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# The Effects of Differentiated Technology Integration on Student Achievement in Middle School Science Classrooms

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This paper examines the effects of integrated technology teaching on student achievement in middle school science classrooms. Thirty-eight middle school science teachers participated in the year-long program titled Rural Science Teachers Teaching with Technology (RST3). The components of RST3, a model for professional development aimed at increasing middle school teachers' pedagogical content knowledge of technology integration in science instruction, are described in this paper, and the effects of the RST3 program on student achievement using teacher-designed lesson tests are reported. The unit of analysis in this study is middle school students disaggregated by four demographic groupings whose scores on lesson tests were randomly selected from a total of 5,043 lesson test scores. Multivariate analysis of variance was performed and the results suggest that technology integration level, SES, and IEP have significant impact on the science achievement scores.

Keywords: technology integration, science learning, middle school

## INTRODUCTION

The Rural Science Teachers Teaching with Technology (RST3) project was designed as a model for professional development aimed at increasing middle school teachers' pedagogical content knowledge of technology integration in science instruction. The RST3 model is based on national standards for science (NRC, 1996) and educational technology (ISTE, 2000) that call for the integration of technology into science and all content areas, and on the national standards for professional development (NSDC, 2003) that call for systemic, research-based programs.

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The goal of this program was to facilitate a professional teaching and learning community that would foster growth in teachers' motivation to increase their knowledge and skills for integrating technology into their science classrooms. This paper will briefly describe the RST3 program, and will then focus on the impact of differentiated technology integration on student science achievement scores by the demographic variables of gender, socio-economic status, special education, and ethnicity.

## THEORETICAL FRAMEWORK

The RST3 professional development model is grounded in situated learning theory that has its roots in Vygotsky's sociocultural theory (Reiber & Carton, 1987). To situate learning involves placing learners within a set of conditions in which they live the subject matter in the context of real-world (authentic) challenges, thus acquiring knowledge that transfers from the learning environment to the realm of practice. Situated learning theory suggests that learning must take place in authentic settings (Lave & Wenger, 1991) involving authentic activities and applications (J. S. Brown, Collins, & Duguid, 1989), and that learning is a social enterprise (Orange, 2002).

Vygotsky posited that social interaction plays a fundamental role in the development of cognition and that everything is learned on two levels—first through interaction and then integrated into the individual's mental structure (Vygotsky, 1978). This idea is a critical component in situated learning that has been applied in the context of technology-based learning activities for schools that focus on problem-solving skills (Technology & Cognition Group at Vanderbilt, 1993).

John Dewey's work and philosophy of experiential education fathered the rise of constructivism, a major theoretical influence in contemporary science and mathematics education (Matthews, 1994). From Dewey's perspective, the "naïve and unspoiled attitude of childhood, marked by ardent curiosity, fertile imagination, and love of experimental inquiry, is very near to the attitude of the scientific mind" (Dewey, 1910, p. vii). He also proposed that meaningful problems challenge learners to actively reflect on what they already know, and through comparing and contrasting ideas, will form reasonable hypotheses to be tested (Moyer, Hackett, & Everett, 2007).

Taken together, these theories about how people learn informed our direction as we developed our project with the goal to optimize learning by situating teachers in a rich learning environment with authentic tasks as a model for what we hoped they would then do with their own students in their own science classrooms. If today's students are to achieve their learning potential—specifically in science—then the tenets of these learning theories must be applied in the classroom using strategies and activities that reflect the best of what we know about how students learn. Students, too, must learn new material with understanding, engage in the process of inquiry as a key element of the culture of science, and reflect metacognitively on their own thinking and participation in science (Bransford & Donovan, 2005). To learn science with understanding requires students to engage in research, the mastery of which is a group responsibility (A. L. Brown & Campione, 1994), includes distributed expertise (A. Brown et al., 1993), and embraces multiple ways of knowing and doing (Armstrong, 1994). Engaging in inquiry means participation in discourse aimed at explaining natural phenomena using processes and activities in the same way that scientists conduct themselves as a community (Bereiter, Scardamalia, C., & Hewitt, 1997). Students must also engage in metacognition by comparing their new understandings to their initial knowledge in order to reflect and understand the development of their own thinking (Dewey, 1910; Moyer et al., 2007).

### The RST3 Model

The focus of the RST3 model was to provide teacher participants with both the training and the equipment to facilitate successful implementation of integrated technology in their science classrooms. A 3-credit graduate course was developed to include the elements of situated learning theory to help increase teachers' pedagogical content knowledge for technology integration in science. Professors and graduate students with expertise in science content, educational technology, pedagogy, and assessment facilitated the course sessions. Each teacher participant was given a technology package that included a laptop computer, an LCD projector, an electronic microscope, a flash drive, and a one-year high speed Internet connection at home. Five week-end class sessions took place over the course of a year with instruction and facilitation provided for appropriate pedagogical practice for technology integration, inquiry science teaching, and assessment.

The technology package provided the means by which teachers brought computers to every class session, which helped situate the learning within an authentic context of technology integration. Teachers participated within small groups that fostered social interaction and dialogue and were provided with rigorous and complex tasks requiring the use of their computers and the Internet, thus advancing their understanding as they negotiated new meanings within each new situation. Such activities provided a model for what they were expected to then implement in their own classroom.

The RST3 professional development model included four strands: teaching-as-research, technology integration strategies, lesson content development, and assessment development. A discussion of each strand follows.

*TEACHING-AS-RESEARCH*

Teaching-as-research is the systematic use of research methods to develop and implement teaching practices that advance the learning experiences and learning outcomes of students and teachers (Mathieu, 2000). It involves developing foundational knowledge, then creating goals for better student learning, defining measures of success, developing and implementing best practice methods, collecting and analyzing data, and making data-based teaching decisions in harmony with selected goals.

A critical feature of the RST3 model was to work together with teachers in some of the research activities as a model for how they might, on an ongoing basis, examine their own practice and determine the effectiveness of any new classroom interventions or teaching strategies they might implement by applying data collection and analysis strategies. The essence of situated learning is when experts and novices work together for a common product or goal within an authentic context. This shared productive activity is also identified as one of the five standards for effective pedagogy and student outcomes developed by the Center for Research on Education, Diversity & Excellence (Tharp, Estrada, Dalton, & Yamauchi, 2000). We included the teachers in several decision-making conversations relative to our research direction for this project. We also provided them with opportunities to apply research techniques in their own practice and bring results back to share with the group.

*TECHNOLOGY INTEGRATION STRATEGIES*

A significant block of instructional time was spent on demonstrating, discussing, and engaging in the various levels of technology integration ranging from what we defined as low interactivity such as using the Web as a source of reading material or using computers for word processing, to high interactivity, such as providing students with a more user-controlled interactive and creative experience including the use of interactive

software or Web sites with dynamic content. Teachers were provided with Web sites and software showing examples of interactive technology with varying degrees of interactivity that they explored and evaluated. Special emphasis was devoted to exploring high interactivity Web sites that required students to enter values for variables that resulted in changing outcomes that could serve as a data source for later analysis. During each session, teachers would share new technology integration ideas and resources they had located during the time between sessions.

### *LESSON DEVELOPMENT*

Lesson development was accomplished by teams of teachers from at least three schools in order to maximize the number of school settings across which data on the same lesson could be collected, and to capitalize on the potential power of social interaction among the teachers (Vygotsky, 1978). Topics for the lessons were selected by the teachers from their regular curriculum. Twenty-two lessons were developed by the teacher teams. Content for each lesson was reviewed by teacher peer groups and university educators for rigor, accuracy, and alignment with state and district science standards. The lessons were then made available online so that individual teachers could select and download the two lessons they would teach during the year of our study.
Based on the technology instruction provided during the course, teachers designed an integrated technology component for each lesson. Teachers had full control over the type and the content of the technology component, with the only parameter being that the technology component must function as a tool for teaching and learning the science content and not for the technology to *be* the content.

### *ASSESSMENT DEVELOPMENT*

Teachers were also provided with assessment training including test item development and test blueprint design that would be used for the end-of-lesson test. The test blueprints specified that each numbered item was to be of a specific type drawn from the cognitive and science content domains. The levels for the cognitive domain items were patterned after the specifications for the Trends in International Math and Science Study assessment (TIMSS, 2003) and included items for factual recall, conceptual understanding, and analysis/synthesis. In addition, three types of questions were developed—true/false, short answer, multiple choice. A final scenario question requiring problem solving skills including analysis and synthesis of science concepts was also developed. Teacher teams then used this test blueprint on their own to develop end-of-lesson tests for every lesson. So, while the content of each test varied by lesson, the format for the all tests was standardized by using the blueprint. For example, item #7 on the blueprint was to be a multiple choice item (type) that tested conceptual understanding (cognitive domain level) of a given concept from the content domain. Tests were peer-reviewed for accuracy and alignment with the test blueprint by groups of teachers during one of our class sessions.

## RESEARCH QUESTIONS

The question of whether or to what degree student achievement is impacted by technology in the classroom continues to be of interest to educational researchers. A major consideration underlying studies on the impact of technology is how the technology is used to facilitate learning. To help delineate uses of technology, some researchers have classified types of technology using differing categories. Uses of

technology as described by Maddux, Johnson and Willis (2001) are classified, using one of their several indicators, as Type I if the technology stimulates passive user involvement, or Type II if the technology stimulates active intellectual involvement. An example of Type I technology use might be using a computer to type a paper, while a Type II use would be entering data into a spreadsheet and graphing the results. Similarly, Reeves (1998) delineates the difference between learning *from* technology when students become passive recipients of knowledge, and learning *with* technology that engages students in real-world problem solving, critical thinking, and conceptual development (see Irving, 2006). Type II uses of technology (Maddux et al., 2001) and activities wherein students learn *with* technology (Reeves, 1998) seem to be more likely to contribute to meeting constructivist learning goals than are Type I uses or the act of learning *from* technology.

The *Inquiry Addendum* (NRC, 2000) to the *National Science Education Standards* (NRC, 1996) also identifies specific uses of technology that would likely be classified as Type II and/or learning *with* technology as "fundamental abilities of inquiry" for middle school students (p. 164). These activities include data collection, storage, retrieval, organization and analysis, along with formulation of logical arguments about cause-and effect-relationships in a given experiment. Reeves (1997) suggests that "cognitive tools" (p. 3) such as databases, spreadsheets, visualization software, etc. have their greatest effect in a constructivist learning environment, support deep reflective thinking (metacognition), and enable mindful, challenging learning. This type of technology use provides opportunities for students to use tools that are similar to the tools used by science professionals, thus making abstract concepts more tangible and dynamic for learners (Darling-Hammond et al., 2005; Edelson, Gordin, & Pea, 1997; Jackson, Krajcik, & Soloway, 2000).

Studies that link a type or category of technology use to student learning are not as prevalent as studies that do not distinguish among types or uses. Wenglinsky (1998) found that technology can be related to student achievement in mathematics, depending upon how it is used. His findings show a positive relationship to student achievement when computers were used to teach higher-order thinking skills, while the teaching of lower-order thinking skills was negatively related to academic achievement. Other studies have also underscored the differing results between Type I and Type II uses of technology. When used only for drill and practice, negative effects are often seen; when used as tools for engaging students in authentic, complex tasks within collaborative learning contexts such as scientific inquiry, the opposite effects occur. (Heibert, 1999; Papanastasiou, Zemblyas & Vrasidas, 2003; Rochelle, Pea, Hoadley, Gordin & Means, 2000; Ringstaff & Kelley,2002).

Without regard for the type or the way technology is used, other studies have found that instruction in classrooms where technology is used infrequently tends to be more teacher-centered (Waxman & Huang, 1996) while technology-rich instruction fosters more student-centered activities and more time on task (Waxman & Huang, 1996; Worthen, Van Dusen, & Sailor, 1994). In a meta-analysis of 20 studies that examined the effects of technology use on students' cognitive, affective, and behavioral learning outcomes, Waxman and his colleagues (Waxman, Connell, & Gray, 2002) found a modest positive effect. In addition, the findings showed no significant differences across contextual categories, thus allowing for generalization across a wide variety of conditions and student, school, and study characteristics. Several studies have also found positive effects for technology use on standardized test scores (Bain & Ross, 1999; Mann, Shakeshaft, Becker, & Kottkamp, 1999; Wenglinsky, 1998).

The current study attempts to establish a direct link between student learning outcomes disaggregated by cognitive type, (e.g. factual, conceptual and analytical) and

the level of technology interactivity used to teach science concepts in middle school science classrooms. Specifically, we sought to answer the following five questions:

1. Are there any significant mean differences in the science test subscale scores (Factual Item Scale, Conceptual Item Scale, and Scenario Analysis Scale) among students at different levels of technology integration?
2. Are there any significant mean differences in the science test subscale scores between male and female students who are at different levels of technology integration?
3. Are there any significant mean differences in the science test subscale scores between high and low SES (socio-economic status) students who are at different levels of technology integration?
4. Are there any significant mean differences in the science test subscale scores between special-education and non-special-education students who are at different levels of technology integration?
5. Are there any significant mean differences in the science test subscale scores among students specified by ethnicity who are at different levels of technology integration?

## METHODS

### *PARTICIPANTS*

Thirty-eight middle school science teachers from six rural Nevada school districts were recommended by their respective school district administrators for participation in the RST3 program. The teachers ranged in years of experience from three to 27 with a median of 11 years. Of the 38 teachers, 27 were female and 11 were male.

More than 2,520 $6^{th}$-$9^{th}$ grade students were enrolled in participating teachers' science classes, and a total of 5,043 test scores from two lessons were obtained from these students. Student scores were disaggregated by the demographic variables of gender (Males, $n$ = 2,626; Females, $n$ = 2,357), special education (Yes, $n$ = 672; No, $n$ = 4,371), socio-economic status as measured by participation in free or reduced lunch (SES) (Low, $n$ = 1,701; High, $n$ = 3,156), and ethnicity (Black, $n$ = 120; Hispanic, $n$ = 822; Asian, $n$ =123; American Indian, $n$ = 167; White, $n$ = 3,809).

### *INSTRUMENTATION*

Two instruments were used in the current study. First, teachers developed tests that were administered to their students at the end of each lesson. Each lesson test contained three subscales: (a) the Factual Item Scale consisting of nine 1-point questions, (b) the Conceptual Item Scale consisting of nine 1-point questions, and (c) the Scenario Item Scale, consisting of one 7-point comprehensive analysis question. Cronbach's alpha was used to evaluate internal consistency for the Factual Item Scale (.86) and the Conceptual Item Scale (.83). Because the Analysis Item Scale consisted of only one item, no alpha was calculated. However, the overall alpha for the lesson tests was found to be .87, suggesting that the scores were reasonably reliable for participants like those in the study (Green & Salkind, 2005, p. 331). Second, in order to determine the level of interactive technology integration for the technology component of each lesson, the researchers developed a simple classification scale along a continuum of interactivity ranging from low interactivity describing, for example, using a computer for simply reading text, to high interactivity describing, for example, using interactive Java applets requiring input from the students that would impact given outcomes that the students would need to then

interpret. The continuum scale was subdivided into three levels: Level 1, patterned after Type I use as defined in the literature (Maddux et al., 2001), Level 2, a middle category that bordered between Type I and Type II, and Level 3, clearly Type II uses of technology as defined in the literature.

To further explain, Level 1 specified that students were using the technology as support for their science learning, but with little personal involvement beyond finding mostly factual information, and reading and/or writing it down. Examples of this from teachers' lessons included viewing Earth images and water cycle presentations online in the *Soil Formation and Properties* lesson, and visual presentations of cells and cell components using an "Ask (Jeeves) for KIDS" search website in the *Cells* lesson. This technology is certainly helpful by replacing encyclopedias with dynamic and colorful images; however, there is virtually no interaction between the student and the technology outside of the searching and reading process.

At Level 2 the students might still engage in a significant amount of online document-reading; however, if for some small part of their lesson, they used technology such as MS PowerPoint, Excel, or some other presentation tool, it would elevate the technology component to Level 2. For example, in the *Kinetic Energy* lesson created by the teachers, students had several opportunities to view roller coasters online and even conduct some interactivity by designing them virtually. However, other than observing these examples, there was little interactivity.

Level 3 sought true interactivity between student and technology in such a way that the student was provided with an authentic experience. A lesson developed at this level, such as the *Population Growth* lesson, required students to create or modify a food chain online, and then observe and analyze the resulting outcomes simulated by the online program. Another example of this was the *Earthquakes* lesson that required students to collect data for earthquake events from online seismic stations, then predict and verify the location of the earthquake epicenter using the seismic measuring tools provided in the program. Their answers generated feedback on their accuracy, and they were then given the opportunity to calculate the earthquake's Richter scale measurement.

### *DESIGN AND PROCEDURES*

Once lesson plans and assessments were completed, the technology components for each lesson were rated using the scale described above. Teachers were asked to self-score their lessons using the scale, and their scores were compared to those of the staff assessment specialist who also rated the lessons. Discrepant scores were resolved by a third staff member. Of the 22 lessons developed, four were rated at Level 3, while eleven were rated at Level 2 and four were rated at Level 1. Each teacher selected two lessons to teach—one per semester for the year. For the first lesson, half of each teachers' classes were randomly assigned to participate in the study. For the second lesson, the other half of each teacher's classes participated. This method was used to reduce the amount of work expected from each teacher in terms of data collection and management.

## DATA ANALYSIS AND RESULTS

### *VARIABLES AND DATA ANALYSIS METHODS*

According to the purposes and research questions of the study, we examined three dependent variables and five independent variables in this study. The three dependent variables were *Factual Knowledge* as measured by the Factual Item Scale, *Conceptual*

*Knowledge* as measured by the Conceptual Item Scale, and *Scenario Analysis* as measured by the Scenario Analysis Scale. The five independent variables were *Level of Technology Integration, Gender, Socio-economic Status, Special Education, and Ethnicity*. Five data analysis procedures were conducted and are summarized in Table 1. Multivariate analysis of variance (MANOVA) with a Bonferroni adjustment (Mertler & Vannatta, 2004, p. 126) was performed in each procedure.

*Table 1.Variables and Data Analysis Method for Each Research Question*

| | RQ1 | RQ2 | RQ3 | RQ4 | RQ5 |
|---|---|---|---|---|---|
| **Dependent Variables** | | | | | |
| Factual Knowledge | √ | √ | √ | √ | √ |
| Conceptual Knowledge | √ | √ | √ | √ | √ |
| Scenario Analysis | √ | √ | √ | √ | √ |
| **Independent Variables** | | | | | |
| *Level of Technology Integration* (3 levels: Level 1, Level 2, Level 3) | √ | √ | √ | √ | √ |
| *Gender* (2 levels: Male, Female) | | √ | | | |
| *Socio-economic Status* (2 levels: High, Low) | | | √ | | |
| *Special Education* (2 levels: Yes, No) | | | | √ | |
| *Ethnicity* (5 levels: five ethnic groups) | | | | | √ |
| **Group Descriptors** | | | | | |
| *n* per group | 650 | 309 | 208 | 71 | 10 |
| Number of groups | 3 | 6 | 6 | 6 | 15 |
| Total *n* | 1950 | 1854 | 1248 | 426 | 150 |
| **Data Analysis procedure: MANOVA** | One-Way 3 levels | 3×2 | 3×2 | 3×2 | 3×5 |

*RANDOM SELECTION OF THE DATA*

The original data set consisted of 5,043 student scores. To produce valid and accurate analysis results, we performed an equal-n random selection within groups on each of the five independent variables. Three steps were performed:

- Step One: Identify the data for this study. Data were transformed to remove cases with missing data in any of the three dependent variables and five independent variables.
- Step Two: Determine the *n* for each group. In the data set identified from the first step, a descriptive analysis was conducted on each independent variable to find out the n on each level (For example, in the variable *Level of Technology Integration*, 650 were at the Level 1, 750 at Level 2, and 805 at Level 3). The smallest *n* therefore was determined to be the n for each group (In this example, 650 became the n for each group).

- Step Three: Formulate equal-*n* random groups. From each level of the independent variable, n cases (in this example, n=650) were randomly selected, while the group with the smallest *n* remained in tact.

In the data analysis procedures for questions 2 to 5, the equal-n random grouping for the second independent variables (*Gender*, *Socio-economic Status*, *Special Education,* and *Ethnicity*) was performed under each level of the first independent variable of *Level of Technology Integration*. Using gender as an example, we randomly selected two groups of students (309 males and 309 females, determined through the second step above) from each of the three technology integration levels, formulating a total of six equal-n groups. Using the same method, the equal-n random selection for grouping was done for all five independent variables. Table 1 shows the n for each group, number of groups, and the total n for each data analysis procedure.

*DATA EXPLORATION*

According to the nature of the five research questions, multivariate analysis of variance (MANOVA) was performed for the data analysis. The first step was to check the Box's Test. If the Box's Test was not significant, the equal variances are assumed, and in the multivariate tests we looked at the value of the Wilks' Lambda test. If the Box's Test was significant, the assumption of equal variances is violated, and therefore in the multivariate tests we used the Pillai's Trace test statistics (Mertler & Vannatta, 2004, p. 126).

In the first four analyses, the Pillai's Trace test statistics were used, because all the four Box's Tests were significant. In the fifth data analysis, Wilks' Lambda test statistics were used, as its Box's Test was not significant.

*DATA ANALYSIS ONE*

To answer the first research question, a one-way multivariate analysis of variance (MANOVA) was conducted. In the analysis, the three dependent variables were the three measures of student science achievements: (a) *Factual Knowledge*, (b) *Conceptual Knowledge*, and (c) *Scenario Analysis*. The independent variable *Level of Technology Integration* was sorted into three levels: (a) Level 1, (b) Level 2, and (c) Level 3. Three groups of data were examined with 650 student scores in each group and a total of 1,950 scores.

The MANOVA results show that significant differences exist among the technology integration levels on the dependent variables: Pillai's Trace value is 0.126 ($F_{(6,\ 3892)}$ = 43.559, $p < 0.0001$, $\eta^2 = 0.063$), indicating that technology integration level significantly affects the combined dependent variables of *Factual Knowledge*, *Conceptual Knowledge*, and *Scenario Analysis*.

A univariate ANOVA was conducted as the follow-up test to examine the main effect of technology integration level on each of the three knowledge areas. The adjusted means can be found in Table 2. The ANOVA results indicate that *Factual Knowledge* significantly differs by the technology integration levels ($F_{(2,\ 1947)} = 79.193$, $p < 0.0001$, $\eta^2 = 0.075$) as do the *Conceptual Knowledge* ($F_{(2,\ 1947)} = 54.853$, $p < 0.0001$, $\eta^2 = 0.053$) and *Scenario Analysis* ($F_{(2,\ 1947)} = 21.963$, $p < 0.0001$, $\eta^2 = 0.022$).

Results from the Scheffé post hoc test identify the locations of the differences, as shown in the results summary Table 3: *Factual Knowledge* student scores at the technology integration Level 3 are significantly higher than those at Level 1 ($p<0.0001$) and Level 2 ($p<0.004$), and students at Level 2 have higher scores than those at Level 1 ($p<0.0001$). *Conceptual Knowledge* student scores at the technology integration Level 3

are significantly higher than those at Level 1 ($p<0.0001$) and Level 2 ($p<0.0001$), and students at Level 2 have higher scores than those at Level 1 ($p<0.002$). *Scenario Analysis* student scores at the technology integration Level 2 are significantly higher than those at Level 1 ($p<0.0001$) and Level 3 ($p<0.0001$), with no significant difference found in the scores between students at Level 1 and Level 3 ($p=0.728$). In summary, students at higher levels of technology integration have higher science achievement scores in factual and conceptual knowledge, while students at Level 2 have higher analysis skill scores than those at Level 1 and Level 3.

*Table 2. Adjusted Mean Scores and Standard Error*

| Data Analysis | Variables | Factual Knowledge | | Conceptual Knowledge | | Scenario Analysis | |
|---|---|---|---|---|---|---|---|
| | | *M* | *SE* | *M* | *SE* | *M* | *SE* |
| Analysis One | **Technology** | | | | | | |
| | Level 1 | 5.777 | .068 | 5.849 | .071 | 4.199 | .075 |
| | Level 2 | 6.641 | .068 | 6.196 | .071 | 4.860 | .075 |
| | Level 3 | 6.949 | .068 | 6.884 | .071 | 4.323 | .075 |
| Analysis Two | **Technology** | | | | | | |
| | Level 1 | 5.798 | .070 | 5.880 | .073 | 4.209 | .073 |
| No interactions | Level 2 | 6.625 | .070 | 6.612 | .073 | 4.862 | .073 |
| | Level 3 | 6.949 | .070 | 6.920 | .073 | 4.303 | .073 |
| | **Gender** | | | | | | |
| | Male | 6.517 | .058 | 6.341 | .059 | 4.431 | .062 |
| | Female | 6.398 | .058 | 6.300 | .059 | 4.484 | .062 |
| Analysis Three | **Technology** | | | | | | |
| | Level 1 | 5.690 | .086 | 5.815 | .089 | 4.013 | .091 |
| No interactions | Level 2 | 6.484 | .086 | 6.022 | .089 | 4.815 | .091 |
| | Level 3 | 6.822 | .086 | 6.691 | .089 | 4.070 | .091 |
| | **SES** | | | | | | |
| | High | 6.645 | .070 | 6.455 | .073 | 4.526 | .075 |
| | Low | 6.019 | .070 | 5.879 | .073 | 4.073 | .075 |
| Analysis Four | **Technology** | | | | | | |
| | Level 1 | 5.732 | .148 | 5.725 | .157 | 4.024 | .159 |
| No interactions | Level 2 | 6.222 | .148 | 5.637 | .157 | 4.736 | .159 |
| | Level 3 | 6.525 | .148 | 6.345 | .157 | 3.796 | .159 |
| | **Special Ed** | | | | | | |
| | Non-special. Ed | 6.561 | .121 | 6.340 | .128 | 4.697 | .130 |
| | Special Ed | 5.758 | .121 | 5.465 | .128 | 3.674 | .130 |
| Analysis Five | **Technology** | | | | | | |
| | Level 1 | 5.540 | .250 | 5.800 | .249 | 4.130 | .287 |
| No interactions | Level 2 | 6.770 | .250 | 6.360 | .249 | 4.800 | .287 |
| | Level 3 | 6.890 | .250 | 6.410 | .249 | 4.240 | .287 |
| | **Ethnicity** | | | | | | |
| | Black | 6.017 | .322 | 6.167 | .322 | 4.267 | .371 |
| | Hispanic | 6.367 | .322 | 5.783 | .322 | 4.633 | .371 |
| | Asian_PI | 6.200 | .322 | 6.133 | .322 | 4.400 | .371 |
| | American Indian | 6.517 | .322 | 6.133 | .322 | 4.050 | .371 |
| | White | 6.900 | .322 | 6.733 | .322 | 4.600 | .371 |

The remaining four analyses were conducted using the same analysis methods as shown above. In the interest of brevity we have simplified the reporting of the results. An expanded version of this section that includes all statistics, as well as the results from the Scheffé post hoc test, is available from the author.

*DATA ANALYSIS TWO*

A two-way MANOVA was performed to answer the second research question in which the same three dependent variables were examined and the two independent variables were *Level of Technology Integration* with three levels and *Gender* with two levels (male and female). Six groups (3 x 2) of data were examined with 309 student scores in each group and a total of 1,854 scores.

In the MANOVA results, the interaction between *Level of Technology Integration* and *Gender* was not significant. The main effect results show that *Level of Technology Integration* significantly affects the combined dependent variable of *Factual Knowledge*, *Conceptual Knowledge*, and *Scenario Analysis* (Pillai's Trace value is 0.130, $F_{(6, 3694)}$ = 42.745, $p < 0.0001$, $\eta^2 = 0.065$). However, no differences exist in *Gender* on the combined dependent variables (Pillai's Trace value is 0.002, $F_{(3, 1846)} = 1.192$, $p = 0.311$, $\eta^2 = 0.002$); and no interactions exist between the *Level of Technology Integration* and *Gender* (Pillai's Trace value is 0.002, $F_{(6, 3694)} = 0.610$, $p = 0.723$, $\eta^2 = 0.001$).

The univariate ANOVA results indicate that the *Level of Technology Integration* has significant impact on all the three dependent variables: *Factual Knowledge* ($F_{(2, 1848)}$ = 70.961, $p < 0.0001$, $\eta^2 = 0.071$), *Conceptual Knowledge* ( $F_{(2, 1848)} = 54.820$, $p < 0.0001$, $\eta^2 = 0.056$), and *Analysis Skill* ($F_{(2, 1848)} = 21.407$, $p < 0.0001$, $\eta^2 = 0.023$). The Scheffé post hoc test results show the locations of differences among the levels of technology integration in the three dependent variables (See Table 3 for details). Consistent with the multivariate results, the univariate ANOVA results indicate that *Gender* effect is not significant on any of the dependent (*Factual Knowledge*, $F_{(1, 1848)} = 2.164$, $p = 0.141$, $\eta^2$ = 0.001; *Conceptual Knowledge,* $F_{(1, 1848)} = 0.233$, $p = 0.630$, $\eta^2 = 0.001$; and *Analysis Skill,* $F_{(1, 1848)} = 0.367$, $p = 0.545$, $\eta^2 = 0.001$). The adjusted means are found in Table 2.

*DATA ANALYSIS THREE*

For the third research question, a two-way MANOVA was performed in which the three dependent variables and first independent variable (*Level of Technology Integration*) were the same, and the second independent variable was *SES* (socio-economic status) with two levels (high and low as measured by participation in free or reduced lunch). Six groups (3 x 2) of data were examined with an n of 208 student scores in each group and a total n of 1,248 scores.

The MANOVA results show that the interaction between *Level of Technology Integration* and *SES* was not significant (Pillai's Trace value is 0.008, $F_{(6, 2482)} = 1.577$, $p = 0.150$, $\eta^2 = 0.004$); furthermore, both *Level of Technology Integration* (Pillai's Trace = 0.134, $F_{(6, 2482)} = 29.743$, $p < 0.0001$ $\eta^2 = 0.067$) and *SES* (Pillai's Trace = 0.039, $F_{(3, 1240)}$ = 116.922, $p < 0.0001$, $\eta^2 = 0.0039$) significantly affect the combined dependent variables of *Factual Knowledge*, *Conceptual Knowledge*, and *Scenario Analysis*.

In the univariate ANOVA test results, the *Level of Technology Integration* has significant impact on all three dependent variables (*Factual Knowledge*, $F_{(2, 1242)}$ = 40.043, $p < 0.0001$, $\eta^2 = 0.067$; *Conceptual Knowledge,* $F_{(2, 1242)} = 26.254$, $p < 0.0001$, $\eta^2$ = 0.041; and *Analysis Skill,* $F_{(2, 1242)} = 23.942$, $p < 0.0001$, $\eta^2 = 0.037$). The effect of *Level of Technology Integration* and the pattern of differences among the three technology integration levels are the same as in the Data Analysis One, and all the differences are at the significant level of $p < 0.01$ (see Table 3).

The univariate ANOVA results also indicate that there were significant differences between the higher and lower *SES* groups on all three dependent variables (*Factual Knowledge*, $F_{(1, 1242)} = 40.028$, $p < 0.0001$, $\eta^2 = 0.031$; *Conceptual Knowledge,* $F_{(1, 1242)}$ = 29.278, $p < 0.0001$, $\eta^2 = 0.023$; and *Analysis Skill,* $F_{(1, 1242)} = 18.383$, $p < 0.0001$, $\eta^2$ =

0.015). The mean comparison (see Table 3) shows that students from higher SES groups have higher scores than those from the lower SES groups on all three dependent variables ($p$<0.0001). The adjusted means are found in Table 2.

*DATA ANALYSIS FOUR*

To answer the fourth research question, a two-way MANOVA was performed in which the three dependent variables and first independent variable (*Level of Technology Integration*) were the same as described above, and the second independent variable was *Special Education* with two levels (special education and regular education). Six groups (3 x 2) of data were examined with 71 student scores in each group for a total of 426 scores.

*Table 3. Summary of the Major Findings*

| | | Factual Knowledge | Conceptual Knowledge | Scenario Analysis |
|---|---|---|---|---|
| Data Analysis One | **Level of Technology Integration** (3 groups: Tech. Level 1, 2, 3) | Level 3>2>1 | Level 3>2>1 | Level 2 >3<br>Level 2 >1<br>Level 3=1 |
| Data Analysis Two<br>No interactions | **Level of Technology Integration** | Level 3>2>1 | Level 3>2>1 | Level 2 >3<br>Level 2 >1<br>Level 3=1 |
| | **Gender** (2 groups: Male, Female) | M=F | M = F | M = F |
| Data Analysis Three<br>No interactions | Level of Technology Integration | Level 3>2>1 | Level 3>2>1 | Level 2 >3<br>Level 2 >1<br>Level 3=1 |
| | **Socio-economic Status** (2 groups: High, Low) | High >Low | High >Low | High >Low |
| Data Analysis Four<br>No interactions | **Level of Technology Integration** | Level 3>1<br>Level 3=2<br>Level 1=2 | Level 3>1*<br>Level 3>2<br>Level 1=2 | Level 2>1<br>Level 2>3<br>Level 3=1 |
| | **Special Education** (2 groups: Special Ed., Non-special Ed.) | Non-Spe>Spe | Non-Spe>Spe | Non-Spe>Spe |
| Data Analysis Five<br>No interactions | **Level of Technology Integration** | Level 3>1<br>Level 2>1<br>Level 3=2 | Levels 3=2=1<br>No Differences | Levels 3=2=1<br>No Differences |
| | **Ethnicity** (5 groups): Black, Hispanic, Asian_PI, American Indian, and White | No Differences among the five ethnic groups | No Differences among the five ethnic groups | No Differences among the five ethnic groups |

- > indicates higher than, and = indicates no difference
- All differences are significant at $p < 0.01$ level
- Only the one with * mark is at the level of $p < 0.021$
- The "no difference" results are at $p \geq 0.05$ level

In the MANOVA results, the interaction between *Level of Technology Integration* and *Special Education* was not significant (Pillai's Trace value is is 0.022, $F_{(6, 838)} = 1.585$, $p$

=0.148, $\eta^2$ = 0.011); furthermore, both *Level of Technology Integration* (Pillai's Trace = 0.130, $F_{(6, 838)}$ = 9.686, $p < 0.0001$, $\eta^2$ = 0.065) and *Special Education* (Pillai's Trace = 0.089, $F_{(6, 2418)}$ = 13.653, $p < 0.0001$, $\eta^2$ = 0.089) significantly affect the combined dependent variables of *Factual Knowledge*, *Conceptual Knowledge*, and *Scenario Analysis*.

In the univariate ANOVA test results, the *Level of Technology Integration* had a significant impact on all the three dependent variables (*Factual Knowledge*, $F_{(2, 420)}$ = 7.311, $p < 0.001$, $\eta^2$ = 0.034; *Conceptual Knowledge,* $F_{(2, 420)}$ = 6.509, $p < 0.003$, $\eta^2$ = 0.0428; and *Analysis Skill,* $F_{(2, 420)}$ = 9.525, $p < 0.0001$, $\eta^2$ = 0.043). The Scheffé post hoc test results show the locations of differences among the levels of technology integration in the three dependent variables (See Table 3 for details).

The univariate ANOVA results also indicate that there were significant differences between the special education and non-special education groups on all three dependent variables (*Factual Knowledge*, $F_{(1, 420)}$ = 22.112, $p < 0.0001$, $\eta^2$ = 0.050; *Conceptual Knowledge,* $F_{(1, 420)}$ = 23.414, $p < 0.0001$, $\eta^2$ = 0.053; and *Analysis Skill,* $F_{(1, 420)}$ = 31.134, $p < 0.0001$, $\eta^2$ = 0.069). The mean comparison (see Table 3) shows that students from non-special education groups had higher scores than students from the special education groups on all three dependent variables ($p$<0.0001). The adjusted means are found in Table 2.

*DATA ANALYSIS FIVE*

To answer the fifth research question, a two-way MANOVA was performed in which the three dependent variables and first independent variable (*Level of Technology Integration*) were the same as described above, and the second independent variable was *Ethnicity* with five levels (African American, Hispanic, Asian-Pacific, American Indian, and White). Fifteen groups (3 x 5) of data were examined with 10 student scores in each group for a total of 150 scores.

In the MANOVA results, the interaction between *Level of Technology Integration* and *Ethnicity* was not significant (Wilks' Lambda = 0.846, $F_{(24, 386)}$ = 0.957, $p$ = 0.523, $\eta^2$ = 0.054); furthermore, *Level of Technology Integration* had significant impact on the combined dependent variables (Wilks' Lambda = 0.862, $F_{(6, 266)}$ = 3.404, $p < 0.003$, $\eta^2$ = 0.071). However, the results suggest that *Ethnicity* does not have significant impact on the combined dependent variables of *Factual Knowledge*, *Conceptual Knowledge*, and *Scenario Analysis* (Wilks' Lambda = 0.923, $F_{(12, 352)}$ = 0.907, $p$ = 0.540, $\eta^2$ = 0.026).

Interestingly, in the univariate ANOVA results, the *Level of Technology Integration* does not have significant impact on *Conceptual Knowledge* ($F_{(2, 135)}$ = 1.846, $p$ = 0.162, $\eta^2$ = 0.027) or *Scenario Analysis* ($F_{(2, 135)}$ = 1.562, $p$ = 0.213, $\eta^2$ = 0.023), but only on *Factual Knowledge* ($F_{(2, 135)}$ = 8.952, $p < 0.001$, $\eta^2$ = 0.117). The Scheffé post hoc test results indicate that *Factual Knowledge* student scores at the technology integration Level 1 are significantly lower than those at Level 2 and Level 3, and no significant differences were found between students at Level 2 and those at Level 3. Consistent with the MANOVA Wilks' Lambda statistics, no differences were found among the ethnic groups on any of the three dependent variables. Table 2 shows the adjusted means.

## CONCLUSIONS

*INTERACTIVE TECHNOLOGY LEVEL*

First, the overall results from the first three data analysis procedures reflect the same pattern that (a) in terms of factual and conceptual knowledge, student achievement

increases as the level of technology interactivity increases, and (b) for scenario analysis, students at Level 2 achieve significantly higher than those at Level 1 and Level 3. Because technology components developed by the teachers were spread out along a continuum of uses and were ordered into three categories rather than being categorized at the two extremes of technology uses, and given that the continuum ranged between learning *from* technology to learning *with* technology (Reeves, 1998), or between Type I and Type II uses (Maddux et al., 2001) a definite middle ground emerged. Students engaging in lessons with little interactivity in the technology component scored significantly lower across most measures. However, once the interactivity level increased, so that even a small amount of the total engagement time was spent using cognitive tools that supported reflective thinking, the middle ground was reached with scores that were significantly different from those levels both below and above for most measures. This finding supports the stance that technology can enhance what children learn through active engagement in authentic tasks (Roschelle, Pea, Hoadley, Gordin, & Means, 2000).

A ceiling effect was found for the scenario analysis with Level 2 scores significantly higher than those at Level 1 or Level 3. Compared to the factual and conceptual knowledge students gained from the lessons, the scenario analysis required higher level critical thinking and problem solving skills, including analysis and synthesis of science concepts. Two examples of scenario questions follow:

From the lesson test on soils: The teacher gives you a soil sample from a new planet and tells you to make as many observations as you can about it. List the properties that you would be looking for and describe the tools and steps you would use.

From the lesson test on Newton's First Law: Two bricks sit in their own identical boxes. One is Styrofoam and the other is mortar brick. Without lifting the boxes, how could you figure out which is which? Write a plan and draw an illustration of what you would do, perform your test, and state your conclusion.

While interactive technology can be used for data collection and analysis to provide factual or conceptual information about the analysis results, it is the students themselves who need to interpret the results, determine what the results mean, and reach a solution to the problem. Indeed, our results suggest that technology may not play a major role in scenario analysis when increasing the level of interactivity beyond Level 2 seemed not to increase the scenario analysis scores. This is an interesting finding, which provides some additional insights in a long-term debate on "how much is appropriate" (Liu & Henderson, 2003). "The more, the better" is not always true for technology integration cases.

Second, results from the fourth and fifth data analysis procedures indicated that (a) in terms of factual and conceptual knowledge, students at lower technology integration levels do not achieve higher scores than those at higher levels; and (b) in terms of scenario analysis, results from the fourth data analysis procedure show the same pattern as in the first three procedures, and results from the fifth analysis do not show any differences among students from the three technology integration levels. This might be because the small size of each ethnic group.

### *DEMOGRAPHIC GROUPS*

No significant gender effects were found, which indicated that males and females performed equally well at each of the three technology integration levels across all assessments. This finding contrasts with research over the past two decades, which suggested that attitudes toward computer use depended upon gender (Arenz & Hiheon, 1990; Chen, 1985). In the past, males seemed to exhibit more self-confidence and less

anxiety about mastering computers. However, the finding from the present study is consistent with current literature that finds no gender differences in the use of technology (Bain & Rice, 2006; Hargittai & Shaver, 2006; Scherer, Sax, VanBiervliet, Cushman, & Scherer, 2005), regarding attitudes, technology skills, and learning outcomes. Educational differences between males and females appear to be shrinking, so it is likely that the technology gender gap will shrink as well.

In addition, no differences were found in science achievement scores among all five ethnic groups. This finding is not consistent with some well-documented literature findings stating that performance gaps exists among ethnic groups that are related to the digital divide (Fairlie, 2005; Levy, 1999). Other researchers have proposed that these performance gaps seemed to be more the product of SES and other factors and not ethnicity itself (Albrecht, 2006; Bimber, 2000; Klein et al., 1997a, 1997b). In this study, we performed random selection for equal n groups that may have influenced our results. It may be that when other factors, including SES, are assumed to have equal variance among gender/ethnic groups, the ethnicity performance differences do not persist.

Our results for the SES group are consistent with current literature. Students of higher SES in our study performed at higher levels than those of low SES. That is, the science achievement scores may be influenced by any single or combination of factors related to a family's SES, such as students' computer access (including home access, technology skills, learning aids, home environments, and education level of parents or expectations from parents).

Performance gaps between regular and special education students are well documented in the literature and were also evident in our study. For special education students, we concur with Hasselbring & Glaser (2000) who indicate that instructional design including use of technology is a critical factor in their performance. However, when Web-based simulations and hands-on engineering design activities were integrated into middle school science lessons in which special education students were given no extra help, Cantrell and colleagues (2006) found performance gaps for special education students were greatly reduced compared to performance on statewide science tests. The lesson design used in this study did not produce such results, suggesting that greater differentiation in lesson design to meet specific needs of individual students may produce better outcomes in future studies.

Finally, no interactions were found in the analysis for research questions 2 to 5, indicating that the level of technology does not have cross impact on the performance of gender, ethnicity, SES, and special education student groups. That is, for all the learners, the impact of technology integration was greater in lessons at the highest level of interactivity than at the lowest level without regard for different population groupings.

## DISCUSSION

In our view, the most important finding from this study was the differentiated impact on student learning relative to the degree or level of interactive technology that was experienced by students as they progressed through different lessons of study. If learning of concepts occurs first through interaction and then integration into the individual's mental structure as postulated by Vygotsky (1978), it may be that students interacting with technology in their research groups contributed to their learning, and increased their learning as the degree of technology interaction increased. This finding certainly raises fertile opportunities for future research on the effects of graduated levels of technology interactivity on student achievement.

The integrated technology activities at Level 3 included the use of visualization software, model construction, data gathering and analysis that helped situate the learners

in a more authentic context for problem solving, which is aligned with the tenets of situated learning theory (Lave & Wenger, 1991). Providing a high degree of interactivity in technology tasks that require students to grapple with real-world problems, such as finding and analyzing earthquake data in order to locate the epicenter and calculate the Richter scale category, would certainly contribute to a deep conceptual understanding of the related science concepts of wave motion through varying Earth materials.

A limitation of this study is that the content of lesson tests was not identical for all students, even though the tests were carefully structured using a test blueprint. Some of our results may be attributable to test content rather than level of technology interactivity. Also, designing test items at specific cognitive levels was problematic for some teachers, so it may be that internal validity of the factual and conceptual scales may be questionable. We recognize the need to refine the scale we used to categorize the levels of technology integration. With an improved assessment test, it may be possible to tease out effects on student learning that the differing interactivity levels have on student performance to a greater degree on elements such as the cognitive domain as in this study, or the content domain as described by Wiggins and McTighe (1998).

Implications for teachers based on the results of this study include useful information for instructional planning. Spending the time and effort to improve knowledge and skills for integrating interactive technology into science instruction pays off in terms of student achievement. By upgrading technology use from "sit and get" activities to higher level interactive activities, students learn with understanding, engage in inquiry, and are better able to reflect about their own learning process.

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