Interdisciplinary Journal of Problem-Based Learning

Volume 8 | Issue 1 Article 5

Published online: 3-25-2014

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IJPBL is Published in Open Access Format through the Generous Support of the Teaching Academy at Purdue University, the School of Education at Indiana University, and the Jeannine Rainbolt College of Education at the University of Oklahoma.

Recommended Citation

Cross Francis, D. , Hudson, R. , Vesperman, C. , & Perez, A. (2014). Comparing Technology-supported Teacher Education Curricular Models for Enhancing Statistical Content Knowledge. *Interdisciplinary Journal of Problem-Based Learning, 8*(1).
Available at: https://doi.org/10.7771/1541-5015.1416

THE INTERDISCIPLINARY JOURNAL OF
PROBLEM-BASED LEARNING

ARTICLE

Comparing Technology-supported Teacher Education Curricular Models for Enhancing Statistical Content Knowledge

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Recent calls have been made to enhance and extend the statistical experiences of K-12 students. However, to ensure that such goals are met, teachers also need to develop deep conceptual understanding and pedagogical content knowledge that are essential to statistical thinking and reasoning. In this regard, over the past two decades, leading thinkers and professional organizations had advocated that teaching and curricula should be focused and organized around problem solving. In this paper we describe three such technology-supported curricula—a project-based learning (PjBL) unit, problem-solving activities (PS) unit, and a model-eliciting activities (MEA) unit—that align with this perspective and discuss the ways in which they supported pre-service teachers' engagement with elementary statistics concepts and technology. Our findings target two specific gaps in the literature—research on the use of technology in the development of statistical literacy and providing empirical support for advancing teachers' statistical knowledge through engagement in the statistical investigation cycle.

Keywords: project-based learning, statistics education, Tinkerplots, technology integration

Solving problems is a part of our daily lives. These problems are often not well-defined and require more than the application of a specific rule or procedure to solve. Many (Lester et al., 1994; Resnick, 1987; Schoenfeld, 1994) have argued that mathematics is one of the few subjects, when taught well, that can help students develop these problem-solving skills. In this regard, over the past two decades, leading thinkers (Lester et al., 1994; Schoenfeld, 1994) and professional organizations (National Council of Teachers of Mathematics [NCTM], 1989) have advocated that teaching and curricula should be organized around solving problems. With this goal in mind, educators within the field of mathematics and statistics have developed a range of curricular approaches that allow students to engage deeply with mathematics and statistics content. Alongside these efforts to advance teaching for problem solving, there has also been a significant push towards incorporating technology to enhance students' engagement in problem-solving (NCTM, 2000). In this paper we describe three such technology-supported curricula (a project-based learning unit, problem-solving activities unit, and model-eliciting activities unit) that align with this vision and discuss the ways in which they supported pre-service teachers' (PSTs) engagement with elementary statistical concepts and technology. Our findings target two specific gaps in the literature—the use of technology in the development of statistical literacy and empirical support for advancing teachers' statistical knowledge through engagement in the statistical investigation cycle (Shaughnessy, 2007).

Literature Review

All problem-centered learning models share a focus on students' engagement in solving complex problems around meaningful content. However, such models tend to differ with respect to process and product. In this section we describe three such models and the research that supports their implementation.

Problem-Centered Learning models

Problem-Solving (PbS)

A problem-solving approach to instruction is geared towards exploring ideas within problem contexts in inquiry-based classroom environments. The focus is on "helping students

http://dx.doi.org/10.7771/1541-5015.1416

construct a deep understanding of mathematical ideas and processes by engaging them in doing mathematics: creating, conjecturing, exploring, testing, and verifying" (Lester et al., 1994, p. 154). Teaching via problem solving is used broadly to encompass instruction that foregrounds students' engagement in solving complex problems through critical thinking and reasoning. Effective complex problems in this regard are ones that can be extended to involve mathematical or statistical explorations or generalizations (Schoenfeld, 1994). Although these problems may be real-world or situated in contexts, this is not a prerequisite, as the focus is on students' sense-making, mathematizing, and abstraction. As such, curricula models aligned with this approach consist of tasks that are connected in ways that will deepen students' mathematical understanding.

Project-Based Learning (PjBL)

We adopted Markham, Larmer, and Ravitz's (2003) definition of PjBL as "a systematic teaching method that engages students in learning knowledge and skills through an extended inquiry process structured around complex, authentic questions and carefully designed products and tasks" (p. 4). Thus, the project does not take place at the end of the unit as a culminating product. Instead, students have a sustained, learning experience as they are guided through the curriculum by a driving question or realistic problem, over the course of several weeks. As Parker et al. (2011) stated, the "project serves as the spine of the course, not the appendage" (p. 538). There are several ways in which PjBL can be implemented; however, there are several key elements that are common across the approaches. They include: i) a focus on solving problems that are complex, authentic, and centered around significant content (Howard, 2002), ii) a commitment to prioritizing self-directed learning driven by students' interest and inquiry (Thomas, 2000), and iii) promotion of collaboration as a critical component of the learning experience as well as an essential skill necessary to productively work in the real world (Krajcik, Blumenfeld, Marx, & Soloway, 1994). At the core of the PjBL model are tasks that are generative, creating a situation where progress towards a final product is driven by students' questions and ideas and the incremental goals they set. Instruction is situated in contexts that support sustained exploration and provide a real sense of the problems professionals face and the knowledge they use to solve them (Howard, 2002). Several studies have reported the positive student outcomes of PjBL including increased motivation, stronger conceptual understanding (Grant & Branch, 2005) and the development of 21st Century Skills (Neo & Neo, 2009).

Model Eliciting Activities (MEA)

An MEA is a complex, problem-solving task set in a realistic context for which solutions are generalizable models that reveal the thought processes of students. They serve to both reveal students' thinking as well as promote mathematical development (Lesh & Doerr, 1998, 2003; Lesh, Hoover, Hole, Kelly, & Post, 2000). They are uniquely designed so that students can "mathematize" or develop "symbolic descriptions of meaningful situations" (Lesh et al., 2000, p. 594). Central to successful completion of these tasks are students making mathematical interpretations of situations—interpretations that will undergo cycles of modifications and refinement through sustained engagement. These tasks are not designed as intermediate activities which often focus on preparing students for more meaningful, complex problems; rather, they are high-quality activities that foreground students' mathematical sense-making, allowing the teacher (or researcher) to assess students' conceptual strengths and weaknesses in activity. With MEAs, students' learning processes are foregrounded through multiple cycles of conjecturing, testing, and revising that students use to build knowledge of the embedded concepts. Similar to PjBL, researchers have documented the positive effects of MEAs on learning (Lesh et al., 2000). MEAs have proven to be valuable as a means for improving conceptual understanding and assessing students' problem-solving processes (Yildirim, Shuman, & Besterfield-Sacre, 2010).

All three models have proven to be successful in promoting students' achievement across a range of subjects. This study focused on examining how well they supported PSTs' understanding of elementary statistical concepts.

Statistics Education and Problem-centered Curricula

Recent calls have been made to enhance and extend the statistical experiences of K–12 students (Franklin et al. 2007; NCTM, 2000). However, to meaningfully engage students in statistical inquiry, teachers need deep knowledge of the content and how students construct ideas related to the content (Conference Board of Mathematical Sciences, 2001; Groth & Bergner, 2006). Prior research has shown the need for continued development of teachers' knowledge related to conceptual properties of measures of center, comparing data sets of unequal sizes (Hammerman & Rubin, 2003; Watson, 2002), variation and distribution (Makar & Confrey, 2002; Mickelson & Heaton, 2004), and sampling (Watson, 2001). To improve the teaching of statistics, researchers recommend that in addition to focused professional development (including pre-service math content and methods courses and in-service math workshops), teachers can develop powerful statistical reasoning skills through involvement in activities where they have to take on the role of statisticians in solving real-world problems (Shaughnessy, 2007). In this regard, "doing statistics" in ways similar to statisticians involves the process of understanding a problem (P), generating a plan (P) to investigate the problem, collecting data (D) and analyzing it (A), and drawing conclusions (C) about the problem using data—referred to as the statistical investigation cycle (PPDAC) (Wild & Pfannkuch, 1999).

In this regard curricula that involve PSTs exploring real-world phenomena and solving complex problems are essential. Problem-centered learning models align well with the goals of statistics education as they provide the necessary structure to focus students' work on reasoning about basic statistical concepts and the application of those concepts to solving contextual problems. They support students' engagement in authentic data collection and analysis consistent with current frameworks of statistical thinking (Wild & Pfannkuch, 1999). Because much of this process engages PSTs in working with real data as statisticians do, the use of technological tools is central. Shaughnessy (2007) and others (Bakker & Gravemeijer, 2003; Cobb, 1999; Friel 2007) underscore the importance of using technology in statistics education, not only as a means of displaying data but also to produce visual representations that can be manipulated as a way of supporting and enhancing teachers' emerging understandings of statistical concepts.

Technology as a Support for Statistics PjBL

Given the inquiry-based nature of the learning models as well as the conceptual focus of the study, technology was a key tool for managing, analyzing and reporting information and for performing these functions efficiently. Technology can absorb some of the cognitive burden when students engage in time-consuming tasks, allowing more time and resources to be devoted to critical thinking and reasoning (Friel, 2007). In statistics specifically, technology has in some ways revolutionized the field, providing multiple viable solutions to previously intractable problems (Chance, Ben-Zvi, Garfield, & Medina, 2007). These innovations have also transformed the teaching of statistics to allow for deeper understanding and application of ideas. For example, Wild and Pfannkuch (1999) coined the phrase *transnumeration,* to describe the linking of representations that can reveal important features and properties of the data previously masked. Landscape-type technological tools (Bakker, 2002) such as *TinkerPlots*, provide opportunities to transnumerate as they allow students to have greater autonomy over exploring and selecting from a variety of data display formats. This class of tools allows for multiple and varied learning paths and agency in problem solving.

Pea's (1985) notion of technology as amplifiers and reorganizers is useful to conceptualize the use of technology in educational settings. In addition to thinking of computers and software as tools for increasing the efficiency of performing traditional drill and practice tasks and extending our capabilities in these areas (as an amplifier), he advocated the use of technology as tools to support and reorganize our thinking (as a reorganizer). Clearly one of the most attractive functions of technological tools is that they help us expedite certain tasks, however when used for supporting learning we must foreground the ways these tools can help transform thinking. In particular, they can help steer attention towards meaning-making and away from routine, mechanical tasks. With respect to statistical thinking, they allow for transnumeration. When used as a reorganizer, technology can redirect the results of statistical inquiry and support the building and transforming of PSTs' statistical conceptions. We draw on this perspective to examine the ways in which PSTs leveraged technology to support their analysis and draw data-based conclusions across three curricula.

Research Questions

In this study we use quantitative and qualitative methods to answer the following research questions:

1. To what extent do PSTs' understandings of elementary statistical concepts change across the three curricula—a project-based unit, problem solving activities unit, and model-eliciting activities unit—from pretest to posttest?
2. In what ways did the PSTs leverage technology to support their statistical claims?

Methodology

Participants

This multi-methods study incorporated 106 PSTs from a large Midwestern university who were enrolled in a mathematics course for elementary education majors. The six-week statistics unit was specifically designed to develop PSTs' statistical content knowledge for the task of teaching (Groth, 2007). PSTs independently enrolled in the course and instructors were assigned to sections based on personal preference of days and times of classes. Each PST only experienced one treatment condition (See Table 1).

Table 1. PSTs assigned to each treatment condition.

Treatment	No. of Sections/ No. of Instructors	Class Size
PjBL	3/1	48
PbS	2/2	26
MEA	2/2	31

The Curricula

All three curricula approached the teaching of statistics from a problem-centered approach where students learned content through solving open-ended problems. However, the type of problems and the nature of the implementation varied across curricula in line with the differences between PbS, PjBL, and MEA outlined above. In addition, they all covered similar content, including measures of center (mean, mode, median) and spread, distribution, and graphing. The curricula were designed to directly address major statistical misconceptions and to support PSTs in using statistical tools to draw data-based conclusions. A third similarity was that the curricula in all three treatments required PSTs to engage with data using *TinkerPlots*.

TinkerPlots

TinkerPlots (see http://www.keycurriculum.com) is a dynamic data exploration software package designed for students in grades four to nine to investigate multiple representations of data. Students can conduct increasingly sophisticated statistical analyses as their proficiency with the software improves. Although initially designed for middle grades students, the software is also appropriate to engage PSTs in statistical investigations to develop their content and pedagogical knowledge and familiarize them with new tools for statistical inquiry. For example, Lee, Hollebrands, and Wilson (2010) have designed a curriculum series for preservice or inservice teachers that include mathematical/statistical objectives. In line with Pea's descriptions of technology (1985), *TinkerPlots* can be used as an amplifier by increasing the efficiency in which a student can create statistical representations (such as dotplots, histograms, and box plots) and calculate statistical measures (such as mean, median, range, and percentages). The dynamic nature of *TinkerPlots* permits the tool to also be used as a reorganizer, largely by creating interactive explorations. For example, *TinkerPlots* allows students to overlay a box plot on a dotplot that displays the same dataset, and see how individual data points have the potential to influence other data representations.

In our project, PSTs used *TinkerPlots* to manipulate data freely to produce a large variety of graphs (examples of the graphic displays are included in the results section). PSTs enrolled in all sections used *TinkerPlots* during classes (to varying degrees) and investigated data about elementary students in a project called *Beeton Elementary*.

Beeton Elementary

Beeton Elementary was designed by a member of the research team and required students to analyze standardized test scores from all the fifth grade students at a fictitious school. The dataset, organized in a *TinkerPlots* file, included raw scores for each student in three fifth grade classes in mathematics, language arts, and science. Student demographic data (gender, race/ethnicity, special needs, English language learner, and free/reduced lunch) along with the school's data regarding adequate yearly progress (AYP) were also given to the PSTs. The PSTs were expected to analyze the data to report on three specific issues: i) discrepancies across the various subgroups, ii) students' performance across standards to determine strengths and areas for improvement, and iii) implications of the data for staff. The final product was a report to the principal and members of the school board including results of their analyses and data-based recommendations. PSTs worked in groups of three or four to complete the project although the level of collaboration varied across groups.

Problem-Solving Unit

The unit consisted of a set of short, inquiry-based tasks that were selected to help PSTs develop conceptual understanding of the key statistical ideas in the unit and resolve common misconceptions. Given our goal of developing the PSTs' statistical knowledge, the tasks went beyond building procedural fluency to developing the PSTs' competence in selecting appropriate statistical tools and using them effectively to support their claims. These tasks were context-rich to provide opportunities for PSTs to apply the concepts meaningfully. For example, we included tasks that encouraged PSTs to closely examine the problem's context to determine the appropriate statistical models to use given the situation (See Figure 1). Unlike the PjBL group where mini-lessons were driven by students' needs, the tasks in this unit were designed and sequenced by concept in advance so students engaged with tasks based on how they were organized in the unit. PSTs in the PbS group used *TinkerPlots* to support their work on the *Beeton Elementary* project as needed, but fewer curricula activities explicitly involved *TinkerPlots* so it was only used during about 40% of class time. PSTs in this group and the MEA group (described below) completed the *Beeton Elementary* project as a culminating experience at the end of the unit.

Project-Based Learning Unit

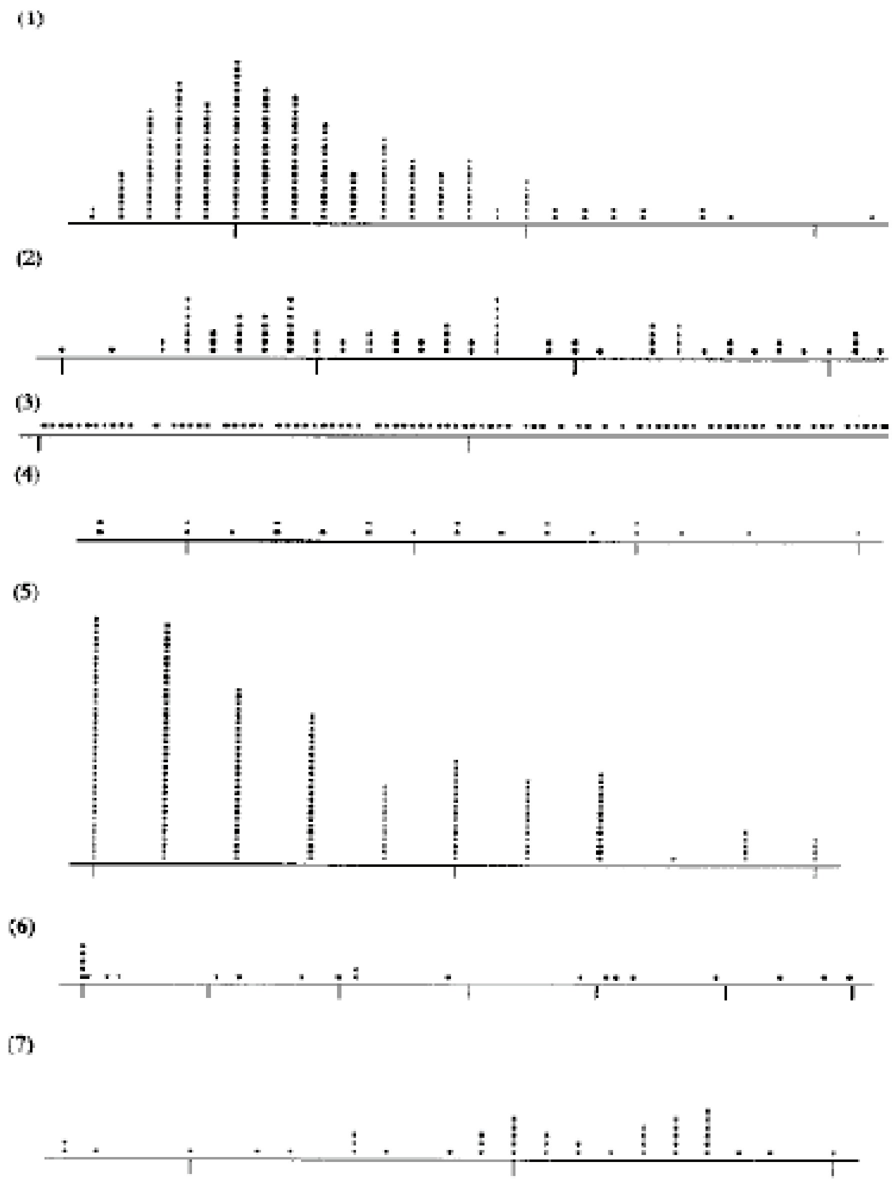
In the PjBL unit, the PSTs took on the role of fifth-grade teachers who were charged by their principal to analyze the recently released results of the state's standardized tests, provide a summary of the overall performance of the fifth-graders and make data-based recommendations about areas of improvement. As students worked to address the issues posed by the principal, they needed to summarize the data in ways that would show differences across classes and demographic groups. To respond to these needs, the teacher had

Figure 1. PS Task: Matching Variables to Dot Plots (adapted from Rossman & Chance, 2001)

Part 2: Matching Variables to Dot Plots

The distributions of the seven variables below correspond to one of the following dot plots. (The scales of the dot plots have been left off intentionally.) Match each dot plot to its corresponding variable and provide a brief explanation for each choice. For each dotplot, add some of the numbers that you think may be represented by the distribution along the horizontal axis.

A. Jersey numbers of the 2006 IU football players
B. Annual snowfall amounts for a sample of cities taken around the United States.
C. Margins of victory in a sample of Major League Baseball games
D. Prices of property on the Monopoly board game
E. Weights of players on the 2006 IU football team
F. Ages at which a sample of mothers had their first child
G. Scores on a mathematics exam



mini-lessons around statistical concepts relevant to the issue at hand. For example, when students were grappling with how to describe the distribution of datasets that were vastly different, the teacher led a mini-lesson about key constructs used when describing distributions (shape, center, spread, and so on). The tasks used in these mini-lessons were often similar in content to those used in the PbS unit. However, they were modified to align with the broader storyline and to be support by the technology as appropriate (See Figure 2). Students in the PjBL group had access to *TinkerPlots* during all classes but it was utilized for about 70% of class time.

Model-Eliciting Activities

In this treatment, students worked in groups of three or four on a model-eliciting activity (MEA). After each group developed a solution, they would present their solution to the class. This was an opportunity for the group to get feedback from the class discussion so they could go back to rethink and revise their models. As the goal was to develop PSTs' statistical understanding, the activities included a real-world problem with the need for a solution and, a set of data (See Figure 3). The MEA unit comprised several model-eliciting activities (MEAs). PSTs in this group completed the *Beeton Elementary* project as a culminating experience at the end of the unit. They also had access to *TinkerPlots* during all classes but it was utilized for about 70% of class time.

Data Sources

There were two main sources from which we drew data.

Pre- and Post-Test

A 10-item test (maximum score of 30) was administered in a pre-post format. There were two parallel forms of the test that were alternated at the pre-post administration. The test consisted of a range of questions on measures of center, graphing and distribution but included a mixture of what Schaeffer (2006) refers to as statistical questions and mathematical questions about statistics. Statistical questions are those that call for reasoning about numbers in context (data) to answer questions of interest (Figure 4). Mathematical questions about statistics were subdivided into mathematical-procedural (Figure 5) and mathematical-conceptual

Figure 2. PjBL Task: Examining Test Scores

Examining Test Scores

Students in Ms. Glover and Ms. Stevens' classes took the same math test. The maximum score that a student could get on the test was 10 points. Below are dot plots showing the distribution of scores in each of their classes.

If you were the 5th grade coordinator, how would you summarize the students' performance in each class? What feedback would you give the teachers based on their students' performance on the test?

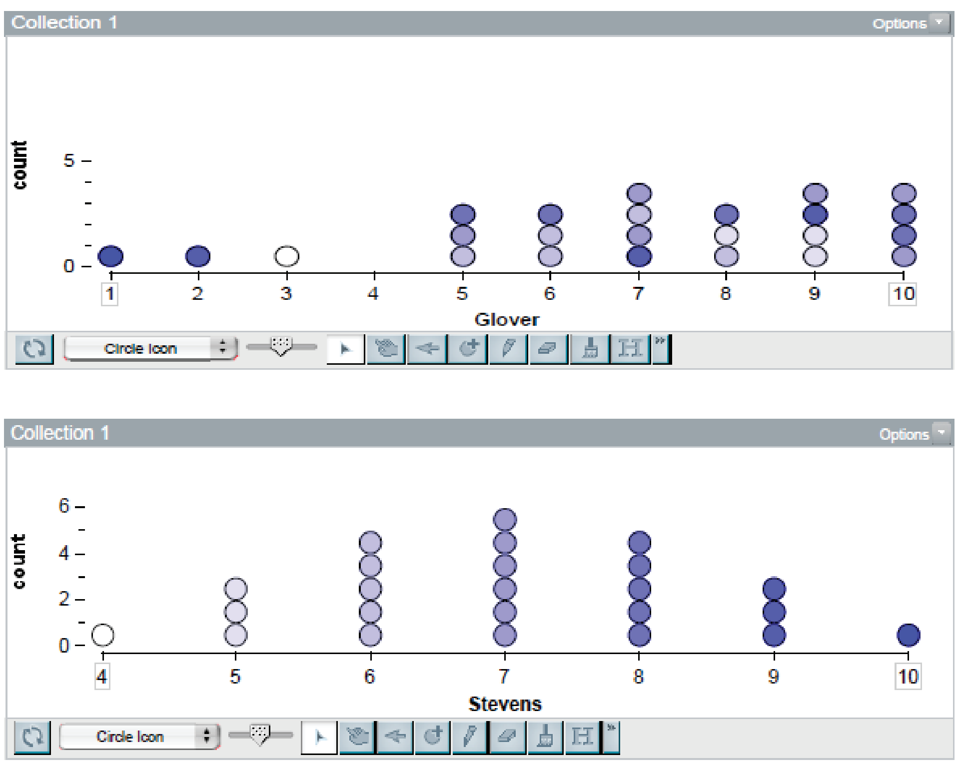


Figure 3. MEA Task: Judging Airlines

Judging Airlines

Information

In June, the Chicago Spanish Club is going on a study abroad trip to Venezuela, and they have hired your team to help them select which airline to fly. Last year the Spanish Club had a miserable experience when traveling to Barcelona. Their connecting flight to Reykjavik, Iceland, was late, so they missed their next flight to Barcelona. The entire class had to stay overnight in the airport.

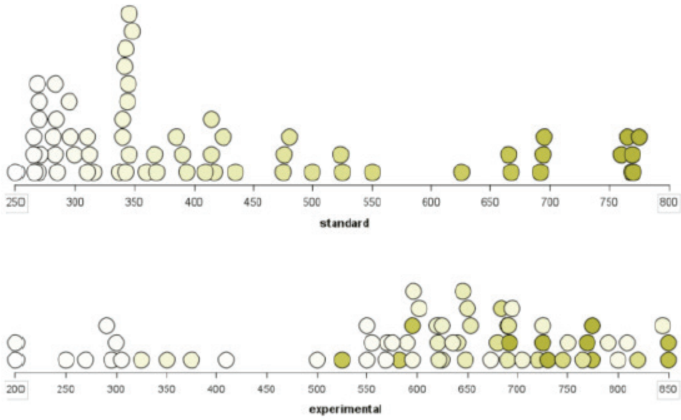
The club has identified five airlines with economical fares that fly from O'Hare Airport to Venezuela, but they are still in the process of identifiying more airlines that fly to Venezuela. Most of the flights have a connecting flight in Mexico City. They are hoping to find the airline that has the smallest chance of departing late from O'Hare so that they are less likely to arrive late in Mexico City. They don't want to miss their one connectiong flight to Venezuela this year! Source: SGMM Materials (https://engineering.purdue.edu/ENE/Research/SGMM

In the table that follows, you will find information about departure times for flights on the five airlines that the Spanish Club has identified thus far. The departure times are for flights leaving from O'Hare Airport and scheduled to arrive in Mexico City. Rank the five airlines in terms of most likely to be on time to least likely to be on time for departing from O'Hare Airport. As you rank the airlines, keep track of your process. Describe your process in a letter to the Spanish Club so that they may use a similar process to rank the additional airlines that they may identify at a later time.

Number of Minutes Late for Flights Departing from O'Hare Airport

Sky Voyage Airline	Central American Airlines	Mexico Express	Sudamerica Internacional	Southeast Airline
5	15	9	0	0
0	9	5	25	5
20	4	5	0	0
5	0	5	9	9
0	0	125	0	40
6	14	10	0	0
0	20	5	4	5
0	15	10	0	25
15	16	0	35	10
0	0	4	0	30
0	0	10	0	12
7	15	10	10	0
0	10	10	5	0
5	10	9	55	10
40	25	7	0	9
4	5	12	0	5
0	20	5	0	0
0	15	0	17	27
0	11	10	5	11
0	12	7	0	0
3	0	13	65	30
60	5	0	5	5
5	0	0	0	0
0	30	10	0	4
7	4	5	2	40
0	5	4	0	0
0	10	6	0	15
123	10	5	75	0
0	25	7	0	6
5	4	5	0	9

Figure 4. Example of a Statistical Reasoning Item



The graphs above show the number of healthy immune cells each patient has: one dot represents one person (so a dot at 350 means that patient has 350 healthy immune cells). This data is from patients who have AIDS. When a person gets AIDS, their immune count goes down—the sicker you are, the *fewer* immune cells you have. The data above is from a clinic that is testing two types of drugs for AIDS patients, their standard treatment and a new experimental treatment. Based on the two dotplots above, which treatment would you recommend?

Figure 5. Example of a Mathematics-Procedural Item

Consider the following numbers:
12, 6, 10, 13, 12, 7

1. What is the median of the data set above?
   a. 10
   b. 11
   c. 11.5
   d. 12
   e. There is no median.

Figure 6. Example of the Mathematics-Conceptual Item

Below are five bags of chips without prices. None of the bags are the same price. If you know that the average price of the chips is $1.75, how much might each bag cost?

Bag 1 price: _______ Bag 2 price: _______
Bag 3 price: _______ Bag 4 price: _______
Bag 5 price: _______

Explain how you found your answer.

(Figure 6). The former refers to questions that require the application of a procedure or algorithm to solve while the latter refers to questions that drew on the PSTs' deep understanding of the concepts. Each item could receive a maximum score of 3 points; therefore the maximum score of the test was 30 points. The test was designed in this way to ensure that we assessed all the ideas PSTs needed to know to teach the statistics effectively in the middle grades.

Group Reports

At the end of their participation in the Beeton Elementary project, each group submitted a final report to the principal and school board with the results of their analyses and recommendations. These reports were analyzed to gain insight into PSTs' understanding and use of technology.

Analyses

To answer research question 1, we conducted a repeated measures analysis of variance (ANOVA) to determine if there were statistically significant differences in the statistical learning gains from pretest to posttest across treatment groups. A Scheffe post-hoc analysis was also conducted to determine if there were paired group differences.

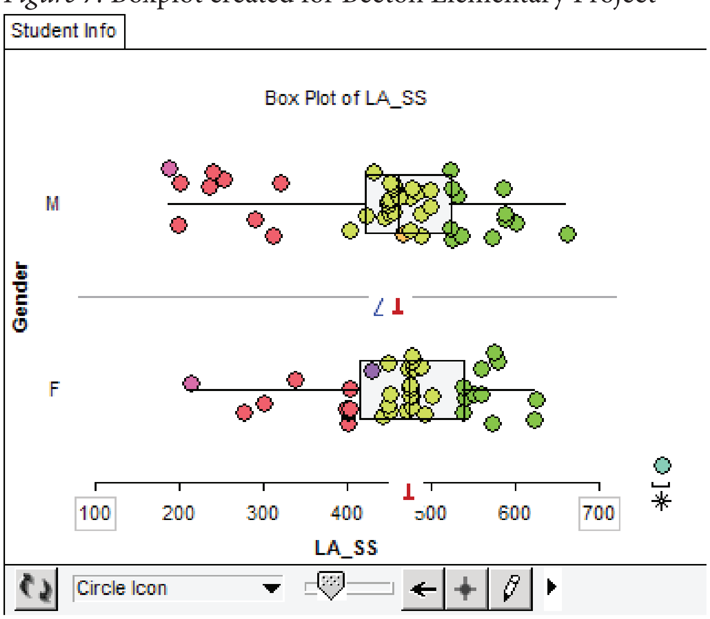
To determine the ways in which PSTs leveraged the technology in their analyses we examined the final reports submitted by all the groups. Using a pre-existing coding scheme, all the projects within each treatment group were examined and the claims (and the reasoning used to justify and interpret those claims) were identified and coded. For example, the following statement referring to students' performance in language arts, "females scored, on average, only marginally higher than males," was coded as a *claim* because the group was making an assertion about the performance of males to females in a particular subject. Statements were double-coded as justification/interpretation and with the statistical measures (such as mean, median and mode) or graph used to support the claim. The above stated claim was supported by the statement "with a central tendency of 445 and females with a central tendency of 467. It is also evident that both males and females have a large range of scores." This latter statement was coded as *justification (measure of center-weak/range-weak)* to indicate that the PSTs used a measure of center (they did not specify which) and range to justify their claim. We also distinguished between the reporting of findings and the interpretation of findings to answer the research questions and make recommendations. A code of *no interpretation* was also assigned because the group did not explain what having a mean of 445 and 467 told them about the performance of the group by gender nor what a large range of scores indicated about the consistency of the performance of the students by gender. For the claim made the group used *TinkerPlots* to calculate range and the measure of center (which was coded as *calculating measures*), to make the boxplot (coded as *creating representations*), and to overlay graphs (Figure 7—coded as *overlaying graphs*). Using *TinkerPlots* to calculate measures and create representations are considered amplifying functions and were coded as such. However, although we considered overlaying graphs to be aligned with reorganizing, the group did not explain what overlaying the graphs revealed; in particular, how the clustering of data points around the median might lead to a different interpretation of language arts performance by gender. After each of three coders had coded one project report we met to resolve through discussion any discrepancies in how the codes were being applied. Then each coder was assigned a set of reports. After all reports were coded, we examined the projects within each treatment group, then across all three groups to identify trends in students' use of technology.

Findings

Research Question 1

The pretest mean scores analysis revealed that the project-based group had a lower starting mean (M = 16.06, SD = 3.67, N = 48) than the other two groups, which were the model-eliciting group (M = 19.37, SD = 3.74, N = 32) and the problem-solving group (M = 17.65, SD = 4.40, N = 26). The posttest mean scores for all three groups were not significantly different (project-based group: M = 21.04, SD = 4.13, N = 48, model-eliciting group: M = 20.91, SD = 4.43, N = 32; and problem-solving group: M = 20.69, SD = 4.58, N = 26).

Figure 7. Boxplot created for Beeton Elementary Project



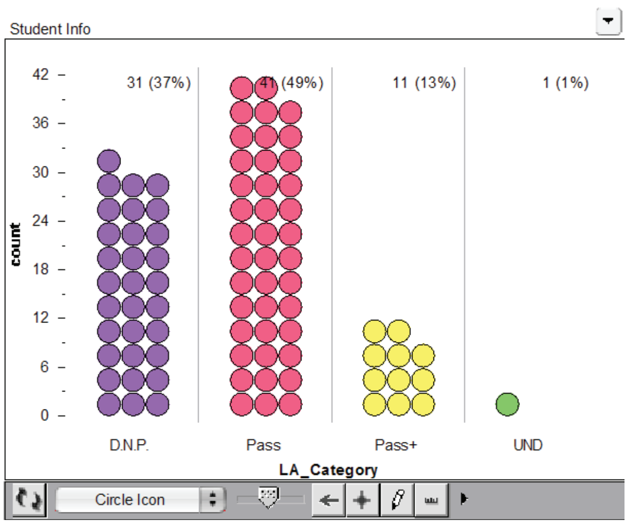
A repeated measures ANOVA analysis was used to address the between-subjects treatments—(a project-based unit, model-eliciting activities, and problem-solving activities) and the within-subject test (that is, the pretest and posttest). The increase in mean gain scores for understanding of elementary statistics was greater for the project-based group (M = 4.98, SE = 0.67), than for the problem-solving group (M = 3.67, SE = 0.78) or the model-eliciting group (M = 1.53, SE = 0.76), $F(2,103) = 6.041$, $p < 0.01$ with a Cohen's d of 0.68 for the measure of effect size. Scheffe post-hoc analysis showed a significant difference ($p = 0.003$) between the project-based unit and the model-eliciting activities.

Research Question 2

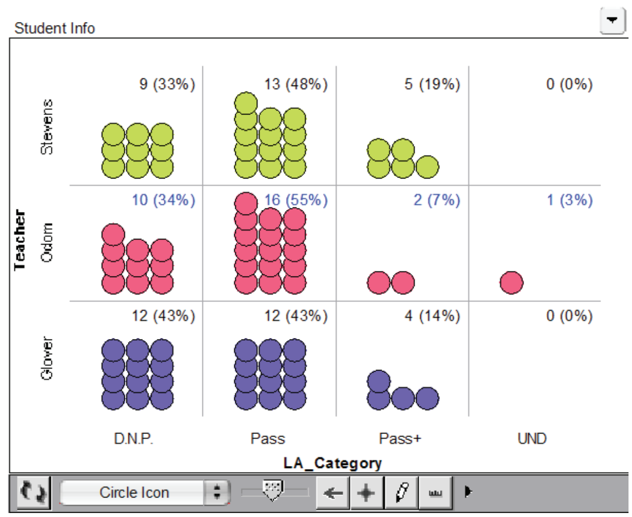
Our analyses of the PSTs' written reports showed that there were no distinct differences in the ways PSTs used technology based on treatment. Given that there were no observed treatment-based distinctions we examined all the reports as a whole to determine how the PSTs leveraged the technology in their analysis of the data. Examination of the reports showed that while some PSTs used *TinkerPlots* in ways that supported rich interpretations of the data (for reorganizing), others utilized the tool in less sophisticated, relatively superficial ways (for amplifying). Specifically, PSTs used *TinkerPlots* as an amplifier, as an efficient way to compute statistical measures or to display data; and also as a reorganizer, to illuminate unusual or unexpected results that were not observable visually or by using summary statistics, and/or to meaningfully reorganize their thinking about the data. These differences in technology use, as an amplifier or reorganizer, were evident in two distinct aspects of their report. First, in the PSTs' choices of data displays; second, in the decision to examine multiple variables simultaneously to yield results that would inform recommendations. Below, we discuss two examples of the PSTs' work that contrast this use of the technology.

Figure 8 represents the data displays constructed by one group of the PSTs to show their analyses of the Language Arts portion of the data for the students of all the fifth grade teachers at *Beeton Elementary*. The first graph they produced showed the overall percentages of passing scores for the fifth grade. In the second graph, these percentages are disaggregated by teacher. The third and fourth graphs group the scores in intervals of 90 and 200 points respectively and show the interval within which the mean and median fall. The PSTs were also able to determine the percentage of students who passed the standardized test by level and by teacher. They determined the range of values within which the measures of center lay, but not the specific value of these statistics. Additionally, they incorrectly interpreted that "36 percent of the students received the mean score" and that "90 percent of the Ms. Odom's students received a score equal to or above the median score." Instead, what the graph showed was that 36 percent of the students received scores that lay between 450 and 539, and the median indicates the score at which 50 percent of the students lie at or above. As a result of the representations shown in figure 8, the PSTs interpreted the mean as an interval estimate, rather than a point estimate. Although the graphs provided some idea of how the students performed on the language arts portion of the test, *TinkerPlots* has the potential to be used to yield additional information about how these results were distributed across the different subgroups. As stated these results are not particularly useful to school personnel for making decisions about how to improve achievement in this area. The PSTs' use of *TinkerPlots* as an amplifier served to efficiently produce summary statistics (percentages, mean) and graphs. However, using the technology as a reorganizing tool, perhaps by creating additional graphs and drawing connections among them, would have yielded valuable information about student achievement. By augmenting their current graphs, the PSTs could have determined what subgroups of students comprised the 67 percent of students who passed in Steven's class, how the scores were distributed, or identified outliers or unusual features that would be masked with the current graphs. Results from such analyses would provide precise

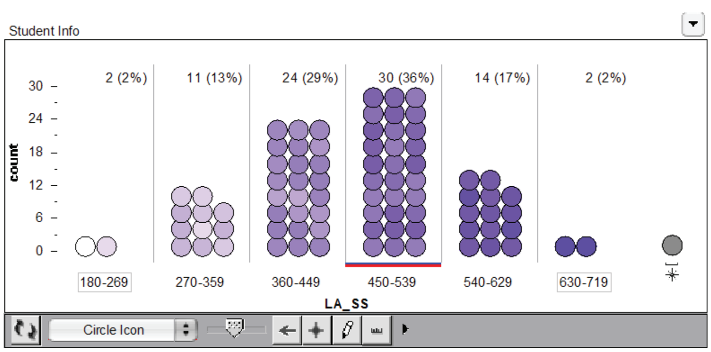
Figure 8. PSTs' Graphs and Analysis of Beeton Elementary Students' Language Arts Grades



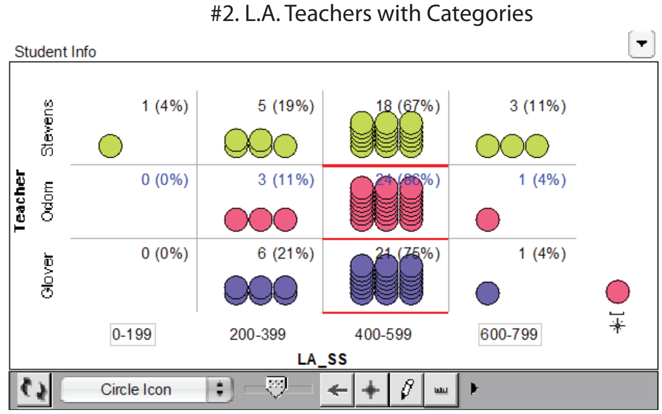
#1. L.A. Categories



#2. L.A. Teachers with Categories



#3. L.A. Individual Scores



#4. L.A. Teachers w/ Individual Scores

By taking the data given to me and making it into four separate organized tables, I was able to analyze the information. Each graph showed me different pieces of information. From looking at the first graph, I learned that 62 percent of the students passed the language arts section of the exam. In the second graph, I saw that each teacher had a different amount of students that passed the language arts section of the exam. In Ms. Steven's class, 67 percent of the students passed. In Ms. Odom's class, 62 percent of the students passed. In Ms. Glover's class, 57 percent of the students passed. From this chart I learned that Ms. Steven's class received the best scores for the language arts section. From the third graph, I noticed that the mean score was between 450 and 539. 36 percent of the students received this mean score. This was also the highest group of scores. In the final graph for the language arts section, I learned that 90 percent of Ms. Odom's students received a score equal to or above the median score. Her class received the best scores for the language arts section.

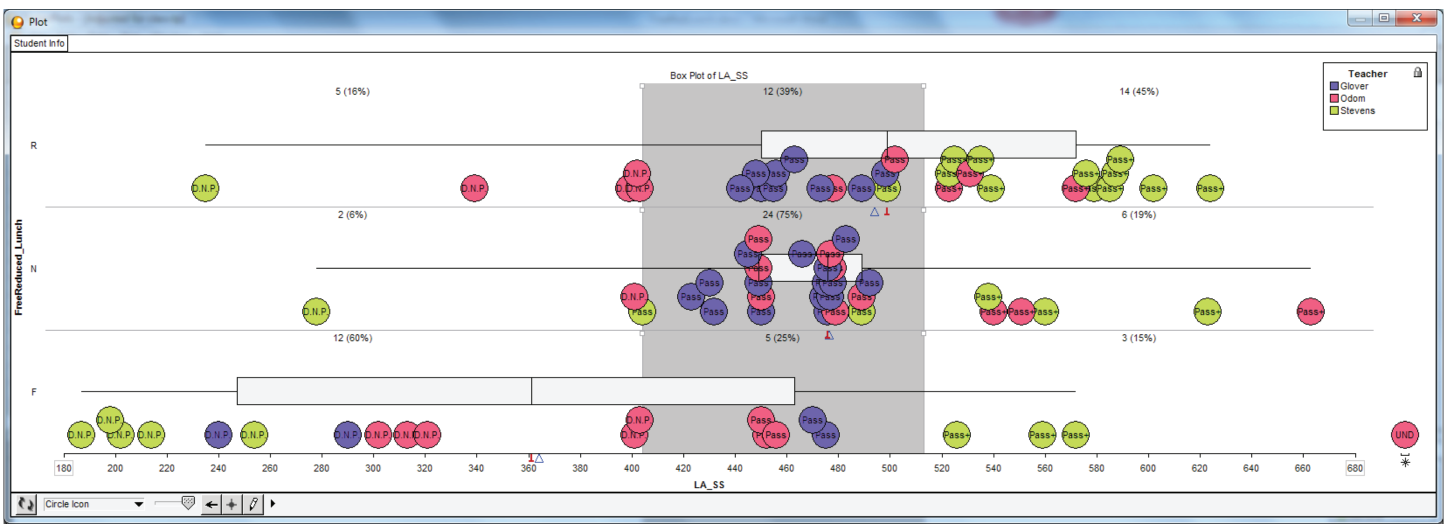
information about what was going well and what needed improvement at Beeton Elementary.

In Figure 9, we provide an example that shows how other PSTs used *TinkerPlots* to restructure their mental activity to foreground analysis and deemphasize the mechanical operations of the tool. After analyzing the scores by teacher, subject and across subgroups, these PSTs identified the analysis of the language arts scores as the most revealing of the correlation between students who did not pass and those who received free and reduced lunch. Through the use of a boxplot, the PSTs were able to see how the language arts scores were distributed by subgroup and teacher simultaneously (see Figure 9: "We can see that most of Glover's students scored within a smaller range than the other teachers' classes. . . . The two students who did not pass are both Special Education, with one of them also being ELL."). Additionally, pairing the use of the summary statistics with the box plot also allowed for identification of relevant features (such as outliers) that may distort or misrepresent some statistical measures. These PSTs took full advantage of the tools provided by *TinkerPlots*, including overlaying the box plots and dot plots, using dividers to group the data and calculate percentages, and using color to investigate trends in the data. Taken together, these technology-based investigations yielded a more accurate and meaningful interpretation that they used to make recommendations (such as "Sixty percent of the students with free lunch did not pass the Language Arts standardized test as compared to the 16% of the students with reduced lunch and the 6% of the students with no lunch benefit.").

Discussion

The results of this study inform research on statistics education and technology-supported PjBL in two key ways. The first finding supports recommendations by researchers and educators in the field (Franklin et al., 2007; NCTM, 2000) that engaging PSTs in the work of statisticians (that is, activities that align with the statistical investigation cycle, PPDAC) would enhance their statistical literacy. Our results indicate that PSTs among all three treatments increased their understanding of the statistical concepts, achieving a comparable final level of understanding despite different mean pretest scores. Given that all three curricula incorporated a problem-solving orientation (which aligns very closely with the tenets of PPDAC) and approached the study of content within relevant contexts, the results provide much needed empirical

Figure 9. PSTs' (group 2) Graphs and Analysis of Beeton Elementary Students' Language Arts Grades



Appendix D, Figure 5. Comparison of Free/Reduced (F/R) Lunch v. Language Arts (LA) Scores with Did Not Pass (D.N.P.)/Pass/Pass+ Labeled, Pass Section Highlighted in Gray, and Teachers Color-Coded. Mean and Median for each are marked by a "△" and a "⊥" respectively.

As mentioned before, the correlation between students that did not pass the standardized test and students with free lunch benefit is most prominent in Language Arts. Sixty percent of the students with free lunch did not pass the Language Arts standardized test as compared to the 16% of the students with reduced lunch and the 6% of the students with no lunch benefit. The ranges of Language Arts scores within each level of benefit have similar spans, but the range for the students with free lunch fall at the lowest end of the scale (Appendix D, Figure 5). Furthermore, the distributions of scores for the three levels of benefits vary greatly from one another. While the scores for the students with free lunch have a normal distribution, they have no peak and are spread fairly evenly across the range. The scores for the students with no lunch benefits are clustered tightly together with two peaks creating a slight negative skew and a few outliers creating the wide range. Additionally, the scores of the students with reduced lunch benefits also have a negative skew, but it is more pronounced and the scores do not have a true peak.

support (Garfield & Ben-Zvi, 2007), that approaching the teaching and learning of statistics can enhance PSTs' statistical understanding. Although modest, we find the increase in scores from pretest to posttest (resulting in higher mean gain scores) for the project-based group encouraging with regard to the potential for a PjBL environment to support the development of statistical literacy. Given the extent of the improvement over time of PSTs in the PjBL group, compared to the model-eliciting group, results suggest that key aspects of PjBL (e.g., intense exposure to content within the context of solving a core problem, extensive collaboration, collective reflection) that are not characteristics of the other approaches may be beneficial for students, especially those who have the greatest deficits in statistical knowledge.

The results of this study also attend to calls in the literature (Shaughnessy, 2007; Friel, 2007) for more research on the ways in which technology-rich environments support conceptual growth of statistical ideas and how learners use technological tools to explore content. The use of technology was integral to the curricula goals in several ways. First, given the design of the *Beeton Elementary* project and the volume of data, PSTs needed resources that allowed them to explore and analyze the data as driven by the demands of the *Beeton Elementary* project. It was essential that the capability of the software aligned with the statistical questions in order for learning to occur and for project goals to be met. As a landscape-type technological tool, *TinkerPlots* was integral to meaningfully engage with the data because unlike other programs used for data analysis (such as Excel), in *TinkerPlots* graphs and plots are not static end products; rather, they are used as dynamic supports for inquiry (Friel, 2007). Second, *TinkerPlots* allowed for critical shifts in the functions and structure of the statistical thinking from the mechanical operations to the sense-making operations (Pea, 1985). It allowed PSTs to efficiently calculate measures, such as mean, median and percentages, providing the opportunity for them to devote more time and cognitive resources to investigating and restructuring the data in ways that would yield meaningful results; thereby using the technology more as a reorganizer and less for amplifying. Analyses of the PSTs' final reports showed that there were common within-groups differences in the use of the technology, with some taking greater advantage of the exploratory features of the technology than others. Instead of using the tool to support transnumeration (Wild & Pfannkuch, 1999), some PSTs limited themselves to using one summary statistic and data display irrespective of the data being analyzed and seemingly without consideration of the larger goals of the project. In many cases examining the data through a narrow lens, limited their ability to uncover hidden features, which had significant impact on their ability to interpret the data accurately and make meaningful recommendations.

In this regard we distinguish here between the time spent using the technology and the nature of the activity in which the technology used. Although there was a significant difference in the time spent working with *TinkerPlots* in MEA and PjBL groups (about 70%) and PbS group (about 40%), these differences in contact time did not yield significant differences in the ways students leveraged the technology to analyze the *Beeton Elementary* data. Research on the use of technological tools to develop statistical reasoning show that unless students' interactions with the tool are well-structured, it is unlikely to greatly impact learning (Lane & Peres, 2006; van Eijck & Roth, 2007). Although class time among treatment groups was organized around solving problems, students' use of *TinkerPlots* was primarily open, needs-driven and exploratory. In this regard, although self-directed learning underlay the three approaches, outside of the initial orientation and play sessions with *TinkerPlots*, the findings would suggest that foregrounding activity that made clear distinctions between the mechanical and more analytical uses of the technology during instruction time would possibly have resulted in more students using the technology as a reorganizer. Cobb and McClain (2004) described the tension between prioritizing the investigative aspects of the tool versus using it to systematically support the development of key statistical ideas. To strike a balance, it is important that classroom instruction focus on discussions that explain how and why organizing the data in particular ways affords insights about the phenomena under investigation, and include activities that help students develop competence in using the technology for dual functions and that explicitly contrast the affordances of each. As such, we find that technology-rich, learning environments that support the development of statistical literacy should involve students exploring statistical ideas within the context of solving authentic problems, provide direct access to technology that can align with and support students' reasoning at each stage of development, and engage students in activities that allow them to distinguish between the tool's computation and analytical functions and develop expertise with both.

Conclusion and Limitations

In this study we investigated the extent to which PSTs' understandings of statistical ideas improved across three different technology-supported, problem-oriented curricula. Additionally, we observed that technology was integral to the PSTs' analyses of the project data and afforded opportunities to transform and examine data to respond to research questions precisely and accurately. However, there are a few limitations that are worthy of mentioning. First, we did not include a control group with which the results could be compared. This limits the claims that we can make about the overall effectiveness of the treatment conditions relative to more traditional instruction. Our gain score analysis showed that the PjBL group made the greatest improvement over time. Although this form of analysis does provide information about the learning outcomes, specifically improvement over time of the sample, statisticians (Rogosa & Willett, 1983) have raised some concerns about the reliability of the gain score variable, so caution should be used in interpretation.

Second, although the sample of PSTs in the three treatment groups were from the same population, we were unable to account for the higher pretest mean scores for the MEA group. An additional consideration is the ways instructors were distributed across the groups. One instructor taught all the classes in the PjBL group, two instructors for the PbS group (one of whom was also the PjBL instructor), and two instructors for the MEA groups (one of whom also taught a PbS class). Different teaching styles may have influenced enactment of the curriculum. Third, although we believe that the distinct features of PjBL influenced the level of improvement, investigation of the ways in which these elements of PjBL may have advantaged some students was beyond the scope of this study. However, we do consider this an important area for further investigation specifically within the context of statistical inquiry. Research findings consistently report that middle grades students and teachers struggle to develop broad conceptions of statistical measures despite being taught these concepts. Understanding the features of PjBl that may have influenced the learning gains observed could have significant impact on how statistics concepts are taught in the middle grades.

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