EXPLORING THE PLIGHT OF THE HONEYBEE: USING DATA SENSORS AND CODAP TO SUPPORT EMERGING BILINGUAL LEARNERS IN REASONING ABOUT BIG STATISTICAL IDEAS

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ABSTRACT

Children require access to high-quality statistics education to develop the skills to participate in a technological and data-reliant workforce. This study consisted of a five-lesson integrated STEM unit designed to develop the statistical literacy of 62 6th-grade (11–12 years old) emerging bilingual (EB) learners. Learning was situated in the study of the honeybee, utilising innovative technologies to gather data and support data visualisation and analysis. Lesson study was used to design lessons targeting understandings of distribution, centre, variability, data comparison, informal measures of association and informal inference. This paper reports on the data comparison lesson. It reveals the influential role of digital technologies in highlighting the relevance of statistics in understanding societal issues and developing students' statistical agency. This qualitative study also revealed that the development of statistical understanding was supported by the use of inclusive pedagogies guided by the principles of universal design and the incorporation of data analysis technologies.

Keywords: *Statistics education research; Innovative technologies; Emerging bilingual learners; Pollinators; Informal Inference; Data comparison*

1. INTRODUCTION

The 21st century is a time of change driven by scientific advances, accelerating globalisation and rapid technological development. These changes challenge education systems to prepare students for jobs not yet created and solve problems not yet predicted. The *PISA Mathematics Framework for 2021* (2018) acknowledges that education must respond to this rapidly changing society:

> In recent times, the digitisation of many aspects of life, the ubiquity of data for making personal decisions involving initially education and career planning, and, later in life, health and investments, as well as major societal challenges to address areas such as climate change, governmental debt, population growth, spread of pandemic diseases and the globalising economy, have reshaped what it means to be mathematically competent and to be well equipped to participate as a thoughtful, engaged, and reflective citizen in the 21st century.
>
> (OECD, 2018, p. 3)

The proliferation of big data and open data make urgent demands for a statistically literate society and poses fundamental questions for statistics educators about how to equip learners to reason in more integrated ways and to move fluidly and responsively amongst disciplinary knowledge. The capacity to make statistical inferences is becoming a critical skill to enhance cross-disciplinary understandings that

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are fundamental to supporting scientists and engineers in drawing conclusions from the data they receive about the world. These STEM-related data are viewed as "numbers with context" (Moore, 1990), and the science and engineering contexts within school STEM (Science, Technology, Engineering and Mathematics) learning environments provide the data context and driving questions that motivate learners to seek and explain patterns revealed in the data (Shaughnessy & Pfannkuch, 2002; Watson, 2018; Wild & Pfannkuch, 1999).

2. REVIEW OF LITERATURE

2.1. INFORMAL INFERENCE AT THE PRIMARY LEVEL

Developing primary students' informal inferential reasoning (IIR) supports not only STEM reasoning, but also develops readiness for more formal STEM learning at a later stage (English, 2012; Makar & Rubin, 2009; Makar et al., 2011). However, identifying the statistical skills that support IIR is complex because IIR integrates many disparate statistical concepts (Chance et al., 2004). Considered together, the frameworks developed by Makar and Rubin (2009) and Zieffler et al. (2008) provide important guidance, describing IIR as (a) making generalisations that extend beyond the data, (b) drawing on prior knowledge to the extent that the knowledge is available, (c) providing evidence-based justifications for generalisations, and (d) using probabilistic language and making reference to levels of certainty when drawing conclusions. Making generalisations beyond the data requires learners to draw on a broad range of competencies, not least understandings about centre and variability, distribution, graphical representations, samples and sampling (Gil & Ben-Zvi, 2014), viewing data as an aggregate (Rubin et al., 2006) and focusing on proportions rather than absolute values (Ben-Zvi, 2006). There is an abundance of research demonstrating the ability of primary learners to harness these understandings when making informal inferences about data (English, 2018; Frischemeier, 2020; Hourigan & Leavy, 2020; Meletiou-Mavrotheris & Paparistodemou, 2015).

2.2. SUPPORTING INCLUSION IN PRIMARY-LEVEL STATISTICS EDUCATION

Classroom and societal perspectives. Inclusion in mathematics education has warranted an increased spotlight on the policy, research, curriculum design and instructional practices arenas. This broad scope of attention has been posited by Artiles et al. (2006) as a factor contributing to the absence of an agreed-upon definition for inclusion (Graham-Matheson, 2012). A recent review of the literature by Roos (2018) on the definitions and roles of inclusion in mathematics education concluded that inclusion is used *ideologically* and refers to inclusion from a societal perspective or *as a way of teaching* and considers inclusion from a classroom perspective. In response to the need identified by Roos for mathematics education researchers "to connect and interrelate the operationalisation and meanings of inclusion in both society and in mathematics classrooms" (p. 25), we present a positioning on inclusion that coordinates both societal and classroom-level perspectives.

Ideologically, we consider inclusion from a STEM education perspective by valuing diversity in statistics education. Inequities in participation in STEM education lead to inequity in participation in STEM careers for minority and female students. Given that these inequities are manifested as early as subject-choice decisions during the transition from primary to secondary school, we consider it the right of all learners to access high-quality STEM instruction from as early as primary school. From a teaching perspective, we recognise the affordances of digital technologies alongside a range of inclusive strategies as tools to encourage the participation of all learners in STEM education. Using technologies in this study, we provide learners access to an authentic STEM societal issue, thereby harnessing their interests and promoting their engagement in high-quality statistics instruction. We believe that generating the curiosity and interests of young learners in STEM through providing access to real-world data and inclusive and technology-enhanced pedagogies that support STEM instruction will provide high-quality inclusive learning experiences that will meet our ideological and classroom-level values and perspectives.

Emerging bilingual learners. Due to growing mobility, multilingual classrooms are increasingly prevalent in EU countries (European Commission, 2015) and further afield (Education Review Office, 2018). Published surveys suggested that 13% of Irish students and 21% of those living in the United States speak a language other than English in their homes (Central Statistics Office, 2017; Ryan, 2013). It is critical that emerging bilingual (EB) learners, who are learning the language of instruction as a second language, receive appropriate supports to reach their potential (Gardiner-Hyland, 2021). Multilingual classrooms are not homogeneous, and while research reports that many EB learners thrive in multilingual environments (Barwell et al., 2017; Clarkson, 2007), there is also evidence of poorer mathematical outcomes and the marginalisation of some learners due to language challenges (de Araujo et al., 2018), particularly learners from linguistic and ethnic minority groups living in low-resource communities (National Mathematics Advisory Panel, 2008; Sarama & Clements, 2009). Research reports a relationship between general language ability and proficiency in mathematics (Fuchs et al., 2015; Trakulphadetkrai et al., 2020) alongside challenges EB learners face due to the linguistic complexity of word problems (Barwell et al., 2017; Vilenius-Tuohimaa et al., 2008) and mathematics assessment tasks (Abedi & Lord, 2001). The sophisticated vocabulary and disciplinary language demands of mathematics, which differ from everyday English, pose challenges in English language classrooms (Barwell et al., 2017; Saxe & Sussman, 2019).

A meta-analysis by Sharma and Sharma (2023) identified four statistically effective practices in multilingual mathematics classrooms: dual language programmes, professional development for teachers, curriculum intervention, and cognitively focused interventions. Examining these studies and others, points to several effective pedagogical approaches and learning activities. Such strategies include linking mathematical concepts with *multiple representations* such as concrete and symbolic resources (Barwell, 2005; Borgioli, 2008; Saxe & Sussman, 2019; Warren & Miller, 2015), using visually stimulating materials to maintain *engagement and focus* on mathematical concepts (Warren & Miller, 2015), *teacher professional development* that emphasises positive mathematics mindset and challenges myths about who can and cannot learn mathematics (Anderson et al., 2018), and the use of *technology-enhanced* instruction that emphasises learning trajectories (Clements et al., 2013). In-depth qualitative studies of multilingual classrooms have also generated valuable insights into the benefits afforded by the use of *high cognitive demand tasks* that are open-ended, involve multiple entry points and solution paths, and require nonverbal representational and oral communication skills (Borgioli, 2008; Secada et al., 1995); classroom participation norms emphasising broad student participation and *collaboration* over competition (Nieto 2000); and a *paradigm shift* away from deficit models to seeing language as a resource, thereby emphasising the strengths that EB learners bring to the mathematics classroom (Borgioli, 2008; Ní Ríordáin & Flanagan, 2020; Sharma & Sharma, 2023). In addition to these specific inclusive strategies determined to be beneficial to EB learners, general features from the *Universal Design for Learning* (UDL) framework (Meyer et al., 2014), a framework that recognises variability in learning and differentiates instruction for all children including those who need diverse support, inform good pedagogical practices that optimise the learning opportunities for all students. The three UDL design features—multiple representations of information, multiple methods of action and expression, and multiple means of engagement—align closely with the needs of students from diverse backgrounds and EB learners (Chita-Tegmark et al., 2012; Doran, 2015).

3. THE STUDY: USING DIGITAL TECHNOLOGY TO SUPPORT STATISTICAL UNDERSTANDINGS AND CITIZEN ENGAGEMENT

This use of statistics as a tool for citizen engagement aligns with the goals of the National Council of Teachers of Mathematics (NCTM) to support students to “identify, interpret, evaluate, and critique the mathematics embedded in social, scientific, commercial, and political systems” (NCTM, 2018, p. 11) and reflects a growing effort to engage young learners in analysing societally-relevant data (Estrella et al., 2021; Verbisck et al., 2023; Zapata-Cardona, 2023). To this end, data sensors were used in this study as a *conveyance technology* (Dick & Hollebrands, 2011) that facilitated the collection, storage and transmission of beehive conditions (temperature, humidity and sound) that would be otherwise inaccessible to learners in primary classrooms. A web-based data science tool, the Common Online Data Analysis Platform (CODAP, https://codap.concord.org/), was then used to analyse these authentic real-world data sets. Consequently, CODAP served as a *math action technology* (Dick & Hollebrands, 2011) by allowing learners to explore and analyse data in ways not possible using traditional pen-and-paper approaches.

Math action technologies such as CODAP, which by their nature support the construction of representations and carry out complex manipulations necessary to solve problems, have been shown to support EB learners in accessing complex mathematical concepts (Saxe & Sussman, 2019) and enhance student learning (Borgioli, 2008; Gadanidis & Geiger, 2012). Indeed, McCulloch et al. (2021) extend the concept, developed by Cohen et al. (2003), of "instructional triangle" to refer to the mathematical spaces generated when teachers work with students to use math action technologies in carefully selected tasks. McCulloch et al. (2021) provided examples of dynamic graphing technologies, virtual manipulatives and interactive applets, which, when combined with carefully designed tasks "create spaces in which all students are positioned as explorers of mathematics" (p. 740). CODAP is a math action technology that enables learners to become statistical explorers by facilitating investigation, identifying patterns, and constructing and testing conjectures.

Although technology enhanced learning (TEL) has become a universally adopted term for some time now (Browne et al., 2008), its advantages are not uncontested. Critics argue that TEL is rarely defined, is under critiqued and often assumes an overly optimistic stance concerning gains arising from their use (Kirkwood & Price, 2014; Selwyn, 2017). Concerns also have been voiced about technology use as "an aid to efficiency or productivity, rather than for learning" (Ryan et al., 2020, p. 2), and there is a growing body of research questioning the extent to which technologies are indeed transforming education and highlighting the "limitations of technology to transform long-standing patterns of educational opportunities and outcomes" (Facer & Selwyn, 2021, p. 2). Consequently, we remained mindful that even if the relationship between technology use and learning gains were established, longstanding concerns exist regarding the digital divide and how unequal access to educational technologies may exacerbate educational inequality (United Nations Children's Fund and International Telecommunication Union, 2020).

Technology was utilised for two purposes in this study. The first purpose was to support learners in using data as a tool to engage with critical societal issues (in this case, bee hive data) and thus address the criticism of school statistics as using "toy data sets" to address questions of little social or personal relevance (Ridgway & Ridgway, 2019). The use of CODAP, as a math action technology, served the second purpose of technology use in this study (i.e., supporting the development of statistical understandings).

Building on the review of the literature, this study focuses on two research questions:

1. In what ways can digital technologies support emerging bilingual learners to engage meaningfully in statistical inquiry?
2. How do we support emerging bilingual learners to develop conceptual understanding of big statistical ideas?

4. RESEARCH APPROACH

4.1. STUDY SETTING AND PARTICIPANTS

The study involved designing and teaching a five-lesson integrated STEM curriculum unit to develop the STEM understandings and statistical literacy of 62 sixth-grade (11–12 years old) EB learners in an inner-city school in Ireland. The school had 426 children, many of whom were newcomers from 46 different countries. The study was conducted as part of a mathematics education elective, wherein 28 pre-service teachers (PSTs) worked with three mathematics teacher educators for three hours per week across an 11-week semester.

4.2. LESSON STUDY STRUCTURE AND STUDY STAGES

Japanese lesson study was used as an organising framework to guide the lesson design, implementation and revision. It was selected due to its iterative and extended process of collaborative planning, classroom implementation, guided observation and reflection aimed at enhancing student learning (Murata, 2011). Within this process, the researchers, who were the mathematics teacher educators teaching the course, guided pre-service teachers through all lesson study stages while assuming the role of knowledgeable others (Hourigan & Leavy, 2019; Leavy, 2010; Leavy & Hourigan, 2016; 2018).

The lesson study process consisted of three stages closely aligned with the 11-week semester.

- *Stage 1 (Weeks 1–5), the research and preparation stage*, engaged participants in reading research relating to the practices of lesson study, understandings about pollinators and the role of data science for citizenship (Makar et al., 2022; National Biodiversity Data Centre, 2021; Science for Environment Policy, 2020), statistical concepts (Hourigan & Leavy, 2020) and inclusive strategies to support EB learners (Baker et al., 2014; Little & Kirwan, 2021; Selmer & Floyd, 2012). PSTs formed five lesson study groups (5–6 members in each group), and each group designed one of a series of five consecutive lessons. Lesson 1 (The Honeybee) focused on bee characteristics, including their lifecycle, the hive and various bee roles (e.g., drone, queen bee, worker bee) and introduced the two local beehives where data regarding temperature, sound and humidity (inside and outside the beehives) had been collected using sensors. Lesson 2 developed a conceptual understanding of measures of centre and variability, while in Lesson 3, children explored a data distribution representing sound in one of the beehives. Lesson 4 supported the development of informal inferences by comparing the distributions of temperatures in the two hives. Lesson 5 explored the relationship between temperature and sound in one hive.
- *Stage 2 (Weeks 6–9), the implementation stage*, involved teaching the series of 5 lessons across five consecutive days to one 6th grade class comprised of 31 EB learners (11–12 years old). Each 60–90-minute lesson was taught by a PST and observed by the lesson study group members and the three mathematics teacher educators. Following each lesson, a post-lesson meeting facilitated sharing of observations, reflections and feedback. Subsequently, each lesson was revised and re-taught 7–10 days later to a second comparable group of 6th grade EB learners in the same school ($n = 31$).
- *Stage 3 (Weeks 10–11), the reflection stage*, involved each lesson study group making an in-class presentation. The presentation reported learning regarding children's statistical understandings, the role of technology, and inclusive strategies when summarising and analysing their taught lessons. PSTs also completed individual written reflections at selected intervals during the semester.

4.3. SPOTLIGHT ON THE DATA COMPARISON LESSON (LESSON #4)

Given that this paper examines Lesson 4, the development of inferences through data comparison, a brief lesson summary is necessary. At the start of the lesson, after being made aware that the optimal temperature in a beehive is 35 degrees Celsius, the class were introduced to a fictitious character, "Jane the Bee Girl," and informed that on visiting the two beehives, she was concerned that one of the hives may be in threat of colony collapse disorder. Given that beehives should not be opened during the colder months of Winter and Spring as a drastic drop in temperature or change in humidity in the hive may be detrimental for bees, the class must make an informed, data-based recommendation to open a hive only if necessary. Children were asked to work in groups to compare the temperature data from the beehive sensors to conclude which, if any, of the beehives should be opened. It was emphasised that recommendations must be justified using data-based evidence collected by the sensors.

The class was divided into six groups that moved between three stations. Each station represented data collected during a period in 2022: May–June (Figure 1), July (Figure 2), September–October (Figure 3). At each station, a group of 4–6 children worked with a PST, who guided them in analysing and comparing the temperatures of the two beehives for the designated period. To ensure consistency of conversation across groups that maintained the focus on higher-order statistical thinking and, in particular, avoided over-prompting and "telling" on the part of PSTs, we developed a set of prompts and questions (Figure 4) drawing from previous positive experiences using this approach (Leavy et al., 2021). Each group of children explored and analysed the distributions using CODAP on a laptop (Figure 5). In addition, the PST labelled relevant statistical landmarks and measures on an A3 laminated printout (Figure 6) while the children recorded landmarks and measures on their worksheets (Figures 7–8).

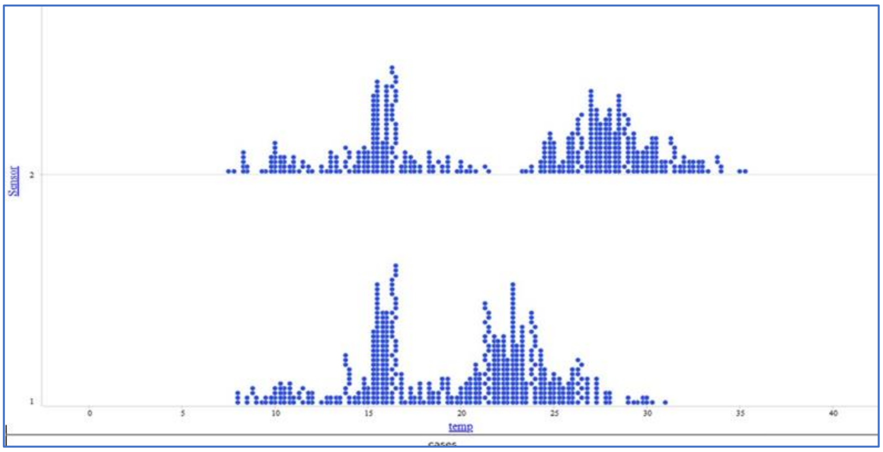


Figure 1. Hive 1 and Hive 2 temperature data from sensors for May–June.

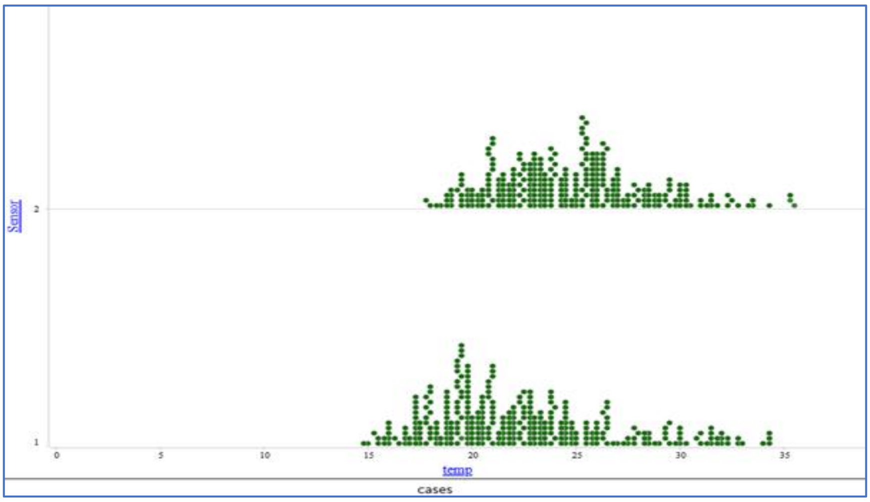


Figure 2. Hive 1 and Hive 2 temperature data from sensors in July

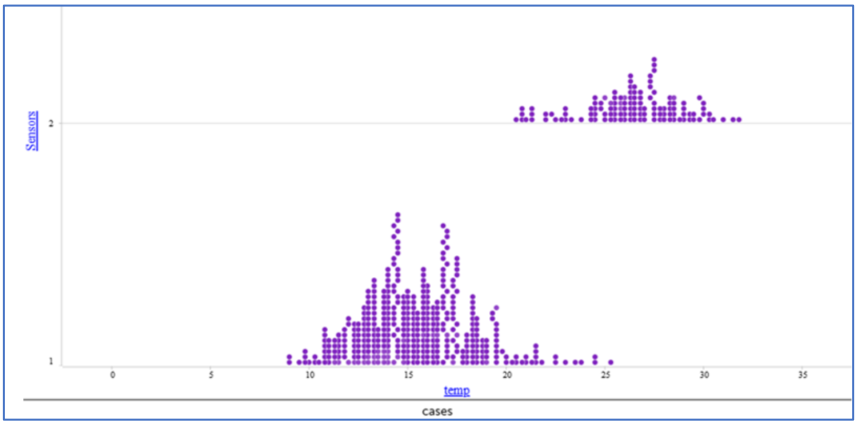


Figure 3. Hive 1 and Hive 2 temperature data from sensors for September–October

Opening Questions
What can you see from the data?
What does the data tell us about the hives?
Is there a difference between hive 1 and hive 2?
What time period do you think this data is from? Why do you think this?

Reading the data
What tells you that one hive is warmer?
So, do you think the bees were ok during this time?
Which hive records the coldest temperature?

Identifying and Reasoning about Statistical Measures
Let's look for the mean…
Predict where the mean could be….
What does the mean tell us about the temperature in the beehives?
What is the median?
What does the median tell us about the temperature in the beehives?
What is the mode?
Predict the mode… which occurs the most?
What is the range? What does it tell us about the temperature in the beehives?
Looking at the graph, what do you think the range is?
What does the range tell us about what we know about the typical temperature of hives?
Are there any gaps in the data?
Can you see any outliers?
Are there any temperatures that occur together (clusters)?
What do you notice about the shape of the data?
What does the shape of the data tell us about the temperature in the hives?
Do you think this hive is at the optimum temperature from what you have learnt?

Reading beyond the data
Is temperature an issue in the hives? Why do you think this? What is your evidence to support this point?
What would you need to see to be concerned?
What temperature would you like to see the hives at?
Do you think that the sensors are accurate?
Which hive, if any, do you think is in trouble and why?
What would be enough evidence to make a convincing and 'correct' argument?

Figure 4. PST prompts and questions

Figure 5. Comparing distributions interactively on CODAP

Figure 6. Modelling of landmarks and measures on A3 printout

Figure 7. Group completing worksheets

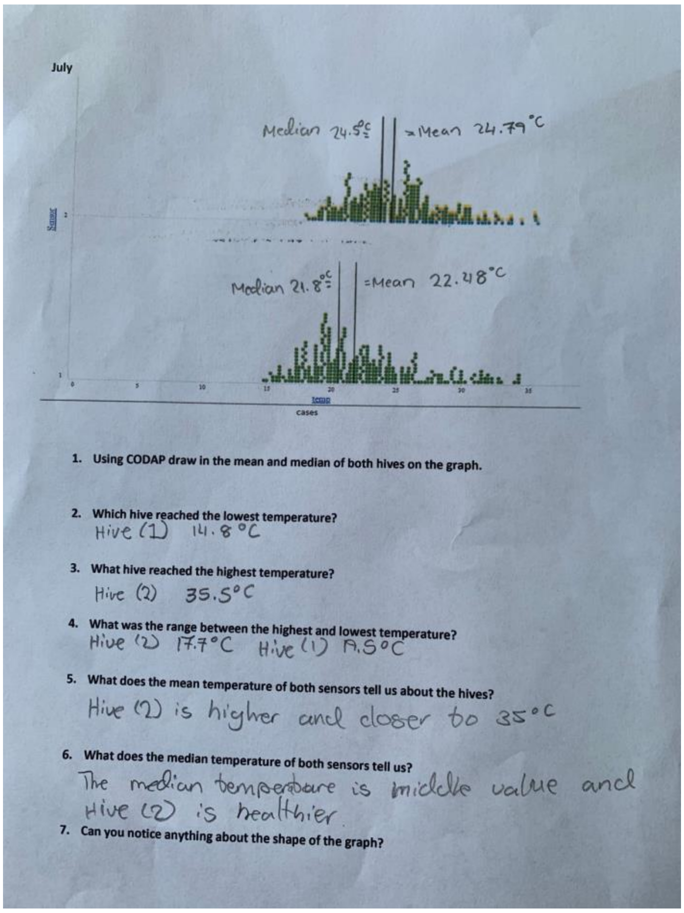


Figure 8. Sample of completed worksheet for July data

4.4. DATA SOURCES AND DATA ANALYSIS

The qualitative data collected across the study is presented in Table 1, which outlines the links between the lesson study cycle and the data collection process.

Table 1. Data collection across the lesson study cycle

Stage of lesson study	Data sources
Stage 1. Research and preparation	Researcher field notes taken during lectures, work sessions and lesson study group discussions Record of resources used to research and design lesson All versions of the lesson plan Feedback on initial drafts of lesson plans Researcher reflective journal entries
Stage 2. Implementation	PST reflection after Implementation 1 Record of changes made to the revised lesson and justification for changes Feedback on drafts of second lesson plan Classroom observations of lesson implementation Audio recordings of children's group work during lesson implementation Samples of children's work Focus group conversations with PSTs following each lesson. Researcher conversations and reflection
Stage 3. Reflection	PST group presentations Researcher observations and fieldnotes PST written reflection Researcher conversations and reflection

After initial data collation and familiarisation, one researcher undertook the preliminary data analysis. This involved examining the data corpus to allocate initial codes closely linked to the relevant literature and responds to the two research questions. This resulted in codes that included *conceptual understanding, misconceptions, language challenges, inclusive strategies, engagement, real context, technology affordances,* and *limitations of technology.* At this stage, a second researcher became involved in the data analysis and together, the researchers completed a succession of examinations, identifying potential relationships between initial codes and instances where they could be merged. This process of constant comparative analysis involving multiple iterations through the data (Charmaz, 2014; Glaser & Strauss, 1967) culminated in the "firming up" of two broad themes that contribute to our understanding of environmental conditions that support EB learners to develop desirable statistical understandings.

Prolonged engagement of researchers enhances a study's credibility (Lincoln & Guba, 1985). Consequently, to further increase credibility and reduce bias, the researchers collected data across all of the lesson study stages (see Table 1) and accounts of researchers' and PSTs' reflections and opinions were transcribed verbatim. In addition, the triangulation methods employed (Lincoln & Guba 1985; Patton 2002) included data triangulation (the use of multiple sources of information), researcher triangulation (observations of multiple researchers), and methodological triangulation (multiple methods of data collection, Table 1). The involvement of two researchers in data analysis was to reduce the possibility of the findings being influenced by the researchers' personal biases (Suter, 2012).

5. FINDINGS AND DISCUSSION

The two research questions drove the analysis of the data:

1. In what ways can digital technologies support emerging bilingual learners to engage meaningfully in statistical inquiry?
2. How do we support emerging bilingual learners to develop conceptual understanding of big statistical ideas?

Two main themes and associated subthemes were identified. The first theme uncovered the influential role of digital technologies in (a) highlighting the relevance of statistics in understanding societal issues, and (b) developing students' statistical agency. The second theme revealed the development of conceptual understanding of big statistical ideas at the primary level supported by (a) the incorporation of inclusive pedagogies and the principles of universal design, and (b) data analysis technologies.

5.1. DIGITAL TECHNOLOGIES PLAYED AN INFLUENTIAL AND CONSTRUCTIVE ROLE IN SUPPORTING LEARNING

Subtheme #1: Digital technologies supported learners in seeing the relevance of statistics in understanding societal issues. The children demonstrated high engagement and motivation when reasoning about the data presented at each station. Our analyses revealed this was associated with the use of technology, which facilitated a meaningful local connection to a universal societal issue and allowed children to engage with real data to explore and provide recommendations to solve an authentic problem:

> Because the context was real, this context of the bees engaged and motivated the children to learn. They were not just examining random data sets—the data collected was from beehives in relatively close proximity to the school! Many children were familiar with the area where the hives were situated. The problem required them to compare the temperature in hives across time. It did not have a definite "yes" or "no" answer, which meant the children had to critically investigate and provide evidence to support their reasoning. Integrating this element of STEM [technology] and using real-life temperatures gathered by specially designed sensors, added more meaning and depth to the lesson.
>
> (Stage 3: Kay, [PST], Written reflection)

The station activities provided children with first-hand experiences of data-based reasoning, which increased their awareness of the power of data in informing decision-making, as commented on by Cora in the quotation below. This new appreciation of the value of statistics in interrogating societally relevant data was not limited to the child-participants in the study. As seen in the reflections from PSTs, they also acknowledged that the experience heightened their awareness of the role of statistics in real-world decision-making (see quotation from Reba) and would inform and influence PSTs' future practice (see quotation from Joanna). Zapata-Cardona (2023) argued that developing awareness of the role and value of using nontraditional data sets in classrooms is essential for those who teach statistics to young children.

> The use of CODAP provided the children with an authentic statistical data experience, allowing them to discover why we monitor sound and temperature in the hives.
>
> (Stage 3: Cora [PST], Group presentation)

> The context of the bees and the use of real data made it highly relevant for both the students and the teacher. It made me realise the importance of statistics as a teacher. It is not just part of the curriculum that we have to cover, it helps us understand information better. If this real-life context of the bees helps a teacher's understanding, it will inevitability improve children's understanding.
>
> (Stage 2: Reba [PST], Focus group)

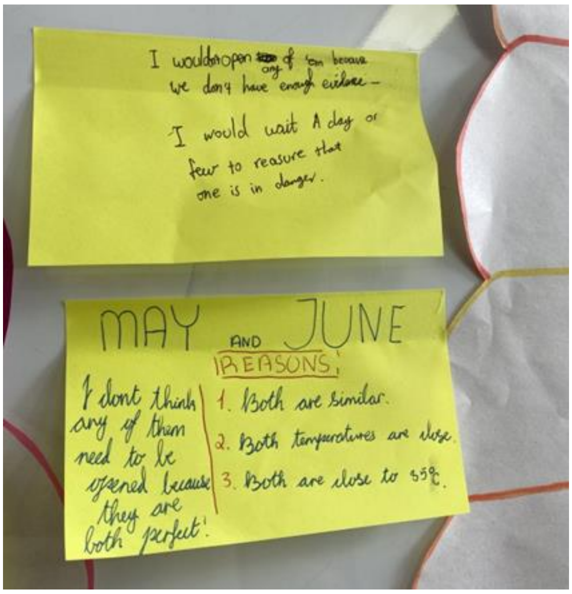
> … when planning statistics lessons, I will use more practical examples to motivate the children but also to highlight the use of statistics and STEM in their everyday lives.
>
> (Stage 3: Joanna [PST], Written reflection)

PSTs and researchers observed that the children took their decision-making responsibility seriously. One PST, Kay, noted in her final written reflection, "The work of the pupils was driven by the reality that the formulation of inaccurate conclusions would cause harm." This was evidenced in the comment of one child, who, after engaging with the three stations, in response to the question, "Which hive do you believe to be in trouble based on all the data?", was reluctant to recommend the opening of a hive and stated:

> Well, I don't know which hive we should open. I'm scared to open the wrong hive! What if I end up killing the healthy bees?
>
> (Stage 2 Group work transcript, Boy aged 11 years)

Sensitivities such as these were common within groups across both classrooms. Despite their apprehension about the potential consequences of their recommendations, children in both classes demonstrated an ability to synthesise their analysis across the three time-period comparisons to come to conclusions and to engage in statistical discourse about these (see Sub-theme #2 below). A smaller number of children, in light of the potential risks of opening a hive, contemplated, “What if I don’t want to open any of the hives?” (Stage 2, group work transcript) as they did not believe there was sufficient evidence to warrant this action. The recorded “official responses” from groups (see Figure 9) included the recommendation that neither hive should be opened. Such conclusions highlight children’s deep engagement with the context, investment in the process and confidence in the valuable role of data in informing their decision-making. This opportunity to work with real data, represents a departure for school statistics from working with “toy data sets” (Ridgway & Ridgway, 2019) and facilitates making a connection with the real world by examining non-traditional data about important societal issues (Estrella et al., 2021; Zapata-Cardona, 2023).

In summary, the children developed an appreciation for the usefulness of statistics as a tool to interrogate data, identify patterns, and reveal insights into beehive conditions. Our analysis shows how children used data-based reasoning to support inferences and justify actions about the beehives. Furthermore, through their efforts to find evidence to support their conclusions, they used digital tools to explore data and, in turn, develop their mathematical proficiency. Harnessing the relevant and engaging context of the beehives contributed to the development, we argue, of a productive disposition towards the use of data.



Upper response:
I wouldn’t open any of ‘em because we don’t have enough evidence.
I would wait a day or few to reassure that one is in danger.

Lower response:
May and June
I don’t think any of them need to be opened because they are both perfect!
REASONS:
Both are similar
Both temperatures are close
Both are close to 35 degrees

(Stage 2: Samples of children’s work)

Figure 9. Sample of children’s data-based recommendations not to open either hive

Subtheme #2: The use of digital technologies supported the mathematical agency of children and positioned them as powerful doers of statistics. Analysis of the data suggested that our efforts to ensure equitable access to STEM education showcased the understanding and abilities of children. CODAP provided the opportunity for children to interact collaboratively with mathematical objects. Through engaging in the dynamic exploration of data distributions, they identified relationships and patterns, made inferences, and engaged in statistical reasoning. Thus, the technology provided a shared learning space where they could make predictions, test those predictions (by comparing means, for example) and engage in statistical discourse, thus becoming “mathematical explorers” (McCulloch et al., 2021). For example, when presented with the hive data, children launched into data exploration—ahead of any instruction to do so! The majority of their attention immediately focused on exploring and comparing both hives’ temperatures in terms of their means, medians, and range:

> Initially, I noticed that each group of children launched into analysis before I could give them any guidelines. They were extremely capable of comparing the data presented to them on the graphs but could also hypothesise the ideal conditions as a third data set. The children compared the mean of Hives 1 and 2 and concluded that Hive 2 had a higher mean and, therefore, better conditions for the bees. They then stated that although the mean of Hive 2 was higher than Hive 1, Hive 2’s mean was still a distance away from 35 degrees (the optimum temperature).
>
> (Stage 3: Ella [PST], Written reflection)

At the three stations, some children focused on landmark features of distributional shape, such as clusters, to compare distributions. Similar to young students in the study by Zapata-Cardona (2023), they interpreted graphic representations and made inferences that could not have been made without using the data visualisation tool. The excerpt below from the conversation between a PST and a child, recorded as one group worked at a station, illustrates their focus on clusters:

PST: So far, what decisions have your group made? What hive, if any, might need to be opened based on the data you examined in the previous two stations?
Aisha: We think we should open Hive 1 because Hive 2 is always warmer.
PST: Why do you say that?
Aisha: Because it's colder because the cluster [in Hive 2] is between 25 and 30 [degrees]. And for Hive 1, it's somewhere around 13 to 18 degrees.

After comparing the hives' temperatures across the three stations (Figures 1–3), as part of group discussions supporting children to identify trends across time periods, PSTs asked, "Which is the best beehive?" In the group conversation that follows, Daniel's statistical reasoning is evident as he coordinates understandings of variability and central tendency to inform the construction of informal inferences. Furthermore, when the PST presented contradictory information by highlighting attention to the minimum temperature in Hive 2, Daniel demonstrated agency in making an argument to support and justify his decision. This type of reasoning, demonstrating an understanding of numbers in context as references for measuring variability in the real world, was also evidenced by Estrella et al. (2021) in their work with primary children when working with tsunami data.

Daniel: Hive 2 is better because it reached the largest temperature, it had the highest mean and median, and it is hotter.
PST: Ok…but didn't Hive 2 also have the lowest temperature?
Daniel: Yeah, but the lowest temperature in Hive 1 is 8 [degrees], and the lowest temperature in Hive 2 is 7.5 degrees which rounds to 8 anyways.

The children were comfortable making data-based conclusions responding to the driving question, "Which hive, if any, is in trouble?" They were asked to justify their inferences and conclusions by presenting evidence, in the form of three reasons, to support their decision. Many children recommended opening Hive 1. The evidence selected by the children (see Figure 10) provided valuable insights into the statistical reasoning underpinning their recommendations. They referred to three main statistical observations: (1) the lowest temperature, (2) the highest range of temperatures and (3) the lower mean and median values. Thus, the affordances provided by CODAP as a math action technology (Dick & Hollebrands, 2011) to construct the representations that facilitated the identification of data ranges, alongside carrying out the calculations of measures of central tendency, enhanced student learning (Borgioli, 2008; Gadanidis & Geiger, 2012) and provided access to complex mathematical concepts for EB learners (Saxe & Sussman, 2019).

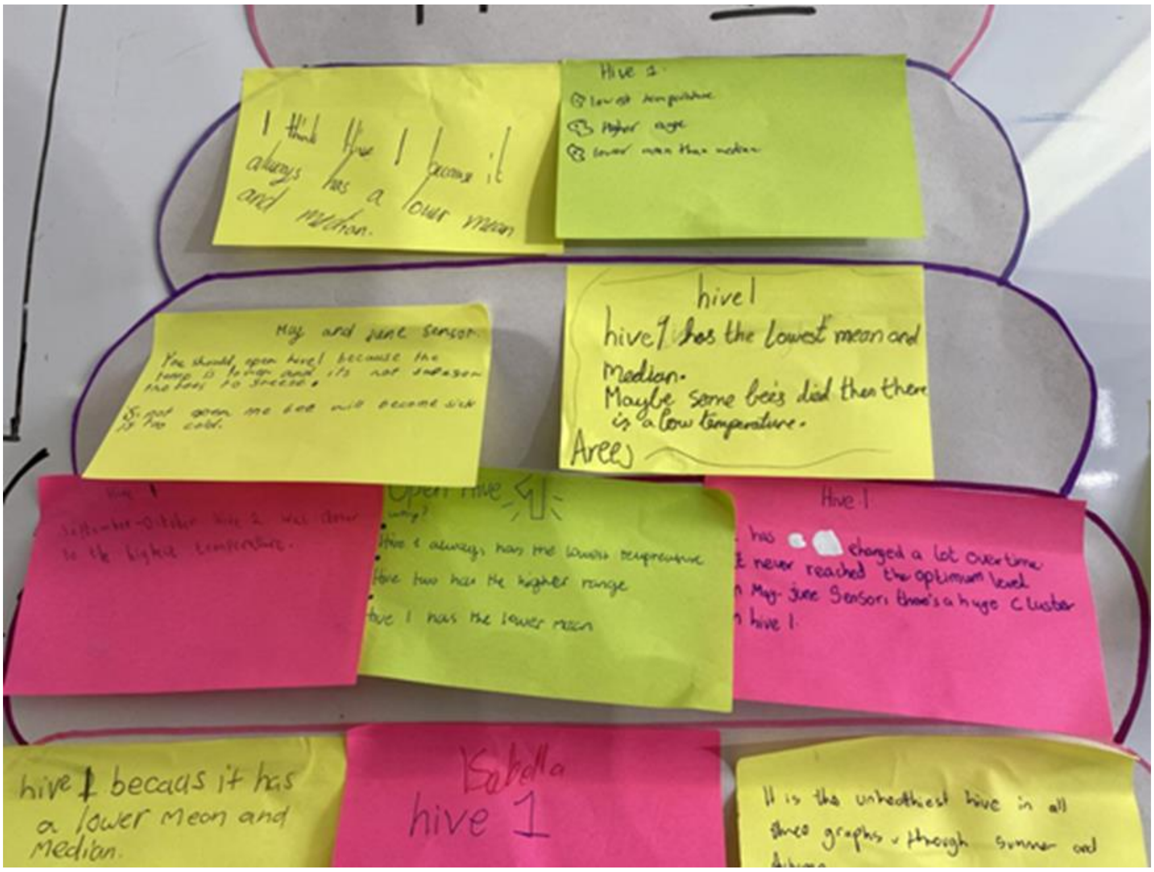


Figure 10. Sample of children's data-based recommendations to open Hive 1

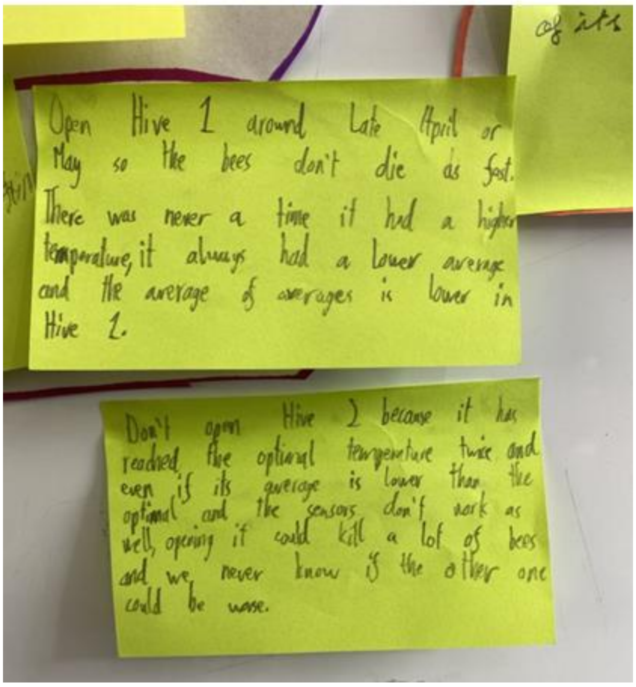
In one group, when children were supported to examine trends across the three time periods, it became apparent that one child, Nicolas, had independently found "the average of averages", that is the mean temperature across the three time periods. This additional layer of analysis provided further evidence to support this group's conclusions.

PST: When you're looking at the highest temperature, is Hive 1 ever higher than Hive 2?
Sophia: No, but Hive 2 was once lower than Hive 1.
Nicolas: I figured out that the average of the averages in Hive 2 is higher by six degrees.
PST: So, did you work out the averages of the hives across all the data you have? Tell us about that.
Nicolas: It's 18.963 and so on [degrees] for Hive 1, and then Hive 2 is 24.6 [degrees], so it's higher by roughly 6 degrees.

Nicolas' group used this analysis in the class discussion to support the recommendation that Hive 1 was in trouble. As they stated in their presentation:

> Hive 1 is in trouble because Hive 1 never had the highest temperature. It always had a smaller average. And the average of the averages for Hive 2 is warmer by six degrees.
>
> (Stage 2: Researcher classroom observation)

One of the children subsequently provided more detailed recommendations to Jane the Bee Girl within a written response focusing on the conditions in both hives (Figure 11).



Upper response:
Open Hive 1 around late April or May so the bees don't die as fast. There was never a time it had a higher temperature, it always had a lower average and the average of averages is lower in Hive 1.

Lower response:
Don't open Hive 2 because it has reached the optimum temperature twice and even if the average is lower than the optimum and the sensors don't work as well, opening it could kill a lot of bees and we never know if the other one could be worse.

(Stage 2: Sample of children's work)

Figure 11. One child's data-based recommendations for Hives 1 and 2

During the final whole class discussion, where individual children shared their recommendations and justifications, their agency and capacity to communicate and justify conclusions that were informed by understandings of various statistical concepts became apparent:

PST: Have you decided maybe one hive is in trouble? (children nodding)Yeah? Does anybody see anything that might be interesting?
Zach: I think Hive 1 might be in trouble.
PST: Why do you think Hive 1?
Zach: I think Hive 1 because as she (pointing to a child in the group) said, if there is less difference between the maximum and the minimum and has less range, it means the hive is doing well. But if it has a higher change this means it has lots of changes in it.
PST: That is very good. If it has a wider range, it means it has lots of changes. So which one has a wider range? You think hive …
Zach: Hive 1 has lots of changes.
PST: That is very good, and if you look as well at September and October, that one has a smaller range for Hive 2. Excellent! Does anyone else agree with Hive 1 being in trouble?
Mira: Yes! Because Hive 1 never had the highest temperature, it always had the smaller average. And the average of the average for Hive 2 is warmer by 6 degrees.
PST: Ok. So, it always had a lower average and a lower mean and never reached the highest temperature. OK, does anybody else want to agree?
Kai: Yeah. I think both [hives are in trouble].
PST: So, do you think both are in trouble? Do you want to tell us why?
Kai: Because in the September graph it has like less.
PST: Yes, like less data, less values. So, it could be in trouble. Is there anything else you would like to say about it?
Kai: Yeah, we might not know if the batteries are not working.
PST: That's a very interesting point. So, you think the sensor might have run out of batteries because there's less data together, and then we don't know if it's in trouble or not.

In addition to drawing on understandings of centre and variability, there were many examples across the data set of children using probabilistic language such as "might" or "maybe", as is evident in the contributions from Kai and Zach above, to communicate their levels of certainty about their recommendations.

5.2. DEVELOPMENT OF CONCEPTUAL UNDERSTANDING OF BIG STATISTICAL IDEAS AT THE PRIMARY LEVEL

Subtheme #1: The incorporation of inclusive pedagogies and the principles of universal design supported the development of statistical understandings of EB learners. A variety of inclusive practices and strategies were purposefully incorporated into the lesson. Combined with a meaningful real-world context, local large data and relevant conveyance and math action technologies, these pedagogies supported children in accessing statistical learning opportunities. This supports the stance of Borgioli (2008) that fairness and equity in mathematics education is possible "but only if the teacher purposefully attends to it as a goal" (p. 186).

Firstly, a range of relatively pedagogically undemanding yet powerful strategies were implemented to help overcome the challenges associated with introducing or revising sophisticated vocabulary and disciplinary language demands (Saxe & Sussman, 2019). In earlier lessons, the use of *visually stimulating images and video* (e.g., photographs) (Warren & Millar, 2015) and the *provision of vocabulary* about pollinators provided support for many learners (see Figures 12a, 12b). Additionally, simple definitions and alternative terms (e.g., the use of the words "ideal" and "best" as alternatives for the word "optimal") ensured clarity for EB learners. For the PSTs, witnessing the benefits of such strategies firsthand within the second classroom implementation highlighted the benefits for learners:

> Each component and resource of the lesson needs to be demonstrated, simplified, rephrased, or illustrated using a visual cue. This can support children to understand new vocabulary and gain attention if props and active demonstrations are used. They can see what is being said to make the learning and meaning less abstract and can hear explanations in a simplistic version to help comprehension.
>
> (Stage 3, Joanna [PST], Written reflection)

Figure 12a. Provision of vocabulary about pollinators

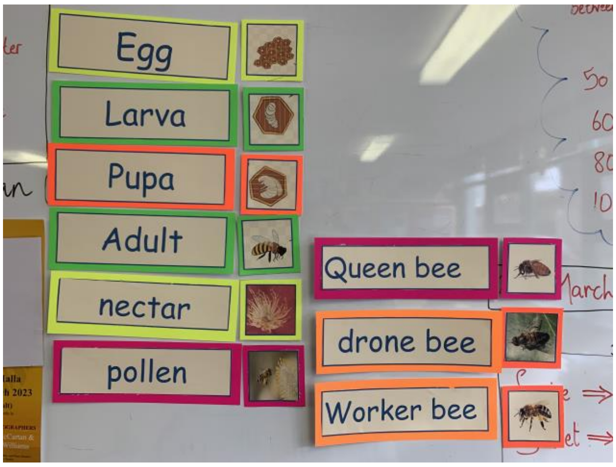


Figure 12b. Images and vocabulary about life-cycle stages and bee-types

Multiple representations (Saxe & Sussman, 2019; Warren & Millar, 2015) of concepts and graphs were provided. For example, in Lesson 2, when teaching the mean, we offered a kinesthetic experience of the "levelling" analogy through the use of manipulatives that closely reflected the CODAP representation (Figure 13). Multiple representations, digital and hard-copy, of graphs were presented through CODAP-constructed dynamic distributions on laptops, printed large A3 laminated sheets for group work, and individual student worksheets. These constituted another intentional support facilitating exploration (CODAP graphs) and recording and annotating (A3 and individual printouts). PSTs modelled how to locate and label data landmarks (e.g., minimum value, gaps, outliers), mark and annotate measures of centre (mean, median, mode), and calculate measures of variation (range) on the laminated A3 graphs (Figure 6). This supported EB learners in accessing, locating, and reinforcing understandings of the statistical concepts and related terminology:

> I used the laminated A3 sheet to demonstrate the measures and features I was discussing by marking them on the graph. This gave all learners a visual object and location (e.g. the mean is 21 degrees, and that's

> "here" on the graph) to look at to support them in completing their worksheet, as measures were presented visually, not just referred to orally. It also aided their comprehension as they could follow what I was saying through what I was drawing. I also wrote spellings of new words on the A3 sheet so they could copy them instead of spending time trying to create the correct spelling of the words.
>
> (Stage 2, Anna [PST], Focus group)

Across all groups, children used their worksheets (graph labels and workings) to support them in selecting and reporting their inferences, conclusions and justifications. The PSTs agreed that there was further potential in future practice to:

> … use reference points (e.g., PowerPoint slides/flashcards/posters with key terminology and complementary images) and annotated graphs to support children's engagement and understanding.
>
> (Stage 3, Ella [PST], Group presentation).

In addition, the opportunity to work collaboratively in groups when comparing data distributions supported EB learners to make initial observations about features of individual distributions, propose the use of specific measures to make comparisons, communicate their understandings about observed differences between distributions, and engage in high-level statistical reasoning by coordinating these shared understandings in the construction and communication of informal statistical inferences. For example, Figure 14 illustrates a group reporting their shared response to a question. In the quotation below, a PST reflected on how these groups were safe spaces, thus promoting collaborative rather than competitive participation, which is recommended for EB learners (Nieto, 2000).

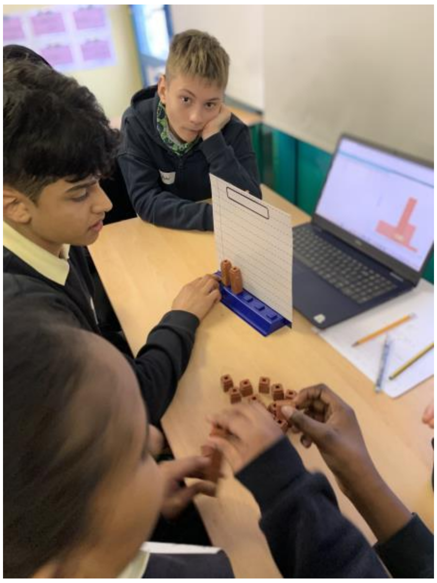


Figure 13. Developing the "levelling" analogy of the mean using cubes

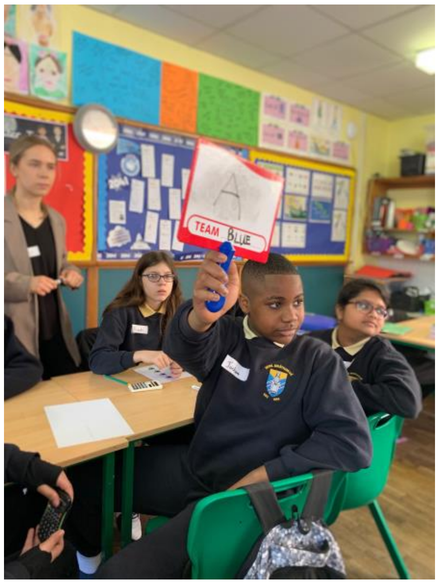


Figure 14. Group sharing their response to a problem

Across the lesson, the ongoing opportunities to collaborate in groups assisted all children in participating (Nieto, 2000). In addition, multiple means of communication were promoted during group work, including oral and nonverbal representational communication (Borgioli, 2008). As one PST stated:

> The students in both classes were great at working together and helping each other, which helped keep EB learners involved and engaged. These intimate group settings provided EB learners with a safe space to share thoughts and ideas and to ask questions. However, this teaching model also allowed us, as teachers, to work with these pupils on a more personal level. We were able to model activities, prompt conversation and aid differentiation in such a way that helped us to broaden pupils' learning and help them to reach their full potential. For these reasons, I believe that group work tasks are a great resource for teaching children with various language needs.
>
> (Stage 3, Kay [PST], Written reflection)

Subtheme #2: The use of data analysis technologies supported the development of conceptual understanding. The use of technologies fast tracked the development of children's conceptual understanding of statistics in three ways: carrying the procedural load of calculations, supporting the exploration of data sets and revealing statistical misconceptions.

First, the measuring tool feature of CODAP instantaneously calculated means and medians, and represented them visually, thereby freeing up time for children to interpret the meanings of the measures of centre and contributing to their unfolding understandings of the data distributions (Saxe & Sussman, 2019). Anna and Ella commented in their reflections on how CODAP facilitated children in exploring big data sets and in effortlessly determining the locations of measures of variability and centre. Also, the researcher field note below, made during observation of the lesson, provided insight into how CODAP supported the development of statistical understandings.

> Statistical concepts frequently need complex calculations and vast datasets. The bee data set was quite vast as we covered all three different time periods. Each of these data sets had timestamps for almost every hour and day in these months. In our class, we used CODAP and had laptops at each station. Incorporating this use of technology made it easier for the students to explore and analyse the data.
>
> (Stage 3, Anna [PST], Group presentation)

> The CODAP platform enabled the data to be accurately represented on the graphs, in comparison to creating graphs on paper… Then, while teaching the lessons, each group had access to the graphs from the CODAP platform on a laptop. Children were then able to get the accurate value of each point on the graphs, e.g., the minimum point. Furthermore, they were enabled to find the exact values of the central tendencies of the mean and median… which would not have been possible to do so on paper.
>
> (Stage 3, Ella [PST], Written reflection)

Also, the researcher field note below, made during observation of the lesson, provided insight into how CODAP supported the development of statistical understandings.

> Children in one group made inferences and predictions about the impact of outliers on measures of central tendency by modifying or deleting outliers and observing the impact of these changes on the measures of central tendency!
>
> (Stage 2, Researcher fieldnotes, Lesson 4)

Furthermore, by not having to calculate the means and medians of large data sets, time was freed up to support the comparison of temperatures between Hives 1 and 2 across three different time periods; this would not be possible with traditional pen and paper activities. Thus, time was dedicated to analysing and comparing large sets, providing opportunities for consolidation of statistical understandings and honing their statistical literacy. This was evident in exploration of the meaning of measures within the context of the bee dataset. For example, PSTs focused on the meaning of the range, highlighting that a larger range meant more variation or changes within the hive, whereas a smaller range suggested less variation and change in temperatures. Children were then asked, "Do you think the bees prefer more changes or less changes in the hive temperature?" They agreed, "Less changes." Their understanding of the range was evident within the lesson conclusion when they were discussing evidence to support the opening of one of the hives:

Kamal:	So, I think Hive 1 should be opened because here [pointing] for the temperature, there is no gap between. Over here [pointing] the temperature, the difference between temperatures in Hive 1 it's bigger than Hive 2, and … when there are less changes, that means that hive is doing better.
PST:	So, is that your first piece of evidence? [child nods] What were you focusing on there?
Kamal:	The range.

(Stage 2, Group work transcripts)

A second affordance of technology was that it supported children's data explorations and allowed them to generate inferences and make and test conjectures. For example, when building on the children's prior understandings of measures of centre and variation developed over the previous lessons, PSTs encouraged the children to estimate these measures, reported similarly by Borgioli, (2008), and Gadanidis and Geiger (2012). These estimations, and the reasoning underpinning the selected estimates, provided valuable insights into and confirmation of the development of conceptual understanding. In the following excerpt from the post-lesson focus group, one PST described how a child in the group she was working with made considered and informed predictions about the mean value in Hive 1 (see Figure 1). It is evident from the excerpt below that the child engaged in relatively sophisticated statistical reasoning to inform the prediction of a mean value. He identified two clusters of data which each contained a high density of data values; such clusters have been referred to in the literature as "modal clumps" (Konold & Higgins, 2003; Frischemeier, 2020; Leavy & Middleton, 2011; Lehrer & Schauble, 2002). Furthermore, he then engaged in proportional reasoning about these clusters, provided a preferential weighting to one of the clumps based on the higher data frequencies, and used this rationale to situate the estimated mean within the cluster. Further evidence of conceptual understanding is his coordination of variation through consideration of the range to justify the location of the estimated mean was conveyed when a PST reported:

> When focusing on the mean of Hive 1, one child estimated the mean temperature to be 22 degrees. When I challenged him as to why he thought the mean was 22 degrees, he stated that "there is a lot of data between 15–20 and a lot of data between 20–25, but there is more data between 20–25." He also used the maximum and minimum values to support his reasoning, outlining, "It only goes up to 31 and 7.5–8, and I feel it would be 22 or 21 degrees."
>
> (Stage 2, Focus group)

Finally, through freeing up time to engage in reasoning about the distributions of data, there were opportunities to address misconceptions as they arose within the context of comparing data. For example, when predicting the location of the median temperature of the hive for May, further opportunities to address developing (mis)understandings became evident:

PST:	Where do you think the median is?
Talia:	[Pointed to the middle of the range but did not consider the distribution of data values within that range of data]
PST:	Why do you think it is there?
Talia:	It is halfway between maximum and minimum
PST:	Do you think half the values are above and below this point? [child nods].

(Stage 2, Group work transcript; Classroom observations)

While children could state that the median is the value that falls in "the middle" of a data set, it became evident that some needed further support to help them develop a thorough understanding of the median, as half of the temperatures in the hive being lower than this temperature and half of the temperatures in the hive being higher rather than the median being the midpoint of a number line extending between the minimum and maximum data values.

> I highlighted the need to consider the clusters of data to make sense of the location of the median on the graph.
>
> (Stage 2: Anna [PST], Focus group)

Another example was of technology facilitating the identification of misconceptions related to interpretations of the range. For some children, there were difficulties understanding the meaning attributed to the range as a measure of variation when comparing distributions. Initially, some children demonstrated confusion when interpreting the contextual relevance of larger and smaller ranges of temperature when comparing distributions of temperature between both beehives, considering a larger range to be preferable:

> The range of Hive 1 is 19.5 degrees, and Hive 2 is 17.7 degrees, so Hive 1 is better as it is closer to 35 degrees.
>
> (Stage 2: Group work transcript)

PSTs observed and commented on technology completing the more arduous and tedious lower-order skills (Saxe & Sussman, 2019) relating to procedures such as calculating means and medians. They remarked on how technology facilitated children in reasoning about these measures rather than merely calculating them. Moreover, it provided a link between theory and practice. By having the opportunity to observe children developing conceptual understanding rather than dedicating time to procedural skill development, PSTs gained an appreciation for the goals of statistics education as espoused in contemporary statistics education research:

> The children could use CODAP, knowing how to find the mean and median but also knowing that hovering the arrow over a dot shows the exact value of the timestamp. This has made me realise that teaching

> statistics does not revolve around drawing graphs but can instead focus on interpreting and comparing them and has influenced me to incorporate technology into teaching statistics going forward.
>
> (Stage 3, Kay [PST], Written reflection)

6. SUMMARY AND CONCLUSIONS

One of the greatest challenges of mathematics education is convincing children of the relevance and utility of the discipline. In this study, situating opportunities to engage in making informal inferences within the context of societal issues is in stark contrast to criticisms of instruction on inference being taught as an isolated subject (Rossman & Chance, 1999). Findings of this study illustrate that getting children to engage with real data about important societal issues stimulates interest in and engagement with data, develops conceptual knowledge of big statistical ideas, advances statistical literacy, and cultivates the development of a critical stance and a disposition to engage with evidence. It seeded an interest in seeking out evidence to support their data-based inferences and inform conclusions and actions stemming from their analysis of the issue.

The strategic two-fold utilisation of technology in the study, as conveyance and math action technologies, was critical to ensuring that we provided "more equitable access and opportunities for each and every learner to actively engage and participate in the learning of mathematics" (NCTM, 2023). While the data sensors collected and conveyed data, the use of CODAP promoted inclusivity. In contrast to some mathematics classrooms where technology use emphasises drill and remediation thereby perpetuating inequity (McCulloch et al., 2021), free-to-use CODAP challenges inequity by providing linguistically diverse children with the opportunity to engage in cognitively challenging tasks thus addressing critiques of technology use (Facer & Selwyn, 2021; Ryan et al., 2020) and freeing up instructional time for EB learners to become mathematical explorers (McCulloch et al., 2021).

The findings of this study reveal the power of inclusive strategies to support all learners' engagement with big statistical ideas. This study lends support to the conclusions of Barwell (2009) who suggested that focusing on language when teaching extends beyond considerations of vocabulary to supporting ways of doing mathematics such as mathematical discourse and argumentation. Across all aspects of the study, there is compelling evidence of the centrality of the teacher aspect of the instructional triangle (McCulloch et al., 2021). While technology plays a critical supportive role, technology alone is not sufficient in promoting EB learners to become explorers of statistics. Only through the careful selection of meaningful, open-ended tasks, the purposeful integration of inclusive learning strategies, and explicit teaching to promote conceptual understanding of statistical concepts can the affordances of math action technologies such as CODAP be optimised, thus enabling EB learners to access authentic statistics experiences. These skills are the remit of the classroom teacher, who needs to possess appropriate pedagogical knowledge for teaching statistical concepts, combined with statistical content knowledge, in order to ensure that all children reap the rewards of engaging with big data through such math action technologies. This requires investment in initial teacher education and continuing professional development for practicing teachers.

This research has a number of limitations. First, it was a case study of two 6th grade (11–12 years old) classes of EB learners; the results of this study cannot be generalised to all children of that age. There is potential for further study to examine EB learners' experiences across a variety of class grades and educational settings. A second limitation is that the study examines the impact of one math action technology (i.e., CODAP) within an instructional unit focused on the living conditions of beehives. It cannot be assumed that equivalent outcomes would be achieved when focusing on a different societal context. In addition, the findings cannot be generalised to all math action tools. Finally, despite the collection of qualitative data across 11 weeks, the study does not measure statistical learning outcomes. While acknowledging these limitations, this study's findings illustrate the nascent potential that exists for all learners to access and analyse nontraditional datasets in the service of interrogating greater societal issues.

Today's mathematics explorers are tomorrow's citizens and change agents (OECD, 2018), who will be required to possess statistical literacy skills that complement STEM disciplinary knowledge. Furthermore, they will require the critical ability to think across the boundaries of STEM disciplines, thus compelling them to extend their disciplinary knowledge and reason in integrated ways to draw conclusions from the data they receive about the world. The findings of this study hold great promise for all children, particularly EB learners, in realising their potential as change agents of the future.

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