Teachers' role in promoting primary school students' integration of mathematical, statistical, and other STEAM reasoning through data-based modelling

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Data-based modelling driven by interdisciplinary contexts has emerged as a means of promoting multidisciplinary reasoning in primary school students. However, teachers play a crucial role in facilitating this process. This study aims to explore teachers' role in promoting students' integration of mathematical, statistical, and other STEAM reasoning through data-based modelling. Specifically, it analyses STEAM practice of a teacher with Grade 4 students. To do this, we adopt an interdisciplinary data-driven modelling (IDDM) framework, which includes six key components: data, an interdisciplinary context, a mathematical model, a statistical model, models in other STEAM subjects, and prediction and decision-making. We use it to identify the teacher's support related to data variability and modelling, aimed at promoting students' multidisciplinary reasoning for prediction and decision-making. The findings provide practical strategies to enhance STEAM education through data-based modelling with skills in mathematics, statistics, data science, and other STEAM disciplines.

INTRODUCTION

As data-driven prediction and decision-making become increasingly essential in today's data-centric world, integrating mathematical, statistical, and data science skills into science, technology, engineering, arts, and mathematics (STEAM) education empowers learners to apply mathematical (deterministic), statistical (non-deterministic/stochastic), and other STEAM (e.g., design-based and scientific) reasoning effectively in interdisciplinary contexts (Biehler et al., 2025; Burrill, 2024; Gal & Geiger, 2022). Recent research has increasingly focused on *data-based modelling* to enhance students' multidisciplinary reasoning in primary school STEAM education (Aridor et al., 2023; English, 2023; Fry et al., 2024; Lehrer et al., 2024; Tytler et al., 2024). However, enabling primary school students to integrate multidisciplinary reasoning requires active teacher facilitation (Doerr et al., 2017; Hourigan & Leavy, 2020; Tytler et al., 2024).

Data are not limited to mathematics and statistics; they are also utilised in other STEAM disciplines in various ways (Watson et al., 2020). Variability-associated data are inherent in both natural and artificial systems, making them essential for scientific enquiry (Lehrer et al., 2024). Additionally, models—as idealised representations of reality—and modelling processes that attempt to explain and predict various phenomena are universal to STEAM disciplines (Hallström & Schönborn, 2023; Hjalmarson et al., 2020). In this context, we explored how primary school students construct, analyse, and refine data-based models using mathematics, statistics, and other STEAM subjects to support reasoning for understanding, explaining, predicting, and making decisions about phenomena in interdisciplinary contexts (Kawakami & Saeki, 2024a, 2024b). The current study examined how a teacher supported students in integrating mathematical, statistical, and other STEAM reasoning through data-based modelling by analysing a Grade 4 classroom.

LITERATURE REVIEW

Recent empirical studies have focused on interdisciplinary data-based modelling that integrates mathematics and statistics with other disciplines and subjects in STEAM education, beginning in primary school (Biehler et al., 2025). For example, English (2023) implemented a modelling activity involving data-driven predictions that integrated mathematical, statistical, and scientific knowledge with primary school students to justify their tsunami inundation predictions. Aridor et al. (2023) and Dvir and Tsybulsky (2025) explored middle school students' integration of deterministic, stochastic, and scientific reasoning, as well as their understanding of the nature of science in a citizen science project on radon contamination. These studies suggest that interdisciplinary modelling promotes back-and-forth movement between deterministic reasoning, stochastic reasoning, and other STEAM reasoning, such as design-based or scientific reasoning, in primary school STEAM education.

In: Birk, L., Loth, G., Jotzo, L., Binder, K., & Frischemeier, D. (Eds.) (2026). *Statistics and Data Science Education in STEAM. Proceedings of the Satellite Conference of the International Association for Statistical Education (IASE), September/October 2025, Münster, Germany*.

Owing to the complexities of interdisciplinary data-based modelling, several researchers have highlighted the importance of teachers' roles in integrating students' multidisciplinary reasoning. For example, Tytler et al. (2024) examined the experiences of students and teachers in a primary classroom, negotiating an interdisciplinary mathematics and science sequence on the flight of paper helicopters. They identified the teacher's role in supporting students' measurements, addressing students' limited experience with decimal notation, and shaping diverse student ideas about the science of flight and data representation. Similarly, Hourigan and Leavy (2020) highlighted the teacher's role in ensuring accurate data collection and measurement, and in guiding students' data analysis in STEM tasks involving catapult construction. However, little is known about how teachers promote students' integration of mathematical, statistical, and other STEAM reasoning in the context of modelling. It is essential for researchers and educators to identify strategies for using data-based modelling to promote students' model-based multidisciplinary reasoning across STEAM subjects. This study addresses that gap.

THEORETICAL FRAMEWORK AND RESEARCH QUESTION

We adopted an *interdisciplinary data-driven modelling* (IDDM) framework (Kawakami, 2023; Kawakami & Saeki, 2022, 2024a) to identify teachers' roles in promoting students' model-based multidisciplinary reasoning in STEAM lesson practices. The IDDM framework generates, validates, and revises mathematical (deterministic) and statistical (non-deterministic/stochastic) models and models in other STEAM subjects based on data and interdisciplinary contexts to make predictions and decisions (Kawakami & Saeki, 2024a). The IDDM framework (Figure 1), which comprises data, an interdisciplinary context, a mathematical model, a statistical model, models in other STEAM subjects, and prediction and decision-making, can model transitions between mathematical, statistical, and STEAM (design-based, scientific) reasoning. Therefore, this framework provides a lens through which researchers can identify teacher support for generating and integrating students' multidisciplinary reasoning during iterative exchanges between data and models and between models. Below, we explain the framework components and the interactions between them. Note that no sequence is assumed for transitions *α, β, γ, δ, ε,* and *ζ* in Figure 1.

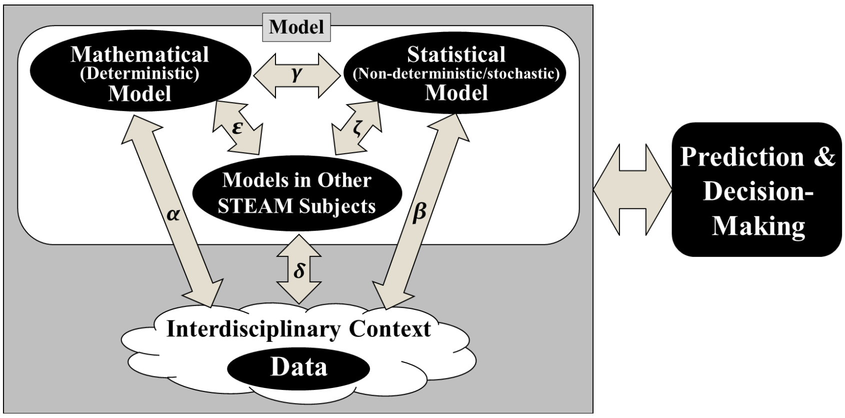


Figure 1. IDDM framework (adapted from Kawakami & Saeki, 2024a, p. 225).

IDDM framework components

- *Data*: Data represents values and numbers in a real-world (i.e., interdisciplinary) context (Cobb & Moore, 1997). Data have a structure comprising a deterministic aspect (signal), focused on exact numbers and causal explanations with certainty, and a non-deterministic/stochastic aspect (noise), focused on uncertainty and variability (Innabi et al., 2023; Konold & Pollatsek, 2002). Sources of variability include nature, measurements, sampling, and accidents (Wild & Pfannkuch, 1999).
- *Model*: A model is a representation of a given system's structure (Hestenes, 2010), reflecting the modeller's series of interpretations of an object (Lesh & Doerr, 2003; Piaget, 1968). This study did not consider the same representation as 'absolute'; rather, it viewed them as relative—i.e., as a mathematical or statistical model which depends on the learner's intention and deterministic or stochastic interpretation of the model.

- *Mathematical model*: A mathematical model is a representation of the signal inherent in the data that reflects the students' deterministic interpretations of the data and context (Kondo, 1976). Such a model can be labelled as a *deterministic model* (Groshong, 2016). A typical example is the linear model $y=ax+b$ (where a and b are parameters), where the value of the variable y can be determined if the value of x is given. Students can use mathematical reasoning to make deterministic conclusions based on mathematical models.
- S*tatistical model*: A statistical model represents the noise inherent in the data and reflects students' non-deterministic or stochastic interpretations of the data and its context (Dvir & Ben-Zvi, 2023). Such a model is also called a *non-deterministic/stochastic* model (Groshong, 2016). A typical example is the linear model $y=ax+b+\varepsilon$ (a and b are parameters), where the value of the variable y cannot be determined even if the value of the variable x is determined, as it is influenced by a random error ε. Students can use statistical reasoning, for example, to conduct data analyses that account for uncertainty based on statistical models.
- *Models in other STEAM subjects*: Models in other STEAM subjects refer to students' interpretations of data and their representations in terms of big ideas from STEAM disciplines other than mathematics and statistics (Chalmers et al., 2017), such as engineering design models (e.g., model/prototypes of seeds) and scientific models (e.g., motion models of a falling body or structural models of seeds). Students can utilise STEAM reasoning, such as design-based or scientific reasoning, based on models from other STEAM subjects.

Interactions between IDDM framework components

- *Transition α and β*: Generating and validating a mathematical or statistical model based on the data/ interdisciplinary context and revising it, if necessary, respectively.
- *Transition γ*: Generating and validating a mathematical model based on a statistical model and vice versa. Generating a statistical model based on a mathematical model involves transforming a deterministic representation into a non-deterministic or stochastic representation or interpretation. By contrast, generating a mathematical model based on a statistical model involves transforming a non-deterministic or stochastic representation into a deterministic representation or interpretation.
- *Transition δ*: Generating models in other STEAM subjects from the data/interdisciplinary context and validating or revising those models based on the data/interdisciplinary context.
- *Transitions ε and ζ*: Interpreting and validating a mathematical or statistical model based on models in other STEAM subjects and vice versa.

Research question

The IDDM framework (Figure 1) provides a lens through which researchers can identify teachers' role in generating and integrating students' model-based mathematical, statistical, and other STEAM reasoning in relation to the components of the IDDM framework and their transitions. Accordingly, we asked, *"How can a teacher support primary school students to generate and integrate model-based mathematical, statistical, and other STEAM reasoning in an interdisciplinary context?"*

METHOD

Research design

To address the question, we analysed a classroom episode from a STEAM education practice conducted in a Grade 4 class (students aged 9–10 years) in Japan. An overview of this practice and an analysis of exemplary students' predictions are provided in a study by Kawakami and Saeki (2024a, 2024b); however, the current study differs substantially from our previous work in that it analyses the teachers' role in promoting primary school students' integration of multidisciplinary reasoning.

Participants had learned bar and line graphs, and 2D tables but were unfamiliar with representative values, dot plots, and histograms. The lessons were codesigned by a researcher and primary school teacher with 20 years of experience. The researcher explained the concepts behind the STEAM activities shown in Figure 1; however, the teacher was unfamiliar with the IDDM framework.

The practice comprised nine 45-minute lessons in mathematics and cross-curricular enquiry classes. Furthermore, it addressed the *seed dispersal task* (Figure 2), which incorporated data-driven predictions into Fitzallen et al.'s (2019) seed dispersal material for integrated STEAM education. The goal of this task was to determine the best shape of Tsukubane (*Buckleya lanceolata*) seeds (Figure 3) to maximise flight time, assuming that the shape could be temporarily altered using genetic technology. After conducting several experiments measuring the flight times of seed models that mimicked the descent behaviour of actual seeds (Figure 3), students were tasked with predicting trends in flight time using the shape of the seed models as a variable and validating their predictions using real data. Through this task, students generated and applied mathematical models (e.g., line graphs), statistical models (e.g., median), design models (e.g., seed models), and scientific models related to air resistance. Aware that the students had not yet learned about the mean, the teacher confirmed the presence of variation and error in the data and guided students to calculate the median from seven measurements taken by each small group. This median was used as the class measure and plotted on a line graph (Figure 3) as the actual data.

> Tsukubane seeds (Figure 3) come in various sizes, and their falling speed appears to vary with seed size. How can the flight time of the seeds be increased?
> After conducting several flight experiments using the seed model (Figure 3), measure the flight time and plot the results on a line graph (Figure 3). Based on these data, make a prediction about how flight time might change if either the vertical length or the gap length of the model is adjusted. After making your prediction, conduct further experiments to test it and validate your findings.

Figure 2. Overview of the seed dispersal task.

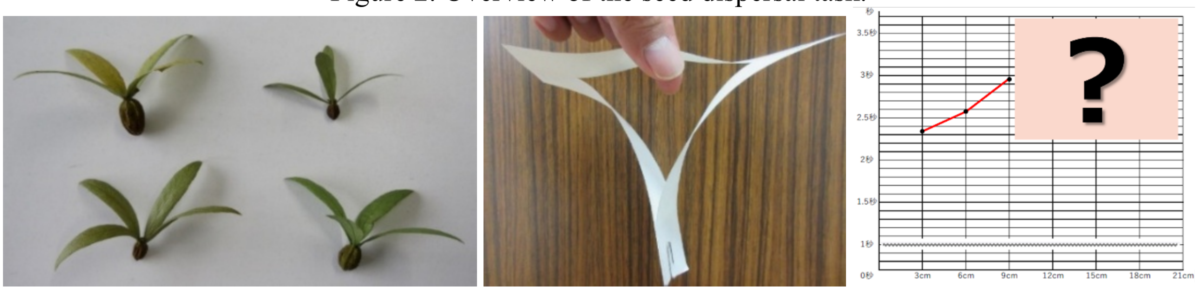


Figure 3. Tsukubane seeds (left), the seed model (centre), and the line graph (right).

Data collection and analysis

The analysed data comprised transcripts of nine lessons created from lesson protocols based on video and audio recordings, student worksheets, and classroom observation reports. The analysis first identified the scenes in which the IDDM framework (Figure 1) components (*data*; *interdisciplinary context*; *mathematical and statistical models*; *models in other STEAM subjects*; *prediction*; and *decision-making*) were discussed, scenes in which the *transitions α, β, γ, δ, ε, and ζ* were relevant, and scenes in which the students' mathematical, statistical, design-based, or scientific reasoning was evident, based on the transcripts. These scenes were grouped into 58 episodes. The analysis then identified episodes in which the teacher facilitated the emergence and integration of students' multidisciplinary reasoning and explored the teacher's role in the episodes. The third author created the lesson protocols, the first author conducted all analyses, and the other authors validated them. Differences in interpretation among the three authors were discussed, and the analysis was revised as necessary.

RESULTS

Owing to space limitations, this paper focuses on three episodes in which the emergence and integration of students' mathematical, statistical, design-based, or scientific reasoning were significantly observed in *transitions γ, δ, and ε* (Figure 1) and explores the teacher's support for this process.

Episode 1: Understanding of the need for data collection using seed models (transition δ)

In Lesson 1, the teacher first drew on the students' knowledge of plants from their science lessons to help them understand that plant seeds have the property of expanding their habitats. The teacher then divided the students into small groups and handed several Tsukubane seeds (Figure 3) to each group. Then, the teacher asked them to drop the seeds and describe what they noticed.

1-73 Tami: Some spin slowly and some spin quickly.
1-74 Mayu: The smaller ones with smaller seeds fall slowly, but the larger ones with larger seeds fall quickly.
1-75 Teacher: I see. So, they fall at slightly different speeds?
1-76 Students: Yes, the speed at which they fall is different.

In this discussion, the students shared their observations of differences in flight times due to individual differences in the seeds (lines 1-73–1-76). This shows students (guided by the teacher) beginning to understand the *interdisciplinary context* (Figure 1).

The teacher then asked the students how the flight time of the seeds could be increased.

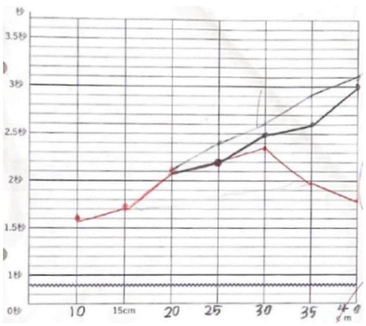
1-132 Seto: We will make the seeds smaller, and make the leaf larger.
1-133 Taro: When dropped from above, the longer the leaves, the longer it takes to fall; therefore, rather than increasing the size of the fruit, the leaves should be lengthened to keep them in the air for a bit longer.
1-134 Teacher: So, various opinions have come up, but I think the two main points are the seed sizes. Do you think smaller seeds remain in the air for longer periods?
1-135 Students: Yes. Yes. [Multiple students spoke.]
1-144 Teacher: Well, how about verifying it? How would you verify it?
1-156 Riku: It may be difficult, but I want to try an experiment using paper. The paper can be cut and attached to Tsukubane to observe what happens when the leaves are long. Then, we can use paper as a substitute for leaves to observe what happens.
1-157 Mina: We can try to make something that looks like Tsukubane.

In this discussion, the students identified the need for data collection using seed models, as shown in Figure 3 (lines 1-156–1-157). By observing real seeds (lines 1-73–1-76), the students recognised their limitations, which led to the need for modified seed models. The design models represent *models in other STEAM subjects* (Figure 1) and serve as tools for conducting flight experiments and collecting *data* (Figure 1), thereby providing an *anchor* for multidisciplinary reasoning grounded in data (see Episode 3).

Episode 2: Emergence of mathematical reasoning along with statistical reasoning (transition γ)

In Lesson 4, the teacher asked the students to compare graphs of hypothetical data with graphs of actual data and asked several students to present the results of their comparative analyses. The following is an exchange that shares Kei's comparison results.

4-156 Teacher: How did Kei describe the predicted graph represented by the black line in Figure 4?
4-157 Students: Zigzag. [Multiple students spoke.]
4-158 Teacher: It looks zigzag. It is steep and gentle. This is not just a simple upward trend. Kei added another element: he focused on how this has risen.



Note:
Graph of hypothetical data (black);
Graph of actual data (red).
Horizontal axis: Vertical length of the seed models; Vertical axis: Flight time.

Figure 4. Kei's predicted graph.

Kei initially predicted a nearly straight line-graph but later revised this prediction to a *zigzag* graph. In this exchange, the teacher emphasised the importance of considering not only mathematical reasoning but also statistical reasoning, which accounts for the variation in values by focusing on the *zigzag* shape of the graph (line 4-158).

The teacher also shared Miki's predictions using the median, considering the variation in values.

4-183 Teacher: When calculating the change in flight time by increasing the length of the seed model by 5 cm each time, there is a variation between 0.15 and 0.33 s. So, Miki took the median.

The teacher implicitly presented to the students the space of *transition γ*—from a mathematical model that interprets line graphs and data in a deterministic manner to a statistical model that interprets line graphs and data in a non-deterministic/stochastic manner (see the arrow from *mathematical model* to *statistical model* in Figure 1). In subsequent predictions, more students focused on variability (Kawakami & Saeki, 2024b).

Episode 3: Integration of mathematical, design-based, and scientific reasoning (transition ε)

In Lesson 8, the teacher asked the students to compare their predictions of flight time—based on changes to the gap length in the seed models—with the actual results, and to explain the factors contributing to accurate predictions as well as reasons for any discrepancies between the predictions and observed results. The following are the students' descriptions.

8-141 Toma: I thought that the reason for the increased flight time of the seed models was that the gaps between the models gradually disappeared as we continued to increase the remaining length. I thought this was due to wind.

8-160 Riku: I should have thought more about balance in the design of the seed models. The flight time decreased because the balance and centre of gravity of the first leaves shifted towards the leaves at the end, making it impossible for the seed model to rotate.

In this explanation, the student integrates mathematical reasoning (proportional reasoning), data-based reasoning (the change in the gap length of the seed models), and scientific reasoning (the influence of wind), as shown in line 8-141. Another student linked changes in the line graph with design-based reasoning (balance in the seed model design) and scientific reasoning (centre of gravity and motion), as shown in line 8-160. The teacher's request for explanations prompted the students to interpret line graphs using seed models and their own physical models of air resistance and gravity (*transition ε*; the arrow from *models in other STEAM subjects* to the *mathematical model* in Figure 1).

DISCUSSION AND IMPLICATIONS

Our analysis highlights two forms of teacher support that are critical for generating and integrating students' multidisciplinary reasoning in data-based modelling within an interdisciplinary context. One is *variability-oriented support*, which draws students' attention to sources of variability (Wild & Pfannkuch, 1999), in line with previous studies (Hourigan & Leavy, 2020; Lehrer et al., 2024; Tytler et al., 2024). This support appeared both before and after the prediction phase. In Episode 1, the teacher allowed students to observe real seeds, helping them recognise individual differences and the resulting natural variation in flight time. This highlighted the need for data collection using variable design models (i.e., seed models), which led to the development of design-based and scientific reasoning. After the prediction phase (Episode 2), the teacher directed students' attention to variation in measurements through flight experiments. A similar emphasis appeared in using the median as the class measure. These strategies supported students' statistical reasoning, which accounts for prediction variability (Kawakami & Saeki, 2024b). These findings in the episodes also confirm the importance of students' understanding of the role of variability in generating data-based interdisciplinary knowledge (Lehrer et al., 2024).

The other form of support is *model-oriented support*, which was also observed both before and after the students' prediction activities. In terms of pre-prediction support, in Episode 1, the teacher created an opportunity for students to interpret and understand the interdisciplinary context while maintaining consistency across the narrative emerging from context, data, and models. As a result, the seed model (Figure 3) served both as a model *of* the interdisciplinary context (seed dispersal) and as a model *for* generating data. Following the prediction phase (Episodes 2 and 3), the teacher helped students validate their models and explain the results by preparing a worksheet (Figure 4) to compare hypothetical and actual data. Consequently, students interpreted and explained the line graph (mathematical model) and associated data in relation to the design of the seed models and their own scientific models of air resistance and gravity, as illustrated in Episode 3. In other words, they integrated model-based multidisciplinary reasoning. While previous studies emphasised teachers' roles in helping students interpret and compare models (Doerr et al., 2017; Tytler et al., 2024), this study shows that teachers use questioning techniques and prediction–data collection–verification activities to support the construction of *model networks* to enhance multidisciplinary reasoning through interdisciplinary modelling.

These findings highlight effective teaching strategies for enhancing STEAM education through data-based modelling—integrating skills in mathematics, statistics, data science, and other STEAM disciplines—to promote students' multidisciplinary reasoning. However, the findings are limited to the analysis of one teacher in one classroom, and they should be verified by other teachers and in other classes in future works.

ACKNOWLEDGEMENTS

This study was supported by a Grant-in-Aid for Scientific Research (KAKENHI) from the Japan Society for the Promotion of Science (JSPS), Grant No. JP25K00852 and JP25K06235, and the CASIO SCIENCE PROMOTION FOUNDATION (J42-45) funds.

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