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Transdisciplinary Learning: Using "Transfer Skills and Tools" for Deeper Learning to Achieve Higher-Order Thinking on Cross-Curricular Content

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Abstract

In this study, researchers investigated the impact of transdisciplinary learning on minority students as they were asked to apply higher-order thinking to solve real-world problems. Minority students, aged 10 to 11, who attended the researcher's elective classes participated. To see the potential in Transdisciplinary Learning, researchers looked at its essence through the use of "transfer skills and tools" such as: metacognition, questioning, Computational Thinking, Common Core State Standards Mathematical Practices (MP1: Make Sense of Problems and Persevere in Solving Them; MP4: Modeling with Mathematics; MP7: Look for and make use of structure; MP8: look for and express regularity in repeated reasoning), digital technology tools, and self-efficacy. The use of these "transfer skills and tools" was monitored to collect data on students' progress and development to see how underrepresented students fare with rigorous instruction that offered them student-centered experiences that would build their capacity to solve "wicked" 21st-century global problems. Results yielded self-efficacy as a critical variable that provided some statistically significant outcomes. While promising for refining future efforts to empower students, the findings for the immediate effects of transfer skills and tools used to increase students' deep learning were inconclusive.

Introduction

Students from underrepresented populations are often inoculated with high-stakes testing and preparation, and their enriched academic learning is inevitably presented as secondary which is not the case to that of their more privileged peers (Amrein & Berliner, 2002, p. 41). The necessary paradigm shift reverses this process, where enriched academic learning opportunities enable students to achieve higher performance levels. It is through transdisciplinary learning that students can gain the skill sets and relevant, real-world experiences that will manifest this as a reality in the twenty-first century (Interagency Working Group on Convergence, Federal Coordination in STEM Education Subcommittee, Committee on STEM Education, & National Science and Technology Council, 2022, pp. 9 -10). This problem led to the primary question, "Is transdisciplinary learning the best student-centered method for deep learning to achieve higher-order thinking?" This question drives the idea of how transdisciplinary learning may be a preferred pedagogical practice to build a global mindset for the 21st century in STEAM education, compared to other student-centered methods, as we cultivate students' problem-solving and decision-making skills. Transdisciplinary learning has been on the minds of researchers and developers for some time as they move toward revolutionary ways to solve global problems. New jobs and careers are at constant flux with the continued advancements in technology. This leads me to my secondary question, "How can the tools from multiple disciplines be leveraged to facilitate transdisciplinary learning through 'transfer skills'?"

Literature Review

Underrepresented students are over encumbered with the demands of high stakes testing and preparation, and the enriched academic learning is posed as secondary to the aforementioned mandates on public schools. Highly scholastic organizations, such as International Baccalaureate (IB) Schools, use transdisciplinary learning pedagogy, a far right of the spectrum with student-centered higher-order thinking, while minority students are stated, by research, to be better suited with direct instruction. Paulo Freire (2000) identifies these dual sides as "banked education" versus "problem-posing education" in his book, "Pedagogy of the Oppressed." Freire (2000) states, "In the banking concept of education, knowledge is a gift bestowed by those who consider themselves knowledgeable upon those whom they consider to know nothing. Projecting an absolute ignorance onto others, a characteristic of the ideology of oppression, negates education and knowledge as processes of inquiry" (p. 72). He continues to state, "The problem-posing method does not dichotomize the activity of the teacher-student: she is not 'cognitive' at one point and 'narrative' at another. She is always 'cognitive' whether preparing a project or engaging in dialogue with students. He does not regard cognizable objects as his private property, but as the object of reflection by himself and the students" (Freire, 2000, p. 80). This is where education appears to have blurred the distinction, where terms are expressed with implied definitions, or maybe the transmission of the message may have distorted its intention.

Common Core State Standards have attempted to make definitions of terms more explicit, as with the concept of "academic rigor." This is displayed in the discussion of the three shifts in math education. The National Governors Association Center for Best Practices and Council of Chief State School Officers (2010) define rigor as "deep, authentic command of mathematical concepts, not making math harder or introducing topics at earlier grades." They further assert "to help students meet the standards, educators will need to pursue, with equal intensity, three aspects of rigor in the major work of each grade: conceptual understanding, procedural skills and fluency, and application" (para. 6). The meaning of rigor as described brings us back to the idea of "banked education" versus "problem-posing education." Freire would likely suggest a need to determine the ideal platform or pedagogical ideology to bestow on our students of underrepresented backgrounds to bring equity, as Freire would suggest. This quandary leads to the question, "Is transdisciplinary learning the best student-centered method for deep learning to achieve higher-order thinking?"

According to the National Science and Technology Council (2022), transdisciplinary learning (TL) is when the "learners identify complex problems and work together to create a shared conceptual framework and draw together theories, concepts, and practices that transcend individual disciplinary boundaries" (p. 14). Jay McTighe and Henry F. Silver (2020) introduce the idea of deep learning in this context by claiming:

> It aligns more directly with the definition proposed by the National Academy of Sciences (2018): Deep learning is a 'process through which an individual becomes capable of taking what was learned in one situation and applying it to a new situation.' More specifically, we contend that deep learning occurs when students come to *understand* and make sense of important ideas and processes—and are able to *transfer* those understandings to new content and contexts. (McTighe and Silver, 2020, para. 3)

This extends the idea that learning requires deep learning, a process of employing creativity and flexibility in one's thinking as Daniela Jeder (2014) notes to be one of the benefits of transdisciplinary learning (p. 127).
Richard Lehrer (2020) talks about a study of young students who underwent two years of learning and transferring knowledge and comprehension:

> Over the course of two years, young children participated in common practices of representational redescription of experiences in mathematics and in sciences (Greeno & Hall, 1997). In mathematics, these involved children's invention and contest of ways of representing measured quantities and of ways of coordinating measured quantities, both of which were governed by relations of necessity (e.g., children decided that all points on a line in a Cartesian graph represented the same ratio between quantities, such as the circumference and height of collections of cylinders). These representational means were extended in sciences to new quantities to describe plant growth and the densities of different materials, providing new ways for children to conceive of these natural systems. (Lehrer, 2020, p. 1464)

The thought becomes, "how do you begin to have students participate in such rigorous learning?" Albert Bandura defines self-efficacy as "our beliefs about our personal competence or effectiveness in a given area" (Woolfolk, 2004, p. 368). This is something that is critical in the development of the learner. According to Bandura, there are four sources of self-efficacy expectations: mastery experiences, physiological and emotional arousal, vicarious experiences, and social persuasion (Bandura, cited in Woolfolk, 2004, p. 369). While each is a contributor to increased self-efficacy, it stands to reason that its inverse is possible through these contributing factors as well, and the action research that would be performed would need to consider these possibilities. In an earlier paper, Bandura (1977) wrote that "extinguishing arousal to threats will enhance self-efficacy, but more so in individuals whose past coping attempts have occasionally succeeded than in those who have consistently failed" (p. 212). The question was now, "How has this effect of self-efficacy been cultivated in students who have been marginalized?"

Methods

In a quest to find the best student-centered pedagogy for developing students' higher-order thinking skills to solve authentic, real-world problems and utilize deep learning practices to master fundamental content understandings, principles, and skills has become paramount. The action research process provided a method for the researcher to investigate, analyze, and reflect on how one's best teaching practices might be refined to be effective in accomplishing the goal of empowering students to tackle global wicked problems and to be change agents of the future.

The action research presented an opportunity to study the variables and nuances of how transdisciplinary learning might be effective in an underrepresented population as it has shown to be in more affluent regions of the nation and abroad as with the example of IB Schools, where students experience transdisciplinary thinking and learning through the "Approaches To Learning" (ATLs) at the very beginning during their primary education which includes the following: "Bloom's taxonomy, Dialectical thought — considering issues from multiple perspectives and arriving at a reasonable conclusion, Metacognition — understanding one's thought processes, self-management skills, communication skills, social skills, and research skills (formulating questions, observing, planning, collecting, recording, organizing and interpreting data, and presenting research findings) (Sabharwal, 2021, para. 5)."

Participants

The participants in this study included minority middle school students, ages 10 to 11, that attended the researcher's elective classes. It was explained that all students will be given the same respect and grades would be separate from the research as identification will be coded to ensure confidentiality. Participants were informed that we would look at the essence of Transdisciplinary Learning through the use of such "transfer skills and tools" as: metacognition, questioning, Computational Thinking, Common Core State Standards Mathematical Practices (MP1: Make Sense of Problems and Persevere in Solving Them; MP4: Modeling with Mathematics; MP7: Look for and make use of structure; MP8: look for and express regularity in repeated reasoning), and digital technology tools, and would monitor their self-efficacy throughout the study. Participants monitored their own progress of these "transfer skills and tools" using self- progress monitoring trackers to incorporate the element of self-agency and the researcher collected this data on students' progress and development to assess how underrepresented students fared with rigorous instruction that offered them student-centered experiences that would build their capacity to solve "wicked" 21st-century global problems. This also included the students keeping a learning journal to log their personal notes, and steps during the learning. The researcher created the STEAM Project-Based Learning unit lessons, the evaluation and monitoring tools, such as the monitoring trackers, and administered the pre- and post-surveys and pre- and posttests.

Research Design

During the research, students worked on developing thinking skills that can be applied across multiple 21st-century disciplines. These skills included, but were not limited to: questioning, metacognition (applying your awareness and psychology of your thinking and learning), Computational Thinking, Common Core State Standards Math Practices-CCSSMPs (MP1: Make Sense of Problems and Persevere in Solving Them; MP4: Modeling with Mathematics; MP7: Look for and make use of structure; MP8: look for and express regularity in repeated reasoning), and learner practices of using digital technology tools. This involved keeping track of the following data: Student work artifacts (i.e. Engineers In Training (EIT) journal entries, exit tickets, assignment products); pretest and posttest (performance task science/ math); pre- and post-survey; progress monitoring system of students' levels of growth in the thinking and applied skills taught, and tracked frequency of using these practices on a daily basis as they developed best practice habits for a period of three months. To build self-efficacy in these skills, students also tracked their own growth and reflected as they learned and built best practice habits with these skills and how to use career related tools to address authentic real-life challenges. For the tracking of self-efficacy, the PBLWorks' Self-Directed Learning: Grades 6-12 Rubric was used. The central focus was on the developmental level of self-regulation. Technology uses were evaluated through the Digital Technology Tools Rubric. CCSSMPs 1,4,7, and 8 were self-monitored with students using the class's "Criteria Rubric: Building Momentum w/ CCSS Math Practice Standards." Metacognition and questioning were also self-monitored using the class's "Metacognition and Questioning Chart and Rubric."

The analysis of the data was completed through the triangulation of the qualitative and quantitative data that was done which was supported using SPSS Version 29 and Excel software. To insure the robustness of our findings given that our very small population sample size (N=16), the Pearson's Correlation Coefficient (r) with 2-tailed p-values, and Spearman's Rank-Order Correlation Coefficient (ρ) and 2-tailed p-values (α) were used to identify growth in a linear relationship, while providing a non-parametric alternative in consideration of monotonic relationships without linearity and normality. Missing data for any student participant was coded as 999 on SPSS which affected the sample size (N).

Data Analysis Summary

This study employed descriptive statistics and exploratory data analysis (EDA) to summarize and explore relationships between variables such as self-efficacy, along with the following transfer skills: metacognition, questioning, Common Core State Standards Math Practices, Computational Thinking (CT) and digital literacy. Though the initial action research was based on the primary question, "Is transdisciplinary learning the best student-centered method for deep learning to achieve higher order thinking?" and the secondary question, "how can the tools from multi-disciplines be leveraged to facilitate transdisciplinary learning through 'transfer skills?" the limited number of 16 participants did not offer a large enough sample size to abstract generalizations for a pattern that may reflect a larger population. Therefore, the data analysis conducted is intended as a preliminary investigation to identify potential patterns and generate hypotheses for future research.

Descriptive statistics, including means, standard deviations, and ranges, were used to summarize the dataset. EDA techniques, such as scatterplots and box plots, were used to visualize relationships and distributions. The Pearson's correlation (r-values) aided in establishing the strength of the associations between the variables used in the research. Non-parametric methods were considered where appropriate to accommodate the small sample size. Standard distributions were calculated using the sample formula (n – 1 degrees of freedom) to account for the small sample size and ensure accurate representation of variability within the data.

During the analysis, the original hypothesis indicated there would be positive correlations for all the variables based on Computational Thinking. Initial analyses were done with one-tailed p-values, but to address the unforeseen negative correlations, all the one-tailed p-values were doubled to accommodate these results and show a more conservative view statistically as two-tailed p-values to respond to any correlations, positive or negative. Due to the small population studied, the original premise through the primary and secondary question could not be generalizable to a broader population where the findings are therefore presented as exploratory. The methodology applied did offer a more comprehensive analysis as transdisciplinarity prescribes, referencing any investigation from multiple perspectives. This was accomplished by comparing the data for self-efficacy differences (growth), pretest and posttest score differences (growth) for science and that of math with transfer skills from the element of surveyed data, and then with tracker data. Self-efficacy, being an introspective belief of personal ability and skill (Bandura, 1977), student data from the trackers and surveys were reflective of this element.

Results and Discussion

Pretest and Posttest for Mathematics

Analysis of the Common Core Mathematics Assessment was taken from the "6th Grade Truffle Performance Task" drafted by the Mathematics Assessment Resource Services (MARS) (University of Texas at Austin, n.d.). The CCSS standards assessed were "Ratios and Proportions (RP)"- 6.RP.1 Understand the concept of a ratio and use ratio language to describe a ratio relationship between two quantities; 6.RP.2 Understand the concept of a unit rate a/b associated with a ratio a:b with b = 0, and use rate language in the context of a ratio relationship; 6.RP.A.3: Use ratio and rate reasoning to solve real-world and mathematical problems, e.g., by reasoning about tables of equivalent ratios, tape diagrams, double number line diagrams, or equations; and "Expressions and Equations (EE)"- 6.EE.9 Use variables to represent two quantities in a real-world problem that change in relationship to one another; write an equation to express one quantity, thought of as the dependent variable, in terms of the other quantity, thought of as the independent variable. Analyze the relationship between the dependent and independent variables using graphs and tables, and relate these to the equation.

Pretest and Posttest for Science

Analysis of the Next Generation Science Standards was based on the "Stanford NGSS Assessment Project Scoring Rubric for Deer Population" of the Deer Population Short Performance Assessment. This performance assessment was based on the NGSS Performance Expectation: MS-LS-2-1 PE (Analyze and interpret data to provide evidence for the effects of resource availability on organisms and populations of organisms in an ecosystem). Students' responses to three test question prompts were evaluated with a rubric score of one (Emerging Score) to a rubric score of four (Excelling).

From the first prompt question (#3) students were to describe the pattern they saw in the graph and table math models, then interpret using claim, evidence, and reasoning from their analysis of "what does the pattern tell you about a possible cause in the change in deer population (Stanford NGSS Assessment Project, N.D., p. 1)?" Looking at the second prompt question (#4), students were to write a claim and support it with evidence and reasoning on the data patterns in the graphs (Stanford NGSS Assessment Project, N.D., p. 2). The third prompt question (#5) required students to identify additional data that would be needed to help them assess a potential cause among the variables in the ecosystem problem and not merely a correlation.

Students Data Tracker

The data tracker was used by the students to self-monitor and evaluate their own progress throughout the three-month period of the research investigation. As students monitored themselves with the use of a rubric scoring themselves from a one (little/no evidence) to four (full application) for each of the categorical data variables (CT-Decomposition, CT-Pattern Recognition, CT-Abstraction, CT-Algorithm, MP1: Make Sense of Problems and Persevere in Solving Them, MP4: Modeling with Mathematics, MP7: Look for and make use of structure, MP8: Look for and express regularity in repeated reasoning, Metacognition, Questioning, Digital Technology Tools, and Self-Efficacy), the data was quantified by the researcher as either a “1” for students’ self-evaluated scores of two or higher, and “0” for scoring of less than a two. This was done in consideration that students' self-evaluated scores may not have been justifiable regarding the degree/ depth of application of the categorical data variables mentioned above though they were to reference all scoring from the rubric. The Digital Technology Tools Rubric was used to reference digital technology understanding and application, a draft inspired by the standards of the International Society for Technology in Education (ISTE). The Metacognition and Questioning Criteria Chart gave students access to work on their problem-solving methods.

During the study, transfer skills were scaffolded into the investigation one to several skills at a time to build gradual development of the skills and use of the tracker showed the stacking for each skill presented. The Metacognition Tracker Daily Frequency along with the Questioning Tracker Daily Frequency were reported with a total of 34 days, Self-Efficacy Tracker Daily Frequency recorded a total of 30 days, Decomposition Tracker Daily Frequency had a total of 29 days, pattern recognition produced 28 days of total monitoring for daily frequency, 26 days were given to track both abstraction and algorithms, nine days for digital technology usage, and six days total for the CCSS MP 1, 4, 7, 8 tracker of daily frequency.

Math Pretest and Posttest Differences compared with Tracked Transfer Skills

Student growth in their math performance was assessed through variable means to triangulate a more conclusive vantage point of associations that might present a pathway for further study. The tracker was a way to offer students a practice for self-monitoring or self-evaluation to reinforce self-accountability. This was to have students build and attest to self-efficacy through personal assessment and personal progress monitoring. Students were to complete the tracker daily as a form of an exit ticket to aid them in the development of personal-accountability and self-reflection with the accommodation of rubrics for each observable transfer skill introduced in the research. In Table 1, the data showed the differences between the pre- and posttest scores for math part 1 and the differences between the pre- and posttest scores for math part 2 paired with the following transfer skills Daily Frequency Percentages: metacognition, decomposition, self-efficacy, digital technology use, and CCSS Math Practices (#1,4,7,8). Analyzing the differences between the pre- and posttest data of math sections part 1 and part 2, the Metacognition Tracker Daily Frequency Percentage and the Decomposition Tracker Daily Frequency Percentage had moderate positive correlations; the differences between the pre- and posttest for math part 2 were found with a moderate positive association when paired with the Daily Frequency Percentage of the Self Efficacy Tracker and the Decomposition Tracker; and the Digital Technology Use Tracker, and the CCSS Math Practices (#1,4,7,8)

Tracker results with the pairing of pre- and post-math tests part 2 differences, whether showing a moderate positive or negative association, did not pass the null hypothesis. This positioned each of the aforementioned as not statistically significant.

Table 1. Correlations: Math Transfer Skills and Daily Frequency Percentages

Transfer Skill	Math Test Part	Pearson r	2-Tailed p-value	Spearman ρ	2-Tailed p-value	N	Interpretation
Metacognition Daily Frequency Percentage	Part 1	0.376	0.186	0.334	0.244	14	Moderate positive correlation (not statistically significant)
	Part 2	0.353	0.216	0.403	0.153	14	Moderate positive correlation (not statistically significant)
Decomposition Daily Frequency Percentage	Part 1	0.437	0.118	0.308	0.285	14	Moderate positive correlation (not statistically significant)
	Part 2	0.357	0.21	0.341	0.233	14	Moderate positive correlation (not statistically significant)
Self-Efficacy Daily Frequency Percentage	Part 2	0.408	0.148	0.396	0.161	14	Moderate positive correlation (not statistically significant)
Digital Technology Use Daily Frequency Percentage	Part 2	0.357	0.21	-0.215	0.459	14	Moderate positive Pearson correlation, negative Spearman correlation (not statistically significant)
CCSS MPs (1, 4, 7, 8) Daily Frequency Percentage	Part 2	0.444	0.112	0.363	0.202	14	Moderate positive correlation (not statistically significant)

Math Pretest and Posttest Differences compared with Surveyed Transfer Skills

For the action research, giving students a survey became another way to gather data. When compared with surveyed transferred skills, associations to the growth scores in math were as follows: the differences in pre/post survey scores on self-efficacy, the differences in pre/post survey scores on algorithms, and the differences in pre/post survey scores on CCSS Math Practice (#1) showed strong correlations that were statistically significant to part 2 of the math assessment which focused on "ratios from graph (6.RP.A.3 & 6.EE.9)." The differences in pre/post survey scores on self-efficacy with a Pearson's correlation coefficient, $r = -0.526$, and a 2-tailed p-value, $P = 0.044$, the differences in pre/post survey scores on algorithm with $r = -0.538$, and a 2-tailed p-value= 0.038, and the differences in pre/post survey scores on CCSS Math Practice (#1) with $r = -0.633$ and a 2-tailed p-value= 0.012, a negative correlation relationship was identified. When Spearman rho-value and 2-tailed p-value was applied to the comparison of the math part 2 pretest and posttest differences, the differences in pre/post survey scores on self-efficacy ($\rho= -0.308$; N=15; 2-tailed=0.264) and the differences in pre/post survey scores on algorithm ($\rho= -0.349$; N=15; 2-tailed=0.202) had a weak negative monotonic relationship that was not statistically significant. Though the differences in pre/post survey scores on CCSS Math Practice (#1) ($\rho= -0.434$; N=15; 2-tailed=0.106) was recognized as having a negative monotonic relationship; it was not statistically significant as well.

Looking further at the associations between the surveyed transfer skills and the math pre- and posttest scores difference, data showed a moderate negative correlation in the comparison of part 2 of the differences in math pre/post test scores with the differences in pre/post survey scores on metacognition ($r = -0.476$), the differences in pre/post survey scores on questioning ($r = -0.228$), the differences in pre/post survey scores on abstraction ($r = -0.356$), and the differences in pre/post survey scores on digital technology ($r = -0.398$). The differences in pre/post survey scores on CCSS Math Practice (#7) showed a moderate positive correlation with part 1 of the differences in math pre/post test scores ($r = 0.403$). Though negative in their associations, the differences in pre/post survey scores on decomposition gave moderate correlations with both part 1 (r being equal to -0.315) and part 2 (where r equals -0.366) of the math pre/post test scores differences.

In light of all the moderate correlations identified, all comparisons were deemed statistically insignificant with Pearson's 2-tailed p-values as presented: the differences in pre/post survey scores on metacognition (2-tailed p-value= 0.074), the differences in pre/post survey scores on questioning (2-tailed p-value= 0.414), the differences in pre/post survey scores on abstraction (2-tailed p-value= 0.192), the differences in pre/post survey scores on digital technology use (2-tailed p-value= 0.142), the differences in pre/post survey scores on CCSS Math Practice (#7) (2-tailed p-value= 0.136) , and the differences in pre/post survey scores on decomposition (2-tailed p-value= 0.252 for part 1, and 2-tailed p-value= 0.18 for part 2). Spearman's 2-tailed p-values echoed the same statistically insignificance in the differences in pre/post survey scores on metacognition ($\rho = -0.237$; N=15; 2-tailed p-value=0.396), the differences in pre/post survey scores on questioning ($\rho = -0.115$; N=15; 2-tailed p-value=0.682), the differences in pre/post survey scores on abstraction ($\rho = -0.334$; N=15; 2-tail-value = 0.224), the differences in pre/post survey scores on digital technology use ($\rho = -0.15$; N=15; 2-tailed p-value = 0.593), the differences in pre/post survey scores on CCSS Math Practice (#7) ($\rho = 0.099$; N=15; 2-tailed = 0.727) , and the differences in pre/post survey scores on decomposition (ρ = -0.321; N=15; 2-tailed = 0.243).

The differences in pre/post survey scores on Metacognition, Questioning, Self Efficacy, Abstraction, Algorithms, Digital Technology Use, and CCSS Math Practice (#1) were all warranted as statistically non-significant as shown with both Pearson and Spearman's p-values and when compared with the differences in the pre/post math tests part 1 scores from receiving a 2-tailed p-value greater than 0.05. To add, the differences in pre/post survey scores on Pattern Recognition, CCSS Math Practice (#4), and CCSS Math Practice (#8) failed to reject the null-hypothesis (H0) when compared with the differences in pre/post math test scores for parts 1 and 2 (see Table 2 for Spearman's coefficients and p-values).

Table 2. Spearman Correlations: Test Score Differences and Daily Frequencies

		Difference Pre- and Posttest Math PT1	Difference Pre- and Posttest Math PT2	Difference Pre- and Posttest Sci PT1	Difference Pre- and Posttest Sci PT2	Difference Pre- and Posttest Sci PT3	Difference Pre- and Post- Self-Efficacy	Self- Efficacy Tracker Daily Frequency Percentage
Difference Pre- and Posttest Math PT1	Correlation Coefficient	1	0.318	0.314	-0.333	0.275	-0.176	0.097
	Sig.	.	0.248	0.254	0.226	0.321	0.53	0.742
	N	15	15	15	15	15	15	14
Difference Pre- and Posttest Math PT2	Correlation Coefficient	0.318	1	0.406	0.308	-0.063	-0.308	0.396
	Sig.	0.248	.	0.133	0.264	0.825	0.264	0.161
	N	15	15	15	15	15	15	14
Difference Pre- and Posttest Sci PT1	Correlation Coefficient	0.314	0.406	1	0.126	0.054	-0.292	0.359
	Sig.	0.254	0.133	.	0.641	0.841	0.291	0.189
	N	15	15	16	16	16	15	15
Difference Pre- and Posttest Sci PT2	Correlation Coefficient	-0.333	0.308	0.126	1	0.022	-0.173	0.466
	Sig.	0.226	0.264	0.641	.	0.935	0.537	0.08
	N	15	15	16	16	16	15	15
Difference Pre- and Posttest Sci PT3	Correlation Coefficient	0.275	-0.063	0.054	0.022	1	0.122	0.141
	Sig.	0.321	0.825	0.841	0.935	.	0.664	0.615
	N	15	15	16	16	16	15	15
Difference Pre- and Post- Survey Decomposition	Correlation Coefficient	-0.321	-0.072	-0.172	0.132	0.129	.665**	0.078
	Sig.	0.243	0.8	0.541	0.638	0.648	0.007	0.791
	N	15	15	15	15	15	15	14
Difference Pre- and Post-	Correlation Coefficient	-0.236	-0.128	-0.093	0.103	0.095	.736**	0.088

		Difference Pre- and Posttest Math PT1	Difference Pre- and Posttest Math PT2	Difference Pre- and Posttest Sci PT1	Difference Pre- and Posttest Sci PT2	Difference Pre- and Posttest Sci PT3	Difference Pre- and Post- Self-Efficacy	Self- Efficacy Tracker Daily Frequency Percentage
Survey Pattern Recognition	Sig.	0.398	0.65	0.742	0.716	0.737	0.002	0.765
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Abstraction	Correlation Coefficient	-0.334	-0.334	-0.084	0.01	0.015	.755**	-0.205
	Sig.	0.223	0.224	0.766	0.971	0.957	0.001	0.482
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Algorithms	Correlation Coefficient	-0.349	-0.293	-0.08	-0.255	-0.079	.747**	-0.504
	Sig.	0.202	0.29	0.777	0.358	0.781	0.001	0.066
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey MP1	Correlation Coefficient	-0.25	-0.434	-0.262	-0.241	0.103	.883**	-0.477
	Sig.	0.369	0.106	0.345	0.388	0.716	<.001	0.084
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey MP4	Correlation Coefficient	-0.178	-0.382	-0.15	-0.213	-0.07	.826**	-0.283
	Sig.	0.526	0.16	0.594	0.447	0.804	<.001	0.327
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey MP7	Correlation Coefficient	0.099	0.076	0	-0.228	0.39	.552*	0.007
	Sig.	0.727	0.787	1	0.413	0.15	0.033	0.982
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey MP8	Correlation Coefficient	-0.037	0.163	-0.098	-0.04	0.298	0.38	0.084
	Sig.	0.896	0.562	0.73	0.886	0.281	0.162	0.774
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Metacognition	Correlation Coefficient	-0.029	-0.237	-0.239	-0.294	0.153	.970**	-0.397
	Sig.	0.917	0.396	0.391	0.287	0.587	<.001	0.16
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Questioning	Correlation Coefficient	-0.063	-0.115	-.564*	-0.327	-0.249	0.399	-.654*
	Sig.	0.824	0.682	0.029	0.234	0.371	0.141	0.011
	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Digital	Correlation Coefficient	0.323	-0.15	-0.073	-0.031	0.181	0.385	-0.237
	Sig.	0.24	0.593	0.797	0.914	0.518	0.156	0.414

		Difference Pre- and Posttest Math PT1	Difference Pre- and Posttest Math PT2	Difference Pre- and Posttest Sci PT1	Difference Pre- and Posttest Sci PT2	Difference Pre- and Posttest Sci PT3	Difference Pre- and Post- Self-Efficacy	Self- Efficacy Tracker Daily Frequency Percentage
Technology Tools	N	15	15	15	15	15	15	14
Difference Pre- and Post-Survey Self Efficacy	Correlation Coefficient	-0.176	-0.308	-0.292	-0.173	0.122	1	-0.304
	Sig.	0.53	0.264	0.291	0.537	0.664	.	0.29
	N	15	15	15	15	15	15	14
Decomposition Tracker Daily Frequency Percentage	Correlation Coefficient	0.308	0.341	0.152	0.241	-0.146	-0.407	.803**
	Sig.	0.285	0.233	0.587	0.386	0.603	0.148	<.001
	N	14	14	15	15	15	14	15
Pattern Recognition Tracker Daily Frequency Percentage	Correlation Coefficient	0.15	0.221	0.023	0.283	0.222	-0.155	.533*
	Sig.	0.61	0.448	0.936	0.306	0.426	0.597	0.041
	N	14	14	15	15	15	14	15
Abstraction Tracker Daily Frequency Percentage	Correlation Coefficient	0.307	0.292	-0.019	0.28	0.246	-0.3	.676**
	Sig.	0.286	0.31	0.945	0.313	0.376	0.298	0.006
	N	14	14	15	15	15	14	15
Algorithms Tracker Daily Frequency Percentage	Correlation Coefficient	0.057	0.139	-0.098	0.452	0.236	-0.248	.733**
	Sig.	0.847	0.636	0.729	0.091	0.398	0.392	0.002
	N	14	14	15	15	15	14	15
Metacognition Tracker Daily Frequency Percentage	Correlation Coefficient	0.334	0.403	0.252	0.146	0.057	-0.174	.748**
	Sig.	0.244	0.153	0.365	0.603	0.841	0.551	0.001
	N	14	14	15	15	15	14	15
Questioning Tracker Daily Frequency Percentage	Correlation Coefficient	0.171	0.265	-0.128	0.246	-0.095	-0.355	.586*
	Sig.	0.559	0.36	0.649	0.377	0.738	0.212	0.022
	N	14	14	15	15	15	14	15
Self-Efficacy Tracker Daily Frequency Percentage	Correlation Coefficient	0.097	0.396	0.359	0.466	0.141	-0.304	1
	Sig.	0.742	0.161	0.189	0.08	0.615	0.29	.
	N	14	14	15	15	15	14	15
Digital Tech Use Tracker Daily	Correlation Coefficient	-0.215	0.262	0.027	0.496	0.122	-0.193	.763**
	Sig.	0.459	0.366	0.925	0.06	0.666	0.508	<.001

		Difference Pre- and Posttest Math PT1	Difference Pre- and Posttest Math PT2	Difference Pre- and Posttest Sci PT1	Difference Pre- and Posttest Sci PT2	Difference Pre- and Posttest Sci PT3	Difference Pre- and Post- Self-Efficacy	Self- Efficacy Tracker Daily Frequency Percentage
Frequency Percentage	N	14	14	15	15	15	14	15
MPs 1,4,7,8 Tracker Daily Frequency Percentage	Correlation Coefficient	-0.206	0.363	0.475	.582*	0.135	-0.439	.674**
	Sig.	0.481	0.202	0.073	0.023	0.631	0.117	0.006
	N	14	14	15	15	15	14	15

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Science Pretest and Posttest Differences compared with Tracked Transfer Skills

Investigating the impact of transfer skills across disciplines included the science content as well. Analysis from the comparison of the differences in the science pretest and posttest scores with the average percentages posted from tracker data on each transferred skill application did offer some promising findings as part 2 of the science test was inspected. The differences in the pretest and posttest scores for part 2 brought to light strong positive associations when paired with the Digital Technology Use Tracker ($r = 0.546$), and the CCSS Math Practices (#1,4,7,8) Tracker ($r = 0.545$). These values were statistically significant for Pearson's p-values where the Digital Technology Use Tracker comparison had a 2-tailed p-value of "0.036", as did in the noted relation with the tracker's identification of the transfer skills for the CCSS Math Practices (#1,4,7,8) having the same p-value. However, only the comparison with the transfer skills for the CCSS Math Practices (#1,4,7,8) passed the null hypothesis with Spearman's p-value ($\rho = 0.582$*; N=15; 2-tailed p-value=0.023) giving acknowledgment to having a moderate positive relationship. This still remained a concern due to the limited duration of transfer skills. The Digital Technology Use Tracker provided nine days of data, and the CCSS Math Practices (1,4,7,8) were tracked for six days.

In regard to the other transfer skills, though some had moderate correlations, all were statistically nonsignificant ranging from a 2-tailed p-value of "0.064" to a 2-tailed p-value of "0.992" (see Table 3, 4, and 5).

Table 3. Pearson's P-Values among Science Part 1 Differences and Frequencies

Difference Pre- and Posttest Sci PT1	Sig. (1-tailed)	Sig. (2-tailed)
Math Practices 1,4,7,8 Tracker Daily Frequency Percentage	0.036	0.072
Self-Efficacy Tracker Daily Frequency Percentage	0.129	0.258
Metacognition Tracker Daily Frequency Percentage	0.154	0.308
Decomposition Tracker Daily Frequency Percentage	0.242	0.484
Questioning Tracker Daily Frequency Percentage	0.341	0.682

Difference Pre- and Posttest Sci PT1	Sig. (1-tailed)	Sig. (2-tailed)
Algorithms Tracker Daily Frequency Percentage	0.358	0.716
Pattern Recognition Tracker Daily Frequency Percentage	0.373	0.746
Abstraction Tracker Daily Frequency Percentage	0.376	0.752
Digital Tech Use Tracker Daily Frequency Percentage	0.488	0.976

Table 4. Pearson's P-Values among Science Part 2 Differences and Frequencies

Difference Pre- and Posttest Sci PT2	Sig. (1-tailed)	Sig. (2-tailed)
Digital Tech Use Tracker Daily Frequency Percentage	0.018	0.036
Math Practices 1,4,7,8 Tracker Daily Frequency Percentage	0.018	0.036
Self-Efficacy Tracker Daily Frequency Percentage	0.032	0.064
Algorithms Tracker Daily Frequency Percentage	0.045	0.09
Pattern Recognition Tracker Daily Frequency Percentage	0.046	0.092
Metacognition Tracker Daily Frequency Percentage	0.089	0.178
Questioning Tracker Daily Frequency Percentage	0.111	0.222
Decomposition Tracker Daily Frequency Percentage	0.135	0.27
Abstraction Tracker Daily Frequency Percentage	0.176	0.352

Table 5. Pearson's P-Values among Science Part 3 Differences and Frequencies

Difference Pre- and Posttest Sci PT3	Sig. (1-tailed)	Sig. (2-tailed)
Math Practices 1,4,7,8 Tracker Daily Frequency Percentage	0.143	0.286
Digital Tech Use Tracker Daily Frequency Percentage	0.205	0.41
Pattern Recognition Tracker Daily Frequency Percentage	0.234	0.468
Algorithms Tracker Daily Frequency Percentage	0.242	0.484
Abstraction Tracker Daily Frequency Percentage	0.277	0.554
Self-Efficacy Tracker Daily Frequency Percentage	0.351	0.702
Decomposition Tracker Daily Frequency Percentage	0.351	0.702
Questioning Tracker Daily Frequency Percentage	0.36	0.72
Metacognition Tracker Daily Frequency Percentage	0.496	0.992

Science Pretest and Posttest Differences compared with Surveyed Transfer Skills

The analysis showed with Pearson's coefficient moderate negative associations between the differences in the science pretest and posttest scores for part 2 with the differences of pre- and posttest surveys scores in the

Metacognition Pre/post surveys (r = -0.397), Questioning pre- and post-survey score differences (r = -0.397), Self Efficacy pre- and post-survey score differences (r = -0.307), Algorithms pre- and post-survey score differences (r = -0.321), CCSS Math Practices (#1) pre- and post-survey score differences (r = -0.321), and CCSS Math Practices (#7) pre- and post-survey score differences (r = -0.3). A Moderate positive correlation was noticed with part 1 of the pre- and post-science test score differences and the pre- and post-survey score differences in CCSS Math Practices (#7) pre- and post-survey score differences (r = 0.38); but moderate negative correlations were then recognized with the Questioning pre- and post-survey score differences (r = -0.495), Decomposition pre- and post-survey score differences (r = -0.362), CCSS Math Practices (#1) pre- and post-survey score differences (r = -0.394), when related to part 1 of the science test score differences with the pretests and posttests.

Ultimately, the findings in the analysis of the data when comparing the differences in the science pretest and posttest scores from parts' 1, 2, and 3, with all the differences calculated within the pre- and post-surveys on the transferred skills revealed that their 2-tailed p-values were statistically insignificant ranging from "0.06" to "0.98" (see Table 6, 7, and 8).

Table 6. Pearson's P-Values among Science Part 1 Differences and Surveys

Difference Pre- and Posttest Sci PT1	Sig. (1-tailed)	Sig. (2-tailed)
Difference Pre- and Post-Survey Questioning	0.03	0.06
Difference Pre- and Post-Survey MP1	0.073	0.146
Difference Pre- and Post-Survey Decomposition	0.092	0.184
Difference Pre- and Post-Survey Self Efficacy	0.178	0.356
Difference Pre- and Post-Survey Metacognition	0.227	0.454
Difference Pre- and Post-Survey Algorithms	0.276	0.552
Difference Pre- and Post-Survey Digital Technology Tools	0.28	0.56
Difference Pre- and Post-Survey Abstraction	0.317	0.634
Difference Pre- and Post-Survey MP8	0.343	0.686
Difference Pre- and Post-Survey MP7	0.401	0.802
Difference Pre- and Post-Survey Pattern Recognition	0.446	0.892
Difference Pre- and Post-Survey MP4	0.46	0.92

Table 7. Pearson's P-Values among Science Part 2 Differences and Surveys

Difference Pre- and Posttest Sci PT2	Sig. (1-tailed)	Sig. (2-tailed)
Difference Pre- and Post-Survey Metacognition	0.072	0.144
Difference Pre- and Post-Survey Questioning	0.072	0.144
Difference Pre- and Post-Survey MP1	0.121	0.242

Difference Pre- and Posttest Sci PT2	Sig. (1-tailed)	Sig. (2-tailed)
Difference Pre- and Post-Survey Algorithms	0.122	0.244
Difference Pre- and Post-Survey Self Efficacy	0.133	0.266
Difference Pre- and Post-Survey MP7	0.139	0.278
Difference Pre- and Post-Survey Abstraction	0.282	0.564
Difference Pre- and Post-Survey MP4	0.301	0.602
Difference Pre- and Post-Survey Digital Technology Tools	0.334	0.668
Difference Pre- and Post-Survey Decomposition	0.359	0.718
Difference Pre- and Post-Survey MP8	0.417	0.834
Difference Pre- and Post-Survey Pattern Recognition	0.49	0.98

Table 8. Pearson's P-Values among Science Part 3 Differences and Surveys

Difference Pre- and Posttest Sci PT3	Sig. (1-tailed)	Sig. (2-tailed)
Difference Pre- and Post-Survey MP7	0.081	0.162
Difference Pre- and Post-Survey MP8	0.231	0.462
Difference Pre- and Post-Survey Decomposition	0.251	0.502
Difference Pre- and Post-Survey Questioning	0.266	0.532
Difference Pre- and Post-Survey Metacognition	0.339	0.678
Difference Pre- and Post-Survey Self Efficacy	0.339	0.678
Difference Pre- and Post-Survey MP4	0.358	0.716
Difference Pre- and Post-Survey Pattern Recognition	0.36	0.72
Difference Pre- and Post-Survey Algorithms	0.369	0.738
Difference Pre- and Post-Survey Digital Technology Tools	0.385	0.77
Difference Pre- and Post-Survey MP1	0.413	0.826
Difference Pre- and Post-Survey Abstraction	0.485	0.97

Under the Spearman Rank-Order Correlation Coefficient the pairing with the science part 1 pre- and post-survey score differences, the Questioning pre- and post-survey score differences (ρ = -.564*; N=15; 2-tailed=0.029) had a moderate negative monotonic relationship that was statically significant. The negative relationship presented inquiry in the research as questioning is generally framed with metacognition.

Self-Efficacy Pre- and Post-Surveyed Differences compared with Tracked Transfer Skills

Self-efficacy was a critical part to consider during the investigation as it was an element that affects the students' social-emotional learning which impacts the learning outcomes in the students' performance. Data was collected in a pre-survey and post-survey for students' initial and final impressions of their own work. The data showed that when compared with the presurvey and postsurvey differences for self-efficacy, the Metacognition Tracker Daily Frequency Percentage, Questioning Tracker Daily Frequency Percentage, Math Practices 1,4,7,8 Tracker Daily Frequency Percentage, Decomposition Tracker Daily Frequency Percentage, Pattern Recognition Tracker Daily Frequency Percentage, Abstraction Tracker Daily Frequency Percentage, Algorithms Tracker Daily Frequency Percentage, Self Efficacy Tracker Daily Frequency Percentage, and Digital Tech Use Tracker Daily Frequency Percentage had a 2-tailed p-value greater than "0.05," placing all variables paired with self-efficacy pre- and post-survey score differences as having no significance statistically which voided the Math Practices 1,4,7,8 Tracker Daily Frequency Percentage as having a moderate correlation using Pearson's p-values. All other associations were identified as weak (see Table 9).

Table 9. Pearson's P-Values**:** Self-Efficacy Survey Differences and Frequencies Percentages

Difference Pre- and Post-Survey Self Efficacy	Sig. (1-tailed)	Sig. (2-tailed)
Math Practices 1,4,7,8 Tracker Daily Frequency Percentage	0.05	0.1
Questioning Tracker Daily Frequency Percentage	0.165	0.33
Decomposition Tracker Daily Frequency Percentage	0.185	0.37
Digital Tech Use Tracker Daily Frequency Percentage	0.187	0.374
Self-Efficacy Tracker Daily Frequency Percentage	0.231	0.462
Metacognition Tracker Daily Frequency Percentage	0.285	0.57
Abstraction Tracker Daily Frequency Percentage	0.313	0.626
Algorithms Tracker Daily Frequency Percentage	0.36	0.72
Pattern Recognition Tracker Daily Frequency Percentage	0.389	0.778

Self-Efficacy Pre- and Post-Surveyed Differences compared with Surveyed Transfer Skills

The data throughout the research appeared bleak, but the analysis of the differences for the pre-survey and post-survey for self-efficacy posed a different picture, with the exception of the Questioning pre- and post-survey differences ($r = 0.391$; 2-tailed p-value = 0.15; $\rho = 0.399$; N=15; 2-tailed p-value = 0.141), Digital Technology Use Pre/post survey ($r = 0.534$; 2-tailed p-value= 0.04; $\rho = 0.385$; N=15; 2-tailed p-value = 0.156), and the CCSS Math Practice (#8) pre- and post-survey differences ($r = 0.268$; 2-tailed p-value = 0.334; $\rho = 0.38$; N=15; 2-tailed p-value = 0.162) being statistically insignificant looking at either Pearson or Spearman's p-values, all other comparisons were found statistically significant. The CCSS Math Practice (#4) pre- and post-survey score differences ($r = 0.715$; 2-tailed p-value= 0.002; $\rho = .826^{**}$; N=15; 2-tailed p-value < 0.001), and the CCSS Math Practice (#7) pre- and post-survey score differences ($r = 0.553$; 2-tailed p-value = 0.032; $\rho = 0.552^{*}$; N=15; 2-tailed p-value = 0.033), modeled strong positive correlations with statistically significant data, and while both had a positive monotonic relationship, CCSS Math Practice (#7) pre- and post-survey score differences carried a moderate relationship as CCSS Math Practice (#4) pre- and post-survey score differences were strong according to the Spearman Rank-Order Correlation Coefficient.

Interestingly, the remaining variables offered p-values of $p < 0.0001$ with Pearson's coefficient. These statistically significant variables displayed strong positive associations to the differences for the pre-survey and post-survey for self-efficacy. They are as follows: Metacognition pre- and post-survey score differences ($r = 0.989$; 2-tailed p-value = 0; $\rho = 0.970$**; N=15; 2-tailed p-value < 0.001), CCSS Math Practices (#1) pre- and post-survey score differences ($r = 0.911$; 2-tailed p-value = 0; ; $\rho = 0.883$**; N=15; 2-tailed p-value < 0.001), Decomposition pre- and post-survey score differences ($r = 0.796$; 2-tailed p-value = 0; $\rho = .665$**; N=15; 2-tailed p-value = 0.007),Pattern Recognition pre- and post-survey score differences ($r = 0.784$; 2-tailed p-value= 0; $\rho = 0.736$**; N=15; 2-tailed p-value = 0.002), Abstraction pre- and post-survey score differences ($r = 0.829$; 2-tailed p-value = 0; $\rho = 0.755$**; N=15; 2-tailed p-value = 0.001), and Algorithms pre- and post-survey score differences y ($r = 0.823$; 2-tailed p-value = 0; $\rho = 0.747$**; N=15; 2-tailed p-value = 0.001). While the comparison of the self-efficacy pre- and post-surveyed differences with Decomposition pre- and post-survey score differences, Pattern Recognition pre- and post-survey score differences, and Abstraction pre- and post-survey score differences had strong positive monotonic relationships, the comparison with Metacognition pre- and post-survey score differences, and CCSS Math Practices (#1) pre- and post-survey score differences pose very strong positive monotonic relationships that are statistically significant as analyzed with Spearman coefficients and 2-tailed p-values.

Self-Efficacy Tracker Daily Frequency Percentages compared with Tracked Transfer Skills

As data was further analyzed, there were variable comparisons that stood out. When provided with the perspective from Spearman Rank-Order Correlation and p-values, the comparison of self-efficacy tracker daily frequency percentages with metacognition tracker daily frequency percentages ($\rho = 0.748$**; N=15; 2-tailed p-value = 0.001), questioning tracker daily frequency percentages ($\rho = 0.586$*; N=15; 2-tailed p-value = 0.022), decomposition tracker daily frequency percentages ($\rho= 0.803$**; N=15; 2-tailed p-value = < 0.001), pattern recognition tracker daily frequency percentages ($\rho = 0.533$* ; N=15; 2-tailed p-value = 0.041) , abstraction tracker daily frequency percentages ($\rho = 0.676$**; N=15; 2-tailed p-value = 0.006), algorithms tracker daily frequency percentages ($\rho = 0.733$**; N=15; 2-tailed p-value = 0.002), digital tech use tracker daily frequency percentages ($\rho = 0.763$** ; N=15; 2-tailed p-value = < 0.001), and math practices 1,4,7,8 tracker daily frequency percentages ($\rho = .674$**; N=15; 2-tailed p-value = 0.006) were all statistically significant.

Each variable had a positive monotonic relationship with the tracker for self-efficacy daily frequency percentages with most presenting strong monotonic relationships. The comparison of the self-efficacy tracker daily frequency percentages with questioning tracker daily frequency percentages and the pattern recognition tracker daily frequency percentages did show moderate positive relationships among this cluster of variable pairs. Among all, the decomposition tracker daily frequency percentages and self-efficacy tracker daily frequency percentages pairing showed a very strong positive monotonic relationship. Tables 10 and 11 include the averages, sample population, standard deviation, and variance of all the variables mentioned.

Table 10. Descriptive Statistics for Tests Differences and Survey Differences

	N	Range	Minimum	Maximum	Mean	Std. Error	Std. Deviation	Variance
Difference Pre- and Posttest Math PT1	15	5	-4	1	-0.6	0.38791	1.50238	2.257
Difference Pre- and Posttest Math PT2	15	6	-2	4	0.0667	0.37118	1.43759	2.067
Difference Pre- and Posttest Sci PT1	16	2	1	3	1.875	0.15478	0.61914	0.383
Difference Pre- and Posttest Sci PT2	16	2	-1	1	0.3125	0.15052	0.60208	0.363
Difference Pre- and Posttest Sci PT3	16	4	-3	1	-0.1875	0.26171	1.04682	1.096
Difference Pre- and Post-Survey Self-Efficacy	15	1.1	-0.72	0.38	-0.1016	0.06708	0.25981	0.068
Difference Pre- and Post-Survey Metacognition	15	1.1	-0.71	0.39	-0.1072	0.06743	0.26117	0.068
Difference Pre- and Post-Survey Questioning	15	1.33	-0.83	0.5	-0.0889	0.11714	0.45367	0.206
Difference Pre- and Post-Survey Digital Technology Tools	15	1.8	-1	0.8	-0.0267	0.11525	0.44636	0.199

Table 10. Descriptive Statistics for Test Differences and Survey Differences (Continued)

	N	Range	Minimum	Maximum	Mean	Std. Error	Std. Deviation	Variance
Difference Pre- and Post-Survey Decomposition	15	1.27	-0.91	0.36	-0.1027	0.08906	0.34493	0.119
Difference Pre- and Post-Survey Pattern Recognition	15	1.12	-0.65	0.47	-0.1137	0.08249	0.31947	0.102
Difference Pre- and Post-Survey Abstraction	15	1	-0.65	0.35	-0.1098	0.07236	0.28023	0.079
Difference Pre- and Post-	15	1.1	-0.8	0.3	-0.1067	0.07136	0.27637	0.076

Survey Algorithms								
Difference Pre- and Post-Survey MP1	15	1.08	-0.84	0.24	-0.128	0.07439	0.28813	0.083
Difference Pre- and Post-Survey MP4	15	1.33	-0.83	0.5	-0.1333	0.10184	0.39441	0.156
Difference Pre- and Post-Survey MP7	15	1.38	-1	0.38	-0.1333	0.10806	0.41851	0.175
Difference Pre- and Post-Survey MP8	15	1.33	-0.83	0.5	-0.1667	0.08452	0.32733	0.107

Table 11. Descriptive Statistics for Daily Frequency Percentages

	N	Range	Minimum	Maximum	Mean	Std. Error	Std. Deviation	Variance
Metacognition Tracker Daily Frequency Percentage	15	0.76	0.21	0.97	0.6902	0.0662	0.25637	0.066
Questioning Tracker Daily Frequency Percentage	15	0.79	0.18	0.97	0.602	0.06743	0.26115	0.068
Self-Efficacy Tracker Daily Frequency Percentage	15	0.73	0.27	1	0.7333	0.06316	0.24462	0.06
Decomposition Tracker Daily Frequency Percentage	15	0.66	0.34	1	0.7494	0.05872	0.22742	0.052
Pattern Recognition Tracker Daily Frequency Percentage	15	0.75	0.25	1	0.7048	0.05764	0.22323	0.05
Abstraction Tracker Daily Frequency Percentage	15	0.69	0.35	1.04	0.5949	0.06062	0.23479	0.055
Algorithms Tracker Daily Frequency Percentage	15	0.69	0.35	1.04	0.6564	0.0576	0.22307	0.05
Digital Tech Use Tracker Daily Frequency Percentage	15	0.89	0.11	1	0.6889	0.07909	0.30631	0.094
Math Practices 1,4,7,8 Tracker Daily Frequency Percentage	15	0.67	0.33	1	0.7222	0.05789	0.2242	0.05

Student Artifacts

Student artifacts were collected in the form of student journals. Though there were 16 participants, only 14 journals were turned in. Evidence of questioning was shown in the form of the Question Formulation Technique (QFT) where four students showed minimal effort in writing questions. Evidence for metacognition was seen with the use of mindmaps, which also was used to teach students to decompose a problem (CT). Ten students showed mind maps in their journals. Reflections were done in 8 journals. Reflection was counted as a form of metacognition. All the students showed evidence of note taking. Notes were also taken for Socratic seminars, but only five students showed evidence. Note taking/making was identified as a form of metacognition as well. There were several students which showed flowcharts which allowed them to practice algorithms. Storyboards were done by 2 students which would have enabled them to practice Computational Thinking with all four components: decomposition, pattern recognition, abstraction, and algorithms.

Limitations and Directions for Future Research

Limitations that were present did place reservations of how the results in the analysis would fare from the very beginning of the research. From the very beginning there were very few students and parents that felt comfortable doing the research even though it was addressed at the start that there would not be any identifiable information of students and parents nor would the data affect grades as grades would be finalized before the data would be used for collection and analysis for the research. To also play a part in the small population size was the effect of constant student absences. Some students missed weeks of instruction.

Teaching math tends to have limits due to the local district prescribing the curriculum of a particular publisher to normalize specific instructional practices and behaviors to meet high stakes testing. This placed some limitations on the freedom of creativity to implement Project-Based Lessons in some core content classes. This limited my pool of students to participate as only students in the elective class were able to join the study. Another limitation is the time frame in which the investigation was carried out. The only time available within the time window to implement the study was around state and district testing, which covered over a month of instructional time. This was also around spring break and ultimately rendering the study 34 days as opposed to the full 3 months of implementation. As with the sample size being small (N=16), the desire to try this investigation again but with a larger size of participants. Maybe enlisting another teacher to collaborate to increase the number of student participants.

Mentioned earlier in the literature review, it was established that self-efficacy builds the capacity of individuals to address challenges as their successful coping attempts reduced the impact of threats which is far more than those who have consistently failed (Bandura, 1977, p. 212). It was important to look at self-efficacy in the research. As the results showed in the research, self-efficacy was the crucial variable that provided some statistically significant outcomes in the data. Though promising in providing a more refined focus for the next steps in the ongoing quest to empower students, the findings were still inconclusive as to the immediate effects of the transfer skills and tools used to increase students' deep learning (McTighe, Silver, & Perini, n.d., p. 3). Could this be the main element to achieving and tackling cognitively challenging tasks and academic rigor through higher order thinking? In a paper written by Nancy Budwig and Achu Johnson Alexander (2020, October 15) it was stated, "The tendency to approach formal learning contexts with an inclination to inquire often depends on the kind of schools students have attended prior to attending college" (para.7). If students are to have opportunities to learn through problem-posing education as Freire (2000) prescribes, there needs to be an affirmative answer to bringing the transdisciplinary learning skills to students of our underrepresented populations to have an equitable opportunity to compete in the race to solve our wicked global problems.

Conclusion

If self-efficacy is the key ingredient, then how practical is it to expect students to engage meaningfully with rigorous, higher-order academic tasks through direct instruction focused solely on content? This challenges the notion that poor performance stems only from a lack of knowledge; perhaps it is the absence of belief in oneself that impedes success. Vygotsky's concept of the Zone of Proximal Development (ZPD) (Woolfolk, 2004, p. 52) prompts us to ask: Is this struggle primarily cognitive or affective in nature? When considering transdisciplinary thinkers—polymaths and Renaissance minds—their pursuit was not limited by what they did not know; rather, they were driven by a relentless quest for knowledge. So why do some individuals hesitate to venture beyond the boundaries of their current understanding? If self-efficacy is indeed the determining factor, the lack of knowledge becomes secondary. Those with strong self-efficacy become fearless seekers of learning.

Here lies a potential leverage point for addressing the achievement gap. Marginalized students, equipped with the belief in their own abilities, could meet the demands of academic rigor and higher-order thinking through transdisciplinary learning. But why transdisciplinary learning? Because it fosters the kind of broad, interconnected thinking that self-efficacy sustains. The next steps must involve identifying strategies that build self-efficacy and empower students to confidently apply transfer skills, making the rigor of transdisciplinary learning accessible and achievable for all.

Recommendations

Future research on the transdisciplinary learning approach should consider two primary recommendations: 1. adjusting the time of the investigation, and 2. implementing self-efficacy practices prior to the main investigation. First, it is advisable to start the research at the beginning of the Spring semester. Though there are a few holiday breaks present for students, the gaps between instructional days may be less impactful. This includes the consideration that state and district testing are not as great a distraction to the learning at the beginning of the second semester of school. This adjustment may also address the concern of fatigue that students might have post high-stakes testing.

Second, the implementation of self-efficacy strategies at the beginning of the first semester. The early development of self-efficacy may provide a stronger foundation for students to engage more fully in the transdisciplinary learning approach. This preparatory phase can support scaffolding of self-efficacy behaviors and habits which are likely to enhance students' perseverance and engagement when they are solving higher-order thinking problems that require transfer skills such as: computational thinking, the math practices, and digital tools applications. By establishing a more robust base of self-efficacy, the research method for examining transdisciplinary learning and its impact on underrepresented students can be more effective. To answer the questions - whether transdisciplinary learning is the best student-centered method for deep learning to achieve higher-order thinking, and how tools from multiple disciplines can be leveraged to facilitate transdisciplinary learning through transfer skills - researchers should incorporate matrices for self-efficacy and academic achievement.

In summary, research on transdisciplinary learning and unrepresented students' abilities to engage in higher-order thinking challenges may gain traction as the underrepresented students' self-concept is more empowered as that of students from more affluent communities. As self-efficacy, being paramount to one's capacity to address challenges, is accounted for pre-investigation of the transdisciplinary approach, the critical variables for supporting students' readiness for transdisciplinary learning may be realized in the refinement of the research design in fostering deep learning and skill transfer specifically among diverse student populations.

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