "amanah" school | "bahagia" school | Total |
|---|---|---|---|
| Spicy food | 3 | 2 | 5 |
| sweet food | 3 | 1 | 4 |
| sour food | 1 | 2 | 3 |
| cold drinks | 5 | 6 | 11 |

Figure 5. Answers from respondents across classes on Questions 12

The answers from students in the treatment class for question number twelve by making a data collection table were not the right table model in the pretest, then in the posttest answered by making a data collection table model correctly according to the required data category. Meanwhile, students in the control class answered by making a data collection table correctly, but this was not the category required in the pretest, Then in the posttest, it was answered by making a data collection table model correctly according to the required data categories, but it is still not quite right in entering the data for the spicy food column of "Bahagia" School should be 3, not 2. Question number twelve asks about the table for collecting data. This question represents the third indicator of mathematical problem-solving ability, namely applying mathematical models to solve problems. In this question, students are required to create problem-solving models. This shows that students in the treatment class were able to create tables to collect data more accurately without errors, compared to students in the control class.

## Conclusion

The results of statistical calculations using SPSS V.22 show that the MURDER learning model has a significant influence on the data literacy of $4^{th}$-grade students of Primary School Cluster 2, Slahung District in the paired sample t-test and independent sample t-test. The results of statistical calculations using SPSS V.22 show that the MURDER learning model has a significant average difference in mathematical problem-solving ability of 4th-grade students at Primary School in Cluster 2 of Slahung District with the paired sample t-test. However, the MURDER learning model does not have a significant average difference in mathematical problem-solving ability 4th-grade students at Primary School in Cluster 2 of Slahung District when testing the independent sample t-test.

The study also concludes that the MURDER model has a significant influence on data literacy both within and between groups of 4th-grade students at Primary School in Cluster 2 of Slahung District. However, its impact on mathematical problem-solving was limited to within-group improvements only of 4th-grade students at Primary School in Cluster 2 of Slahung District. These findings suggest that while cognitive scripting effectively builds literacy, additional logical scaffolding is required to bridge the gap in complex mathematical problem-solving.

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