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Across the Great Divide: The Effects of Technology in Secondary Biology Classrooms

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Abstract

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This study investigates the relationship between technology use and student achievement in public high school across North Carolina. The purpose of this study was to determine whether a digital divide (differences in technology utilization based on student demographics of race/ethnicity, gender, socioeconomic status, and municipality) exists among schools and whether those differences relate to student achievement in high school biology classrooms. The study uses North Carolina end-of-course (EOC) data for biology to analyze student demographic data and assessment results from the 2010-2011 school year from the North Carolina Department of Public Instruction. The data analyses use descriptive and factorial univariate statistics to determine the existence of digital divides and their effects on biology achievement.

Analysis of these data described patterns of technology use to determine whether potential variances resulted in a digital divide. Specific technology uses were identified in the data and then their impact on biology achievement scores within various demographic groups was examined.

Research findings revealed statistically significant variations of use within different population groups. Despite being statistically significant, the relevance of the association in the variations was minimal at best – based on the effect scale established by Cohen (1988).

Additional factorial univariate analyses were employed to determine potential relationships between technology use and student achievement. The data revealed that technology use did not influence the variation of student achievement scale scores as much as race/ethnicity and socioeconomic status. White students outperformed Hispanic students by an average of three scale score points and Black students by an average of six scale score points. Technology use alone averaged less than a one point difference in mean scale scores, and only when interacting with race, gender, and/or SES did the mean difference increase. However, this increase within the context of the biology scale score range was negligible.

This study contributes to the existing body of research on the effects of technology use on student achievement and its influence within various student demographic groups and municipalities. The study also provides additional research information for effective technology utilization, implementation, and instruction in educational environments.

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Chapter 1: Introduction

There is a high school science classroom in the United States where students are using computers and probes to run laboratory simulations and experiments. They are collecting real time data, analyzing the results, and forming hypotheses. The technology supports the students' knowledge and allows them to explore different ways the knowledge can be applied. Students are provided directions in what to do but also have the flexibility to design their own experiments. They have the freedom to *play* with technology to enhance understanding of science concepts. Students are engaged and students are on task.

At a different high school science classroom, students are directed to use the computers to access the Internet and use a website to work on science problems. The teacher instructs the students to use their textbooks and notes for reference. As students are working online, the teacher circulates around the room to assist and answer questions. Later in the class period, several students log on to Facebook, while others watch videos on YouTube or tweet from their smartphones. Some students begin discussing plans for the long upcoming weekend. In a few more minutes, over half the students in the class have completed the assignment. The rest of the students continue to surf the web or chat with one another.

These are just two examples of the ways educational technology is used in science classrooms across the country. The question of whether to integrate technology in the classroom no longer has any relevance. Today, technology is universally present in schools (Gray, Thomas, & Lewis, 2010) which emphasizes the importance of educators and policymakers comprehending the association between the use of technology and student achievement (Bailey, Henry, McBride, & Puckett, 2011; Wenglinsky, 2006).

The priority of the No Child Left Behind Act of 2001 (NCLB) is improving achievement for all children and closing achievement gaps among gender and ethnic and socioeconomic groups, as well as students with disabilities and English language challenges. A mandate of NCLB is the integration of technology in elementary, middle, and secondary schools via building access, increasing accessibility, and parental involvement (Learning Point Associates, 2007).

The mission statement of the North Carolina State Board of Education is aligned with NCLB policies, and its focus calls for every student to graduate from high school. Additionally, all students will have developed skill sets for postsecondary education and the globally competitive workplace and for life in the 21st century. Similar to the priorities of NCLB, the North Carolina State Board of Education also emphasizes the integration of technology in public schools by building access and increasing student accessibility. Also, the goals highlight development of technology skills for students to become lifelong learners and teacher skills to effectively deliver 21st century technology that ensures student learning (North Carolina State Board of Education, 2006).

The North Carolina State School technology plan states, “Equal access to technology and 21st century opportunities are critical to ensuring the success of all North Carolina students” (North Carolina Commission on Technology, 2011, p. 2). However, the plan notes that technology access is not equitable across the state. Many high-poverty schools lack the resources to leverage effective technology integration of more affluent schools. This phenomenon of variance in technology integration based on gender, race, ethnicity, and socioeconomic status (SES) is known as the *digital divide*.

The origin of the term digital divide is unclear and first appeared in research reports during the late 1990s. Prior to this time, more generalized terms were used such

as computer/media literacy, information inequality, information or knowledge gap (van Dijk, 2006). It is commonly defined as the gap between those with access to technology and those without (Gunkel, 2003). To better understand the concept of a digital divide, it is important to recognize the context from which it is derived. Gunkel (2003) and van Dijk (2006) agreed the term digital divide has likely confused more than clarified and, depending on the context, can have a variety of different meanings. The context for this study examined the digital divide in regards to technology use and academic achievement on two levels – student and district. Within these levels, the study analyzed the relationships of technology use and achievement within gender, racial, socioeconomic, and municipal groups across schools and districts in North Carolina.

Since its inception, the digital divide has been a program concern for closing these gaps of technology access and use in schools. As society has become more dependent on technology, schools face mounting challenges preparing students for the 21st century workforce (Fullan, 2013). Friedman (2005) described the world as becoming *flat* – a closer, more connected, information-driven, and competitive global society. For schools to overcome these obstacles, it is crucial that not only sufficient technology access is available, but also that students learn effective use of technology. Quality implementation of sound digital literacy and pedagogy will ensure all students have technological opportunities to learn (Fullan, 2013; Pflaum, 2004; Wenglinsky, 2005).

During the late 1990s, federal and state policies concentrated on integrating technology in schools and addressing social imbalances associated with access to technology. Educators and policymakers realized there was potential in utilizing technology as a learning resource. The result was a flood of computers and Internet connections into schools; at the same time, schools were executing major changes across

the nation. Schools encountered additional challenges of both technology and reform implementation. Today, most teachers and students are engaged daily with technology in their schools (National Center for Education Statistics [NCES], 2013).

In exploring the possibilities of a digital divide, this study offered a descriptive outline of the effects of technology in schools and districts with respect to gender, ethnicity, SES, and municipality. Its purpose was to study the relationship and extent of these effects with student achievement in secondary science. To examine these potentials more clearly, the study began with a discussion of learning theories that relate to technology in education. Additionally, technology utilization from the perspectives of access, use, and efficacy were deliberated as a context for the digital divide and technology's effect on academic achievement.

Technology and Learning

According to Richey (2008), the Association for Educational Communications and Technology defined educational technology as "the study and ethical practice of facilitating learning and improving performance by creating, using and managing appropriate technological processes and resources" (p. 3). Typically technology is associated with computers and other devices, but technology also refers to the infrastructure designs and the environment that engages learners (Lee & Spires, 2009). Often viewed as interchangeable, the terms *information technology* and *information communication technology* both refer to the administrative and instructional roles sustained by technology resources (Culp, Honey, & Mandinach, 2003; Roblyer, 2005).

Learning theory developments have demonstrated that technology can support learning in the classroom (Kadel, 2008; Lei & Zhao, 2007; Odom, Marszalek, Stoddard, & Wrobel, 2011; Schacter & Fagnano, 1999). Not only does the evidence support the

effectiveness of technology in behaviorism, but also there is evidence that constructivism theories are effectively empowered by technology (Drayton, Falk, Stroud, Hobbs, & Hammerman, 2010; Lei & Zhao, 2007; Odom et al., 2011; Prensky, 2012; Tam, 2000; Tamim, Bernard, Borokhovski, Abrami, & Schmid, 2011). Constructivism defines learning as an active process that creates meaning from various experiences. In other words, students learn best by making sense of something in their own way with the teacher serving as a guide to help them through the process. Constructivism is best when learning happens in a real-world setting focused on collaboration and problem solving (Odom et al., 2011; Prensky, 2012; Tam, 2000).

The communications and interactive capabilities of technology allow the enhancement of curricula with activities based on real-world situations (Bransford, Brown, & Cocking, 2000; Tam, 2000; Wenglinsky, 2005). Visualization capabilities of technology through graphics and multimedia create learning experiences which guide students through models and intricate simulations toward developing a deeper comprehension of the content (Bell & Smetana, 2008; Osberg, 1997). Technology's ability to access and analyze data offers opportunities for reflection, revision, and response for learners (Kara, 2008; Linn, 2003). The networking capabilities of technology connect teachers and students to others outside of the classroom (Prensky, 2012). This creates a forum to stimulate conversations, share ideas, and interact with others in the course of building knowledge and comprehension (Bransford et al., 2000; Fullan, 2013).

Technology Utilization

It is important to understand that utilization of educational technology should not be view as an isolated event (Wenglinsky, 2005). Fullan (2013) described technology's

utilization as a piece of a larger puzzle of how teachers teach and students learn. This study explored technology utilization from three different perspectives: access, use, and teacher efficacy. Through these lenses, technology's use in student populations and its effect on achievement can be examined more closely.

Technology access. The first perspective: How much technology does a school have? The perspective of technology access has consistently evolved since the late 1990s – from a narrow focus on the availability of devices, Internet, and media to a larger perspective of *sociotechnical elements* that influence how people access technology (Warschauer & Matuchniak, 2010). Hitch (2013) stated access information is typically requested by parents and community leaders wishing to know what technology is available in schools. Statistics and reports can be employed to describe numbers and kinds of technology, amounts of technology support, networking ratios, and how districts compare in regards to technology budget expenditures (North Carolina Department of Public Instruction [NCDPI], 2013a).

National trend data indicate a rapid deployment of technology in schools over the past 2 decades that has gradually plateaued in the last several years. In 1994, 35% of public schools in the U.S. had Internet access (Gray et al., 2010). By 2003, 100% of all public schools had access to the Internet in some capacity. As the number of computers in schools increased, the ratio of students to computers decreased (NCES, 2013). Also in 2009, 97% of teachers had at least one computer in their classroom (Tamim et al., 2011). Data published in the Education Week's Technology Counts 2006 report showed that in 1999 there were 5.2 students to every computer in the classroom as compared to 1.8 students for every computer in 2009 (Education Week, 2012; Gray et al., 2010). Despite these national figures, there were noteworthy differences in the student-to-computer

ratios throughout school systems in the U.S. (NCES, 2012; National Education Association, 2008).

Various factors can impact the access to technology in schools. Many goals of federal, state, and local policies have been to boost technology access in schools (Learning Point Associates, 2007). A major influence is the demand of parents and educators for greater access to technology in schools for teaching and learning (Wenglinsky, 2005). From the retail perspective, technology manufacturers are producing products at lower costs and developing marketing strategies that specifically target the education sector (Cuban, 2001). Parallel with the reduction in cost is the emergence of portable devices and cloud technologies that expand the mobility, flexibility, and convenience of technology use. The result is an extraordinary level of technology access with respect to computing devices and the Internet in schools across the nation (Education Week, 2012; Fullan, 2013; Prensky, 2012).

Technology use. A second view of technology utilization emphasizes how frequently technology is used by students in schools. Since technology has become a vital element in the learning process, one focus of this study was the instructional use of technology in secondary science (Collins & Halverson, 2009; Wenglinsky, 2006). This study defines technology use as the various ways students and teachers utilize technology resources to complete specific instructional tasks.

There is a vast array of technology resources available to schools: computers, tablets, iPads, interactive white boards, digital cameras, network devices, televisions, projectors, etc.; however, critics claim there is a common but unsubstantiated belief that computers are widely and frequently used in schools (Cuban, 2001; Cuban, Kirkpatrick, & Peck, 2001; Pflaum, 2004). Despite the variety of resources, technology use fluctuates

across schools and districts – both positively and negatively (Cuban, 2001; Pflaum, 2004). Research studies reveal some teachers will use technology more with students than others regardless of the amount of technology in a school (Cuban et al., 2001; Papanastasiou, Zembylas, & Vrasidas, 2003; Pflaum, 2004; Ravitz, Mergedoller, & Rush, 2002).

The versatility of technology provides a vast array of uses in the classroom (Wenglinsky, 2005). Text, graphics, audio, video, animation, mobility, communications, and computation combine together to create unlimited possibilities for use by teachers and students in daily classroom activities. Computers, mobile devices, cloud, and Internet resources are commonly used for administrative, instructional, and assessment purposes today (Muir-Herzig, 2004; Osborne & Hennessy, 2003; Thomas & Lee, 2008).

Measuring technology use is a challenging endeavor (Pflaum, 2004). Research usually defines *use* based on frequency, which measures technology use on a time continuum (daily, weekly, etc.). In this context, frequency is aligned with quantity without regard to the quality of use (Lei, 2010; Pflaum, 2004). Also, additional evidence indicates that frequent inappropriate use of technology can have negative effects on learning (Fouts, 2000; Wenglinsky, 2005). Research has not clearly defined the most effective use of technology in student learning. It still remains a topic of considerable debate, and with the rapid evolution of technology in our culture, the debate will continue (Bailey et al., 2011; Cuban, 2006; Lei, 2010; Pflaum, 2004; Schacter, 1999; Wenglinsky, 2005).

Technology self-efficacy. Can the use of technology improve student outcomes? Despite the wide scope of this question, a common denominator exists: the role of the teacher. An expectation for teachers is not only to utilize technology in their teaching but

also guide the student experience with technology in daily classroom activities. Achieving such responsibilities requires a knowledge base and skill set that facilitates a use of technology aimed to enrich teaching and learning (Becker, 2000; Cuban, 2001; Niess, 2005; Wenglinsky, 2005). This capacity is known as technology self-efficacy. For this study, technology efficacy is defined as a teacher's perception of his/her abilities and strategies to bring about desired student outcomes (Hakverdi-Can & Dana, 2012; Hoy, 2000).

A key component of many school reform efforts has included technology standards that promote more effective and significant uses of technology in the classroom. These provide a framework for expectations of what teachers should be able to do with the technology in their schools. For the past decade, most states have created standards for teachers and administrators to help address technology skills (Ansell & Park, 2003). A review of technology plans from California, Kentucky, and North Carolina provide examples of standards and expectations for educators to use technology as a part of daily instruction. These expectations also include developing lesson plans that integrate technology, creating technology-based assignments, and supporting students in the development of their technology skills (Fullerton School District, 2011; Granville County Schools, 2012; Jefferson County Public Schools, 2013; Winston-Salem/Forsyth County Schools, 2012). According to the International Society for Technology in Education (ISTE, 2008), teachers must fundamentally comprehend computer operations; have the skills to leverage Internet, cloud, and mobility resources; and also effectively employ applications such as word processing, presentation tools, spreadsheets, and databases.

A survey conducted by the National Education Association (2008) indicated these

types of reforms have been met overall with positive results. Teachers have taken advantage of increased professional development opportunities to increase their technology skills and knowledge. Many of these programs focus on easing teacher apprehensions of technology and building confidence levels to where they can positively integrate technology in their classrooms. Over half (60%) of the educators responded that their school districts mandated technology training participation. The survey also reported that more than three-fourths (76.4%) of the respondents agreed that they were satisfied with their knowledge levels of technology and using it in their schools. This was an increase of 23% from their previous survey conducted in 2003.

Digital Divide

The term *digital divide* has risen to an elevated status in the constant debates around technology and its impact in public education. In some capacity, the digital divide continues to appear in research studies, professional conferences, policy analysis, political rhetoric, and various media venues. Because the contextual emphasis of the digital divide is so broad, statements coming from these venues are exceedingly diverse (Swain & Pearson, 2003). Despite its current status, the origin of the term digital divide is uncertain (Gunkel, 2003).

The expression digital divide first appeared in a 1999 National Telecommunications and Information Administration (NTIA) report entitled Falling Through the Net. This report defined digital divide as "the divide between those with access to new technologies and those without" (NTIA, 1999, p. 12). Today, the digital divide has transformed through various frameworks and has essentially become a moving target. Gunkel (2003) explained that there is no longer a single digital divide but an arrangement of technological, economic, and social differences that all share the name of

digital divide. There is no single construct of the digital divide but a number of factors that shape technology's amplification of these inequalities (Warschauer, Knobel, & Stone, 2004). For the purpose of this study, digital divide was examined through the lens of technology utilization and its variations in student populations (i.e., gender, municipality, race, and SES) and effects on academic achievement.

The digital divide has been a concern for more than 20 years and still remains in the public spotlight. Extensive research into the digital divide indicates that it is a national and international complex challenge. Concerns regarding the digital divide in education are viewed in the context of differentiated access and use of technology among various student groups based on gender, race, ethnicity, SES, location, physical abilities, and language (Brown, 2000; Carvin, 2000; Jackson et al., 2008; McGraw, Lubienski, & Strutchens, 2006; Sutton, 1991; Valadez & Duran, 2007; Volman & van Eck, 2001; Warschauer, et al., 2004). Another term that has recently been found in research is *digital equity*. This refers to equal access and opportunity to use digital tools and resources in an effort to increase digital skill sets, awareness, and knowledge (ISTE, 2008).

The 1980s witnessed the rise of widespread computer use in schools and along with this rapid increase emerged apprehensions for inequalities in access and use. The concerns for equity in technology led to an extensive activity of research in the education sector. It was quickly determined that more affluent schools bought more equipment for instruction. White students had greater access to technology as compared to African-American students, and girls use computers less frequently than boys (Sutton, 1991). This study explored gender, municipality, race, and SES as factors that define the digital divide and its bearing on student achievement.

Educators, researchers, and policymakers intensely debate as to whether the digital divide continues to exist. Through state and federal grants and subsidiary programs such as e-rate, schools have increased technology access which has successfully reduced and even closed some of the technology gaps. Some have suggested that the technology access divide in schools between racial and SES groups has been closed since 2003 (Ching, Basham, & Jang, 2005; Valadez & Duran, 2007; van Dijk, 2006). However, it is important to note that much of this research limited its analysis to student-to-computer ratios and percentages of schools with Internet access (Vigdor & Ladd, 2010). Other research utilizes additional measures to study variations of technology access and use in schools. The evidence suggests that the digital divide still exists for disadvantaged students and expands to include technology access in the home and the quality of technology integration in schools (Ching et al., 2005; Warschauer et al., 2004; Warschauer & Matuchniak, 2010).

A national survey of teachers conducted by NCES (2012) found gaps in technology use based on poverty levels. The survey revealed that students in low-SES schools (66%) used technology resources for routine research and learning activities as compared to students in high-SES schools (56%). Research data also found that high-SES schools (83%) compared low-SES schools (61%) used technology more often for data analysis, simulations, projects, and demonstrations (Gray et al., 2010; Warschauer et al., 2004).

Another national study by the National Education Association (2008) found differences among teachers and their perceptions of technology use and proficiency skills based on the poverty levels of their schools. The survey data showed that 56% of teachers in low-SES schools felt sufficiently trained to effectively integrate technology

into their classroom instruction as compared to 67% of teachers in high-SES schools (National Education Association, 2008).

State-level research indicates that in North Carolina the average ratio of students to computers in both high-SES (3.9) and low-SES (3.7) schools is very close. Additional data show a similar comparison of students per high-speed Internet computer ratio with high-SES schools at 3.8 and an average of 3.7 for low-SES schools (Education Week, 2007). A review of North Carolina NAEP assessment data in STEM (science, technology, engineering, and math) subjects, eighth-grade science reduced the poverty gap over a 5-year span. However, eighth-grade math in North Carolina actually increased the poverty gap slightly. Despite the science reduction of 3.1 scale score points, the gap still remains significantly large (Education Week, 2008). Given this limited scope of evidence, this study examined technology utilization and its impact on the digital divide and student achievement in North Carolina schools.

Technology and Student Achievement

Despite the ubiquitous nature of technology, there remains inconclusive evidence linking technology use with increased student achievement (Richtel, 2011). Student achievement is defined as observations of how students do or achieve in a single point of time on a standardized assessment (Linn et al., 2011). A number of studies have revealed low use of technology across public schools (Bain, 2004; Cavanaugh et al., 2007; Cuban, 2001; Rodrigo et al., 2008); and where technology is deployed, it is often used for low-level tasks such as Internet searches, presentations, word processing, and completing tests or quizzes (Cuban, 2001; Drayton et al., 2010; Pflaum, 2004; Shapley, Sheehan, Maloney, & Caranikas-Walker, 2010; Suhr, Hernandez, Grimes, & Warschauer, 2010). Often, technology is used simply to support daily traditional instructional practices or on

special occasions where the technology is incorporated as a supplement to the curriculum (Pederson & Yerrick, 2000; Cuban, 1998).

One main goal for technology integration in schools is to improve student learning. Although used interchangeably with student achievement, student learning takes a longer view at student progress over a period of time rather than at a single point. It is defined as the knowledge, skills, and abilities a student has gained as a result of his/her engagement in an education experience (Linn et al., 2011). In the context of student learning, technology literacy and academic achievement are two outcomes commonly associated with technology utilization in schools. More importantly, academic achievement serves as a catalyst for federal and state education and technology policies – with an emphasis on closing achievement gaps between the different student populations.

The primary goal of the Enhancing Education Through Technology Act is "to improve student academic achievement through the use of technology in elementary schools and secondary schools" with an additional goal of closing achievement gaps (U.S. Department of Education, 2004, p. 5). The achievement gap is described as differences in academic achievement among student groups based on race, ethnicity, SES, gender, and disability. For example, Asian and White students consistently score higher than African-American and Hispanic students on math assessments. Also, students from higher income families have better math scores than students from lower income families (Aud, Fox, & Ramani, 2010; Barton & Coley, 2010; Reardon, 2011).

Since the introduction of technology in schools, another debate has persevered in the education arena: Does technology enhance student learning? The body of research on the influence of technology in teaching and learning is diverse. Wenglinsky (2005) and

others discussed how inappropriate use of technology can have a negative impact on learning (Becker, 2000; Cuban, 1998; Lei, 2010; Li, 2007; Pflaum, 2004). However, other research provides evidence of effective use of technology and its positive results in student learning (Davis, 2008; Kadel, 2008; Meyers & Brandt, 2010; Wenglinsky, 2005).

Another facet of improving student learning is the emphasis on *technology literacy*. Technology literacy is a term used to describe the 21st century skills necessary to prepare students for participation in a more global technological world. Technology literacy is considered as specific skill sets that involve technology in the acquisition and processing of information, as well as personal productivity, creativity, critical thinking, and collaboration (Eisenberg, 2008; ISTE, 2007). Organizations such as ISTE and the Partnership for 21st Century Skills have developed extensive frameworks and standards that outline the various skills considered essential for technology literacy. They recommend that students and teachers infuse academic rigor, higher order thinking processes, and technology proficiencies to guarantee the U.S. remains a viable player in the information-based global economy (ISTE, 2007; Partnership for 21st Century Skills, 2008).

Research Problem

The challenge of conducting research on the impact of technology in public education stems from the rapid evolution of technology (Pflaum, 2004; Schroeder, Scott, Tolson, Huang, & Lee, 2007). Many schools have multiple and sometimes competing strategic goals that influence technology integration. This creates a difficult scenario when attempting to discern the effects of technology as opposed to other intervention strategies.

The problem addressed by this study is in order for technology to be effectively

utilized to improve student learning and achievement, as outlined in the North Carolina State School Technology plan and the North Carolina State Board of Education mission statement, an exhaustive body of knowledge is needed of technology's availability, utilization, and impact for all students and teachers. However, there are only a few investigations regarding the digital divide in North Carolina public schools beyond access to technology. This study is an attempt to add a broader scope to this narrow body of research.

Purpose of the Study

The purpose of this research study was to analyze various aspects of technology use and its effect on student achievement. Additionally, the study examined technology use and student achievement through the lens of the digital divide to determine its prevalence in North Carolina high schools.

Importance of the Study

This study complements an extensive body of research on educational technology by describing the relationships of technology utilization and its effects on academic achievement in North Carolina high schools. Research regarding the digital divide in North Carolina public education is limited, and this study attempted to fill in these deficiencies by extending the analyses of technology use and achievement based on race, municipality, gender, and SES.

Both NCLB and NCDPI include technology literacy and academic achievement as goals for all students. This study explored how high school students in North Carolina use technology in their biology classes and provides insight into assessing student progress toward meeting these goals.

Chapter Summary

This chapter provided an introduction to the study, including an overview of its purpose and relevance. The research problem was identified with an explanation of the significant issues of educational technology in education. Chapter 2 presents a review of research literature on the use of technology in teaching and learning, the digital divide, and their relationship to student academic achievement. The summary of present research literature provides a framework for the study. Research questions and test hypotheses that guide the research are presented at the end of the chapter.

Chapter 3 describes the methodology, data sources, and statistical procedures used to address the four research questions. The results of the research findings are presented in Chapter 4 with the outcomes of the null hypotheses testing reported in detail. A discussion of the research findings in the study is reported in Chapter 5 and concluded with suggestions for future research.

Chapter 2: Literature Review

Chapter 2 provides a summary of educational technology research in relation to technology utilization in the context of access, use, and efficacy. This chapter also reviews research concerning the effects of technology use on the digital divide and student achievement. Embedded in the philosophy, psychology, and sociology of research literature, this study appraised the role of technology in education. Additionally, this study addressed matters regarding social stratification, educational equality, and differences in learning opportunities (Becker, 2000; Carvin, 2000; Ching et al., 2005; Sutton, 1991; Warschauer & Matuchniak, 2010).

Related literature to equity in technology originates from early application of technology and educational reform efforts directed toward excellence in education. As researchers began evaluating implementation of technology in schools, many found tendencies of large, poor, and urban schools to have less access to technology with less sophistication of its utilization (Becker, 2000; Hess & Leal, 2001; Waycott, Bennett, Kennedy, Dalgarno, & Gray, 2010). These schools also tended to have higher African-American and Latino student populations. Additionally, the research included information on how girls often feel left out from participating in school-related computer group activities (Becker, 2000; Mims-Word, 2012).

One argument declares that technology skill development is directly related to an individual's use of technology (Kadel, 2008; Lei, 2010; Swain & Pearson, 2003). As a consequence, the limited access experienced by minorities will result in less learning opportunities and potential for employment (Aud et al., 2010; Brown, 2000; Carvin, 2000). Along with these concerns regarding equity, researchers view technology as a potential valuable instructional tool to support teaching and learning (Bull & Bell, 2008;

Wenglinsky, 2005). In the view that all children can learn, students should have access to and opportunities to use technology in means that will potentially assist their learning. Additionally, similar literature sees technology as a resource that advocates equity of learning opportunities in education and policies that seek gap reductions in the digital divide (Ferro, Helbig, & Gil-Garcia, 2011; Hilbert, 2011).

Overall, the digital divide is a complex and dynamic social concern (Dijk & Hacker, 2003; Warschauer et al., 2004). A confusing myth surrounding the digital divide is that students are either in or out, included or excluded, regarding access to technology (van Dijk, 2006). This myth leads to a second misleading assumption that those who have access to computers and the Internet are actually using them (Pflaum, 2004; van Dijk, 2006). Analyses of technology implementation may point out patterns of access and use in schools that often mimic and strengthen existing inequalities rather than improving them (Cuban et al., 2001; Schofield & Davidson, 2004; Warschauer & Matuchniak, 2010).

School Reform and Technology

How does technology fit into education reform efforts? Does technology actually help students learn more? These questions are often raised in research literature regarding educational technology and school reform (Tamim et al., 2011; Wenglinsky, 2006). Opinions are extreme and vary across the spectrum. Some debate that educational technology is obvious only by its nonexistence or by its cursory use in schools (Cuban, 2001; Fullan, 2013; Pflaum, 2004). Cuban (2001) wrote, “The history of school reform aimed at substantially altering teachers’ routine classroom practices is replete with school boards and superintendents adopting ambitious designs that often ended in little classroom change” (p. 815). Fullan (2013) continued, “Technology has

dramatically affected virtually every sector in society that you can think *except* education" (p. 72). A "distressing conclusion," according to Prensky (2012, p. 71), is the sense of urgency experienced by educators to add technology to bring classrooms and education up to date. More often than not, new technologies are deployed before teachers know what to do with them pedagogically, and because of its rapid evolution, many times the technology is obsolete before it can ever add instructional value (Cuban et al., 2001; Prensky, 2012).

Others argue that technology can be the ideal vehicle for education transformation in the 21st century (Kadel, 2008; Noeth & Volkov, 2004). Technology can accelerate learning experiences in a variety of scales with nominal expenses beyond the initial startup investments (Eisenberg, 2008; U.S. Department of Education, 2010). Integrating technology with the appropriate pedagogy can open students and teachers to entirely new worlds of learning (Fullan, 2013). Some researchers describe pedagogy and technology development as converging elements that will create a new digital learning environment on a massive scale for all students and teachers (Fullan, 2013; Means, 2010)

An issue with the above debate is the extreme polarization that often offers minimal correlation to how schools should use technology in the classroom (Cuban et al., 2001). A key perception of educational technology is that it must be understood as a piece of the puzzle – of how teachers teach and students learn (Fullan, 2013; Prensky, 2012). Also, instructional technology is not an isolated event and its role is not only in support of new teaching paradigms but good teaching itself (Ertmer & Ottenbreit-Leftwich, 2010; Means, 2010; Prensky, 2012; Wenglinsky, 2005).

Cuban (2001) identifies three major goals for technology use in education reform:

1. Technology will make schools more productive and efficient. The

expectation is that schools can also improve productivity through technology utilization, based on the productivity gains experienced in the private sector.

2. Technology will transform teaching and learning into an engaging and active process connected to real-world experiences. In efforts to promote more constructivist learning strategies in the classroom, technology is used to motivate students to engage in more problem solving, collaborative learning that is linked to real-world concepts.
3. Technology will prepare students for the future workforce, which will require more technological skills.

Cuban (2001) also outlined several assumptions about technology deployment in schools:

1. Increased technology availability in the classroom, along with a technologically skilled teaching staff, would lead to increased use.
2. The resulting increased use would lead to improvements in teaching practice, make instruction more effective, and result in improved student learning, increased test scores, and improved workforce skills.
3. Improved teaching and learning would produce more knowledgeable graduates with technological skills that enable them to compete successfully in the global workplace.

As a school improvement strategy, researchers tend to agree that technology is often difficult to implement and evaluate (van Dijk, 2006; Wenglinsky, 2006). Different and often competing goals for using technology are associated with the difficulties of effective evaluation (Hilbert, 2011; Pflaum, 2004). Also, there is debate among educators as to which goal(s) are most important (van Dijk, 2006). Schools tend to choose multiple goals for technology implementation, which creates an even more

complex evaluation process (Education Week, 2007). Each goal represents variations in measurement and implementation that add to the complexity of determining technology's effectiveness (Cuban, 2001; Education Week, 2007).

A report by Lemke, Coughlin, and Reifsneider (2009) cited six purposes for technology in education: (1) improve learning, (2) improve student economic viability, (3) increase student engagement in learning, (4) increase the relevance of real-world applications, (5) reduce the digital divide with the increase of technology literacy, and (6) build 21st century skills, including critical thinking, communication skills, information literacy, global awareness, scientific reasoning, productivity, and creativity. These 21st century skills demonstrate the multifaceted nature and complexity of technology in schools. It is this complex culture that influences various aspects of technology use, accessibility, instructional practice, assessment, and program evaluation (Fullan, 2013).

Educational Technology Policy

The drive to bring computers and new technologies into schools and classrooms involved three essential players: federal and state governments and the private sector. The fundamental work of these groups emerged from the wake of the 1983 report, *A Nation at Risk* (National Commission on Excellence in Education, 1983) which prompted the push to "save America's schools from mediocrity" (Wenglinsky, 2005, p. 12). Many of these leaders believed that technology would be the single most efficient tool to improve schools and ensure accountability. One result of these simultaneous efforts to increase technology in schools is an increased average 5:1 ratio of students to computers (Valadez & Duran, 2007). However, in recent decades, technology and related skills have raced ahead of education. This is not because of technology's rapid change but rather the slow adaptation and growth of education (Fullan, 2013).

Federal Technology Policy Background

The federal government has historically offered broad support for technology in schools. Computer technology and infrastructure was largely introduced in schools during the 1970s with assistance of federal programs such as Title 1, Star Schools, and E-Rate. Early use of technology in schools was primarily computer-assisted drill and practice applications for elementary reading and mathematics (Cherian, 2009). Papert (1982), during the early 1980s, developed and introduced LOGO, a programming language designed for young children. This pioneering work set a foundation for using computers as a tool to assist in thinking skills development in elementary classrooms.

The marketing of low-cost personal computers by IBM and Apple for the education sector resulted in widespread acquisition of computers in both homes and schools. This initiated the first major expanse of technology access and experiences for students. *A Nation at Risk* (National Commission on Excellence in Education, 1983) called for increased computer competencies in schools to better prepare students for a more technologically skilled work force in the emerging information age. The National Assessment of Educational Progress (NAEP) conducted in 1986 the first nationwide assessment of student computer competencies to learn how students were using computers in schools across the nation (Sutton, 1991). The assessment revealed the majority of computer uses were for literacy and programming, with limited utilization in core subjects.

It was during this time that information technology began “taking root” in different areas of the U.S. economy. During the late 1980s and early 1990s, educational technology was identified by political and business leaders as a tool to provide technical skills necessary to fill emerging jobs in the information economy (Cherian, 2009).

Wenglinsky (2005) explained further.

> In their view, technology such as personal computers and networks was revolutionizing the workplace, unleashing major productivity gains that resulted in an unprecedented period of economic growth in the 1990's. By using such media in schools, they believed that they could initiate similar gains in educational productivity, leading students to meet the new, challenging academic standards. (p. 13)

This new perspective was reflected in the start of federal initiatives designed specifically for educational technology. Federal involvement began in 1994 with the Technology for Education Act that called for increased exposure of students to technology. The legislation was a part of the larger Improving America's Schools Act of 1994 and purposed to help students learn at high standards as well as promote effectiveness and efficiency (U.S. Department of Education, 1994).

Based on this act, two technology initiatives were introduced by the Clinton administration in 1996. The Technology Literacy Challenge Fund (TLCF) and the Technology Innovation Challenges Grant (TICG) were significant investments in educational technology with two distinct approaches. The TLCF focused on developing infrastructures for student technology literacy by offering $5 billion over 5 years to states. This was to provide states and school districts with resources to equip schools with computer hardware, software, and teacher training opportunities (Cuban, 2001).

The emphasis of TICG followed a different path, to experiment with various utilizations and integrations of technology to improve student learning in core subject areas. The 5-year grant would provide resources for educators, researchers, and industry to start, refine, and develop system-wide technology initiatives that supported one of the

six following activities:

- develop standards-based curricula in a wide range of subjects,
- provide professional development for teachers,
- increase student access to technology and online resources,
- provide technology training and support for parents in low-income areas,
- devise techniques for assisting teachers in developing computer-based instruction,
- create strategies for accelerating the academic progress of at-risk children via technology, and
- develop new approaches to measuring the impact of educational technology on student learning (U.S. Department of Education, 2009).

Nineteen ninety-six proved to be a milestone regarding federal technology funding programs. Congress authorized the Telecommunications Act of 1996 which included provisions for a universal service fund, commonly known as the E-Rate program. E-Rate provides discounts to assist most schools in the United States to obtain affordable telecommunications and Internet access. High-poverty school districts (with more than 75% of students qualifying for free or reduced lunch) were given funding preference and less-poor districts shared any remaining funds (Cherian, 2009; Cuban, 2001; Warschauer & Matuchniak, 2010; Wenglinsky, 2005).

A third Clinton administration initiative, known as Preparing Tomorrow's Teachers for Technology (PT3), was launched in 1999. This program supported the activities of school districts and higher education institutions to prepare teachers in technology use and integration. These projects also emphasized student groups that were underrepresented in technology and economically disadvantaged (U.S. Department of

Education, 2006).

The Bush administration continued on a similar course with its technology programs. Building on the earlier Clinton activities, Title II of the NCLB legislation provided resources for educational technology, grant programs for states, and varied national technology initiatives. Approved in 2001, this technology policy was referred to as the Enhancing Education Through Technology Act or EETT. This policy emphasized the importance of technology to enhance curricula, increase student achievement, and develop job-ready skills. The legislation also acknowledged the existence of a digital divide in computers with connectivity to the Internet, with a 9:1 ratio in high-poverty schools compared to a 6:1 ratio in low-poverty schools (U.S. Department of Education, 2004; Wenglinsky, 2005).

Transforming American Education Learning Powered by Technology is the current education technology plan from the U.S. Department of Education (2010) and states,

> The plan recognizes that technology is at the core of virtually every aspect of our daily lives and work, and we must leverage it to provide engaging and powerful learning experiences and content, as well as resources and assessments that measure student achievement in more complete, authentic, and meaningful ways. Technology-based learning and assessment systems will be pivotal in improving student learning and generating data that can be used to continuously improve the education system at all levels. Technology will help us execute collaborative teaching strategies combined with professional learning that better prepare and enhance educators' competencies and expertise over the course of their careers. To shorten our learning curve, we should look to other kinds of enterprises, such

> as business and entertainment that have used technology to improve outcomes while increasing productivity. (p. ix)

The 124-page document lays out a determined agenda to utilize technology for transforming teaching and learning. The plan consistently emphasizes 21st century learning and related competencies that include critical thinking, problem solving, collaboration, and multimedia communication (Bailey et al., 2011; U.S. Department of Education, 2010).

North Carolina Technology Governance and Policies

Coinciding with new federal technology policies, the North Carolina General Assembly created the State School Technology fund in 1993 under the direction of the North Carolina State Board of Education. This legislation provided funds to assist school districts in the development and implementation of local technology plans. These plans were designed to improve student performance by utilizing learning and instructional technologies (Mesibov & Johansen, 2007).

In addition to providing funds for technology, statute 115C-102.5 also created the Commission on School Technology purposed to advise the State Board of Education on the development of the state school technology plan. The components of the state technology plan were to serve as a model for local districts and to ensure that effective use of technology is built into the North Carolina public schools. The plan also guarantees school technology equity and access for all student population groups. The Commission meets two times each year and provides feedback on the state school technology plan prior to its approval (North Carolina General Assembly, 2009).

The Annual Media and Technology Report (AMTR) is a legislatively mandated instrument that provides data on school media and technology programs to school-,

district-, and state-level stakeholders. The information is based on the school- and district-level media and technology inventories on July 1 of each year. This report gives both the legislature and the public a yearly snapshot of the state of media and technology programs in North Carolina's schools.

Questions included in this report are based on the requirements in the North Carolina Educational Technology Plan and requests data from agencies within NCDPI and state government. Accuracy is essential as these data can affect fund allocations from state and federal agencies. Once collected and analyzed, these data are used by federal and state governments, the North Carolina State Board of Education, divisions of NCDPI, school districts, and the public.

Frequently, budgetary and resource allocation decisions are impacted by this data. The data generated from the AMTR may be used to (1) determine eligibility for grant funding, (2) support the needs addressed in grant proposals, and (3) evaluate and improve school media and technology programs. The reports generated from this data are disseminated at state and national conferences and in publications at the national, state, and local levels. These reports are also published on NCDPI websites and utilized as part of the ABC Report Card process (NCDPI, 2013a).

Technology Access in Schools

Access is a term used to describe various technology resources, computers, Internet, software, and support (Collins & Halverson, 2009; Lemke et al., 2009). Typically in research literature, measures of access are reported at the national, district, and school levels including by gender, race, locale, and SES (Education Week, 2007; National Education Association, 2008). Warschauer and Matuchniak (2010) stressed the importance of regarding technology access in the context of not only what is available but

also how the technology is supported.

A widely used standard for describing computer access is the ratio of students to computers (Norris, Soloway, & Sullivan, 2002). This ratio is calculated by dividing the total number of students by the total number of computers – the lower the ratio, the greater the number of computers available to students. Trends in access show that the ratio has significantly decreased over time, indicating increased numbers of computers deployed in schools (NCES, 2013).

The student-to-computer ratio is a useful measure since it takes into account the number of students who potentially have access. Because the ratio calculation is based on the entire student population of a school, it does not show the number of students who share a computer in a classroom (Norris et al., 2002). Student-to-computer ratios at the school level are totaled to develop district-level ratios. State-level computer access would then be the mean (average) and median (middle) of student-to-computer ratios calculated across all the districts. When the median is less than mean, it represents large ratios that skew the distribution away from the normal curve. These ratios provide a systematic mechanism to compare levels across various schools or districts (Ronnkvist, Dexter, & Anderson, 2000). Access ratios can be used in a variety of capacities from the facilitation of comparisons of computer access in schools across the state to comparisons with schools in other states or national averages (Agodini, Dynarski, Honey, & Levin, 2003).

There is little agreement among researchers as to what constitutes the ideal student-to-computer ratio or specifications for the ideal level of computer access in schools (Organisation for Economic Co-Operation and Development, 2002; Tab, 2005). The National Education Association (2008) reported the current number of classroom

computers were not sufficient to effectively support instruction. The U.S. Department of Education's Office of Education Research and Improvement (U.S. Department of Education, 2003) suggested a student-to-computer ratio of 5:1 as an adequate level for efficient use in schools. North Carolina and many other states have surpassed this level for effective use (NCDPI, 2013a; NCES, 2013).

Another argument is the frequency-of-use measurement as another indicator of computer access (Cuban, 2001; van Dijk, 2006). Frequency of use may present a clearer picture of student access, but accurate data are difficult to acquire (Valadez & Duran, 2007). School ownership of computers is reflected in the student-to-computer ratio; however, computers may be underutilized or unused (Cuban et al., 2001; Pflaum, 2004; van Dijk, 2006). Levels of technology spending additionally can serve as computer access indicators; however, this metric also reflects technology ownership by schools and not necessarily the access for student use (Lei, 2010; Wenglinsky, 1998).

Additional indicators of technology access in schools include computer density, computer capacity, computer renewal, computer location, software, and Internet access (Anderson & Ronnkvist, 1999). Also, these indicators have been used to determine learning opportunities for students in schools (Ronnkvist et al., 2000).

Computer density is a description of the concentration of computers in a classroom, school, or district (Anderson & Ronnkvist, 1999). Numbers of actual computers are not as significant as a measure of computer density unless they take into account the number of students. Lower computer densities make it difficult for students to spend time engaged in meaningful learning with instructional technology. Taking student-to-computer ratios into consideration, computer densities can indicate how likely students would have to share computers at school (Anderson & Ronnkvist, 1999). The

smaller the ratio, the greater the computer density in a classroom, school, or district.

Computer capacity is an indicator of the computer's processing power or potential processing power based on how it is equipped. Older computers typically are slower and often unable to run newer, more complicated software. High-end computers have faster processing speeds which are capable of running latest versions of software that typically include intensive graphics (Ronnkvist et al., 2000).

Computer renewal refers to the amount of time computers are used in schools before they are replaced with new models. Instructional technology changes at a rapid pace, and schools are adjusting to the progressively shorter replacement demands and purchasing many more computers. The average computer is now obsolete in 4 years or less; if a school has a median of 80 computers, it will purchase approximately 20 new computers annually to maintain capacity (Ronnkvist et al., 2000).

Computer location is significant regarding technology access for teachers and students in schools (Anderson & Ronnkvist, 1999). The presence and number of computers alone does not mean access is readily available. If computers are not located in a certain classroom, then teachers and students may not have access to effectively use the technology for learning. If schools deploy computers in a shared location such as a computer lab, they ensure limited resources are available to more students and teachers (Ronnkvist et al., 2000).

Software is likewise essential for students and teachers to benefit from technology in their teaching and learning (Anderson & Ronnkvist, 1999). The total amount of software available in a school is known as *software saturation*. Additionally, another measure of software in schools is the availability of specialized software known as *software diversity*. According to Anderson and Ronnkvist (1999), high schools typically

have higher software diversity but lower software saturation than elementary schools.

Internet Access in Schools

Internet access is perhaps the fastest growing measure of communication technology in educational history (Fox, Waters, Fletcher, & Levin, 2012). Since 1995, almost 100% of U.S. schools have some form of Internet access (NCES, 2013). A comparison of 2000 and 2008 data shows the national student-to-computer with Internet ratio was reduced by over 50% from 6.6:1 to 3.1:1 in U.S. public schools (NCES, 2012). However, a recent report by the State Educational Technology Directors Association (SETDA, 2008) indicated that 72% of schools do not meet the basic Internet bandwidth requirements of 100 kbps (kilobits per second) per student (Fox et al., 2012). This is considered the minimum requirement to run a school-wide 1:1 computer initiative (Fairbanks, 2014).

Current literature takes into account the universal connectivity in schools and refines its focus on the amount and quality of Internet access (Fox et al., 2012; U.S. Department of Commerce, 2011). This redefined measure has gained much consideration in conversations describing and comparing technology access in schools (FCC, 2009; Prieger & Hu, 2008). Further, a 2013 survey conducted by the Consortium for School Networking and Market Data Retrieval revealed an astonishing 99% of school districts indicated a need for increased connectivity. The survey also reported that only 64% of high schools and 57% of elementary schools had wireless Internet capability (Consortium for School Networking, 2013).

The Internet has become the essential linking tool for many to access and share information, data, and resources (Wenglinsky, 2005). A Pew Internet Project survey found 87% of all youth between the ages of 12 and 17 used the Internet (Rainie & Hitlin,

2005). The Broadband Task Force established by the FCC reported approximately 71% of teens said the Internet has been a primary resource for recent school projects (FCC, 2009). The report also stated that at least 65% of surveyed teens used the Internet at home to complete homework. For a growing percentage of the online teen population, schools have become an important setting for Internet use for a substantial number of teens (Rainie & Hitlin, 2005).

Increased connectivity and Internet speeds allow schools, teachers, and students to access a wide range of instructional resources from electronic textbooks to virtual simulations to social networking to online classes (Groff & Haas, 2008; Pool, 2006; Wenglinsky, 2005). March (2006) described evolving Internet access as "A new world of personalized, device-delivered digital content and functionality hovers just over the broadband horizon. The new WWW – offering us whatever we want, whenever and wherever we want it" (p. 14).

Internet Access in North Carolina

North Carolina has seen similar trends in school connectivity. The 2012 AMTR stated that 99.8% of North Carolina schools were connected to the Internet. The ratio of student-to-computers with Internet connectivity also decreased from 3:1 in 2008 to 1.8:1 in 2012 (NCDPI, 2013a) Since the late 1990s, the North Carolina Research and Education Network (NCREN) has provided Internet connectivity exclusively to K-12 schools, community colleges, private and public universities, research and healthcare institutions, and state and local governments across the State of North Carolina. Today, NCREN provides broadband Internet connectivity to all 115 school districts in North Carolina at no additional cost to the LEAs (Herman & Staker, 2010; MCNC, 2014).

Home Internet access in North Carolina has risen significantly over the past

decade. In 1999, approximately 36% of North Carlina homes reported some form of internet access. By 2011, the number of connected homes in North Carolina increased to 79% (Powers, Wilson, Keels, & Walton, 2013). However, according to an FCC Internet service report, North Carolina ranks last in the nation in the percentage of households with Internet connections with download speeds of at least 3 Mbps, which is the minimum connection speed for basic broadband service (FCC, 2013).

Technology Use in Schools

One focus of this study is the instructional use of technology in secondary science classrooms. Since the introduction of the Apple IIe computer in 1983, technology has symbolized a wide range of interests and has been the subject of many interpretations (Cuban, 1986). In school districts across the nation, technology has been the center of curriculum reform efforts and school budget deliberations (Fullan, 2013). It has become the catchphrase for leading many districts into the 21st century (Cuban, 2001; Moersch, 1995; U.S. Department of Education, 2004).

Over the last 3 decades, computer and Internet technologies have emerged into significant roles in the evolution of science instruction (Lei & Zhao, 2007; Osborne & Hennessy, 2003). Their increasing prevalence and diversity of use in the classroom offers promises and challenges to teachers and students (Campbell, Wang, Hsu, Duffy, & Wolf, 2010). In addition, this challenge of change has been constant throughout education's history, and the impact of technology and its use in the classroom has tremendously accelerated this process (Culp et al., 2003; Tamim et al., 2011). Fullan (2013) asserted that technology, change, and pedagogy are all connected collectively and make an invincible combination. He stated, "The convergence is so strong that we may well see in the in the immediate future multiple lines of breakthrough solutions

radicalizing how and what we learn" (Fullan, 2013, p. 5). Despite this rapidly evolving environment of technology, a U.S. Department of Education (2003) report indicated that 85% of teachers felt "somewhat well-prepared" to use technology in classroom instruction (p. 12).

Technology influences teaching and learning in the sciences by promoting activities and practices that are closely relate to real-world situations (Lee & Tsai, 2013). Although technology is becoming more significant in science education, it is unlikely to replace the classroom teacher (Fullan, 2013). Moreover, a weak teacher's ability will not be improved by using technology in their classroom (Matray & Proulx, 1995; Phillips & Moss, 1993). The use of technology in the classroom is naturally shaped by the teachers' perceptions of what science education is supposed to be (Drayton et al., 2010). These factors reveal the importance of effective and extensive teacher training which has a clear purpose and allows teacher ownership in the planning and reform efforts (Fouts, 2000).

However, technology can offer a variety of opportunities for teachers to present science concepts in more exciting and engaging ways (Ash, 2011; Osborne & Hennessy, 2003). In this type of environment, the teacher role moves from lecturer to guide as students are allowed to actively explore scientific processes rather than passively memorize facts (Odom et al., 2011). Even in these transformations of roles, technology will not change what is taught in the science classroom, only the way in which it is taught (Drayton et al., 2010; Fullan, 2013; Gado, Ferguson, & Van't Hoof, 2006).

Technology's complex nature lends itself to a variety of uses, which include individual and group learning, information processing and sharing, communications, instructional management, distance learning, and assessment (Lee & Spires, 2009; Muir-Herzig, 2004; Wenglinsky, 2005). Linn (2003) explained that these technologies are the

cutting edge of visualizations and venues for collaboration, communication, simulation, and data processing.

Computers, mobile devices, and cloud and Internet resources are commonly used for administrative, instructional, and assessment purposes today (Muir-Herzig, 2004; Osborne & Hennessy, 2003; Thomas & Lee, 2008). However, the versatility of technology provides a vast array of potential uses in the classroom (Pool, 2006). Text, graphics, audio, video, animation, mobility, communications, and computation combine together to create unlimited possibilities for use by teachers and students in daily classroom activities (Groff & Haas, 2008).

Laboratory experiences are also an important component of the biology curriculum which should not be supplanted by technology. Instead, computers and software can allow students to conduct specific laboratory exercises that would not otherwise be available due to lack of time, equipment, and/or resources (Bull & Bell, 2008). In these situations, for example, computer simulations can provide an accessible medium to conduct experiments and collect and analyze data in a more conventional environment (Matray & Proulx, 1995). Students also can visualize important ideas in biology that occur on a microscopic level which are often difficult to comprehend (Davis, 2008; Wenglinsky, 2005).

Previously stated, technology offers various tools for use in a wide range of instructional programs and activities in the science classroom. Osborne and Hennessy (2003) organized technology for science instruction into several process-oriented categories:

- data collection, processing and analysis.

- simulations and virtual experiments.
- presentation and publishing.
- information and communication systems.
- digital recording and projection.

These categories of instructional technology can enhance the theoretical aspect as well as the practical part of teaching and learning in the science classroom (Bailey et al., 2011; Thomas & Lee, 2008). Supporting exploration and freeing up time for collaboration and analysis, according to Osborne and Hennessy, are two ways technology can augment instruction. Wenglinsky (2005) added that technology not only improves motivation and engagement, but also "produce far greater opportunities for all students to learn to high standards, promote efficiency and effectiveness in education" (p. 20).

Data collection, process, and analysis. Tools for data collection, processing, and analysis are considered the most relevant group of technologies for science instruction. The centerpiece of this group is data probes or data logging systems. This technology can be found everywhere from the grocery stores, automobile factories, doctor's offices, and in the hands of students after school (i.e., smart phones).

Before 1970, the first application of using technology for data collection was the Calculator and Laboratory Calculus (CALC) project that consisted of a calculator, interface, and x-y plotter. This mathematics-based application allowed students to improve their conception of important topics in calculus (Tinker, 2004). In the late 1970s, data collection technologies began to emerge in physics laboratories across many universities in the United States.

During the 1970s and 1980s, several arguments developed over the value of such

technologies with many detractors claiming that automating laboratory processes would hurt student collaboration and learning. However, Park (2008) reasoned that while data probes and other data collection technologies could be used in *cookbook* science activities, using these technologies in conjunction with inquiry-based methods can increase learning. Tinker (2004) agreed with this reasoning by asserting that “Good experiments that use probes still leave it to the student to decide what to measure and how to interpret the results” (p. 3). Data collection and analysis tools have existed for decades and yet their potential continues to be discovered as more schools incorporate their use into instruction (Drayton et al., 2010).

One impact of using data collection technologies is reduction of data collection time and elimination potential collection errors (Drayton et al., 2010; Osborne & Hennessy, 2003). Educators emphasize that data collection tools can eliminate errors in data recording, improve accuracy, and allow for increased repetitions of experiments (Drayton et al., 2010). Research findings by Gado et al. (2006) concluded that students have more time to devote design and interpretation with the use of hand-computers and probeware. Use of data collection technology can also increase motivation, improve student understanding of science concepts, and enhance mathematical abilities (Drayton et al., 2010; Gado et al., 2006).

The power of probeware and other data collection technologies is their capability to produce real-time data. Various research studies reported that students working with real-time data demonstrated significant learning advantages over environments that only produced delayed data. Research by Russell, Lucas, and McRobbie (2003) observed 29 high school physics students as they participated in four consecutive lessons involving microcomputer-based laboratory (MBL) technologies. Students performed tasks that

involved collecting data and graphs of constant and accelerated motion in a variety of vectors and magnitudes. Students analyzed the motion data and described the various aspects of the observed motion within small working groups of two or three students.

The study concluded with eight assertions: (1) students viewed the graphical displays as representative of the experimental problem, (2) the small working groups completed most of the tasks at a deeper level of engagement, (3) the graphical displays supported deeper learning, (4) students employed critical evaluation skills, (5) conceptual change was fostered by the learning environment created by the MBL, (6) students shared technology resources to collaborate in activities designed for data interpretation, (7) MBL technology supported the working memory of participating students, and (8) probing questions from the teacher encouraged more thoughtful responses relating to the analyzed motion graphs.

Marcum-Dietrich and Ford (2002) investigated the impact of computer probeware on student learning and discovered positive results in tenth-grade biology classes. Their study was conducted in five biology classes with students divided into two groups. One group conducted laboratory activities using traditional practices, and the other groups conducted the same activities using computer probeware technology. Pre and posttest data, laboratory procedures, lab reports, and student interviews were used to measure student understanding.

The study revealed students using probeware technologies performed slightly better on tests, lab reports, and procedure design than the traditional group. Marcum-Dietrich and Ford (2002) concluded that technology's greatest benefit was its ability to give "meaning to the complex data" and provide "students with a bridge between laboratory's data and the general phenomenon being investigated" (p. 376). Spanning

this disconnect allowed students to better analyze and interpret data which resulted in stronger connections and understand of concepts.

Another advantage is the availability of data collection software for calculators, computers, and mobile devices. Vendors commonly include such software with the data collection hardware packages. Additionally, this software allows users to manipulate various settings to customize their experiments and collect more refined data and display data in graphic or tabular forms. Its data analysis capabilities allow students to perform graphical and statistical tests such as standard deviation, chi-square, line of best fit, line/curve slope, and area under a curve. Today, probeware is used in the physical, life, and earth sciences measuring a multitude of variables such as acceleration, CO_2 concentration, pH, relative humidity, turbidity, and voltage (Park, 2008).

Simulations and virtual experiments. A computer simulation is defined as a program that uses a process or model of a natural or artificial system. Perkins, Loeblein, and Dessau (2010) described simulations or sims as programs that "create animated, game-like environments in which students learn through scientist-like exploration" (p. 47). Simulation programs have become more accessible as technology has advanced over time. They have transcended the science laboratory and are now easily found in museums, classrooms, and science centers, as well as "on the web" (Bell & Smetana, 2008).

Various research finds that computer simulations offer many advantages as a supplement to well-established curriculum and effective teaching methods (Bell & Smetana, 2008; Perkins et al., 2010; Rutten, van Joolingen, & van der Veen, 2012). Akpan's (2001) review of literature concluded the use of simulations provides a potential for greater learning results in ways not previously possible in science classrooms. They

make it possible for students to access and explore processes, physical situations, and phenomena that would otherwise be impractical, time-consuming, and/or dangerous to conduct the actual experiment (Akpan, 2001; Bell & Smetana, 2008; Steinberg, 2000). Steinberg (2000) explained that in using computer simulations, students are learning in profoundly different ways from the original experiment process experienced by scientists.

Good simulations can actually be pedagogically more effective than similar classroom demonstrations and exercises conducted with real laboratory equipment (Perkins et al., 2010; Wieman & Perkins, 2006). However, simulations do not automatically come with a pronounced "pedagogical power" (Perkins et al., 2010, p. 234). Wieman and Perkins's (2006) research, involving hours of student testing, revealed that simulations can be "boring, frustrating and misleading" or also "be fun, engaging, but educationally worthless" (p. 291). They concluded that in order for computer simulations to be effective, designs should feature (1) highly interactive animation that immediately responds to user interaction; (2) an appealing environment with sophisticated graphics to encourage users to explore and discover; (3) simple controls that requires minimal reading; and (4) connections to real-world processes, physical situations, and phenomena.

Regarding the impact of simulations on student achievement, Bell and Smetana (2008) cited a study which examined the effects of computer simulations on student achievement in chemistry. They found higher achievement scores for students who participated in simulated labs as compared to students involved in the traditional hands-on labs. Similar research was conducted by Lazarowitz and Huppert (1993) which revealed significantly higher achievement scores in the experimental simulation groups. Their study involved 181 students in five biology classes which consisted of an

experimental group that used simulations and a control group that used laboratory work alone. In addition to the higher achievement scores, the experimental group also performed better on science process skills such as graph communication, data interpretation, and variable control.

The research of Blake and Scanlon (2007) showed that simulations can assist the teaching of science by freeing up instructors' time, allowing teachers to interact with students rather than managing and supervising the experiment processes and equipment. They further explained that computer simulations offer simplified methods to control experimental variables. This feature provides additional opportunities for students to explore and hypothesize. They concluded that the variety of simulation formats (diagrams, graphics, animation, video, and sound) enhance learning and understanding. Additional research concurs that simulations can aid science teaching; however, they cannot replace the work of a good science teacher (Akpan, 2001; Blake & Scanlon, 2007; Perkins et al., 2010; Rutten et al., 2012; Steinberg, 2000).

Emerging technologies. Students in the classroom are becoming content creators (Bull & Bell, 2008) and can be characterized as *digital natives* due to the fact that many have grown up with the Internet (Prensky, 2012). They create and share original media such as photography, artwork, videos, web pages, and blogs. The majority of these students interact and communicate with peers via social media, text messaging, and video conferencing (Bull & Bell, 2008; Fullan, 2013). Prensky (2012) described a number of areas where these digital natives are "creating their own way of doing things" (p. 62). This often occurs under the radar of teachers and adults who have not grown up in the Internet age – referred to as *digital immigrants* (Prensky, 2012).

Digital natives are communicating and socializing differently. Communication for everyone has significantly changed since the establishment of the World Wide Web. Long distance and international communication went from expensive to essentially free (Prensky, 2012). Technology today allows for asynchronous communication (only one communicating group needed at a time) such as email and text as well as synchronous communication such as chat and instant messaging. As a result, a new phenomenon has emerged – online friends and acquaintances (Bull, Bull, Garofalo, & Harris, 2002). Digital natives have embraced this emergence and integrate multiple elements of communications simultaneously as a natural part of daily activity (Berk, 2010). In this new communication culture, digital natives have developed methods to speed up these tools to simulate talking by using abbreviations and codes of existing language (Prensky, 2012).

Digital natives are sharing differently. Email and texting are both forms of sharing, and yet students have utilized other specific technologies to share details about occurrences in their daily lives. The increase of 3G/4G mobile networks and personal devices easily allows information to be shared on a regular basis, even simultaneously as events are experienced (March, 2006). Web logs (known as blogs), podcasts, web cams, and camera phones are all engaging platforms that allow students to interconnect in ways never imagined (Pool, 2006; Prensky, 2012). A study by Tatar and Robinson (2003) indicated that digital cameras increased student learning of process skills in two biology lab activities. There was also anecdotal evidence which indicated the experimental group demonstrated a greater interest in setting up the equipment and had fewer mistakes in lab procedures than the control group.

Digital natives are creating differently. According to Prensky (2012), “One of

the defining characteristics of Digital Natives is the desire to create" (p. 93). Students have become adept at constructing websites, producing videos, and other online creations – including whole new worlds like Minecraft and Second Life (Berk, 2010). They now have access to various programming and editing tools which allow them to surpass content created by the original developers. Importantly, students expect to have access to these powerful tools and know how to use them by teaching themselves and one another (Groff & Haas, 2008).

Digital natives are learning differently. One can easily speculate as to what is on the horizon for learning with new technology (Pool, 2006; Prensky, 2012). Students are extremely aware that if they *want* to learn something, digital tools and online resources are available for them to learn it on their own; they have been empowered to become free agent learners (Project Tomorrow, 2010). Social media allows students to easily interact and teach each other – a form of digital apprenticeship (Bailey et al., 2011; Berk, 2010).

Prensky (2012) stated,

> Today, when a student is motivated to learn something, she has the tools to go further in her learning than ever before – far beyond what even adults could have done in the past. The Digital Natives exploit this to the fullest, while ignoring, to a larger and larger extent, the things they are not motivated to learn, which unfortunately, includes *most*, if not all, of their school work. (p. 96)

In the 2009 Speak Up survey conducted by Project Tomorrow (2010), approximately 51% of the 38,000+ teachers surveyed indicated their students were motivated to learn using technology in their classroom. Approximately 25% of the teachers reported students were taking ownership of their own learning as a result of the

same technology use. Similar findings have been found in other studies that examine student learning and achievement with classroom technology use (Corn, Huff, Halstead, & Patel, 2011; Lopez-Perez, Perez-Lopez, Rodriguez-Ariza, & Argente-Linares, 2013; Odom et al., 2011).

While some teachers are afraid of new technology and others question its value, digital natives as a whole will not go back to the old ways (Fullan, 2013). Prensky (2012) summarized this thought:

> Yes, there will be some digital natives who still hand-write letters, just as there are musicians who play 16th century music on old instruments. But letter writing in longhand is a thing of the past, like it or not. So are things like holding only one conversation at a time, looking people in the eye to know if you trust them, shaking hands as the final rite of a deal, hiding porn under the mattress, keeping information to oneself for personal status, paying for music, buying without easy comparison shopping, games where you don't create parts yourself, dating that isn't technology mediated, reputations based on status rather than performance, excuses for not having information, and many, many other things. Get used to it. (p. 100)

Measuring Technology Use

Research usually defines *use* based on frequency, which measures technology use on a time continuum (daily, weekly, etc.). However, measuring technology use is a challenging endeavor (van Dijk, 2006), and in time continuum context, frequency is aligned with quantity without regard to the quality of use (Lei, 2010). Another consideration is technology may not be appropriate for all instructional situations and its use depends on the teacher's goals and objectives (Cuban et al., 2001; Drayton et al.,

2010).

ISTE advocates that technology in education has a positive influence on student achievement when implemented appropirately (Kadel, 2008). ISTE identified seven key elements necessary for effective technology use:

1. Effective professional development for teachers in the integration of technology into instruction is necessary to support student learning.
2. Teachers' direct application of technology must be aligned to local and/or state curriculum standards.
3. Technology must be incorporated into the daily learning schedule.
4. Programs and applications must provide individualized feedback to students and teacher must have the ability to customize lessons to meet individual student needs.
5. Student collaboration in the use of technology is more effective in influencing student achievement than strictly individual use.
6. Project-based learning and real-world simulations are more effective in changing student motivation and achievement than drill-and-practice applications.
7. Effective technology integration requires leadership, support, and modeling from teachers, administrators, and the community/parents. (Kadel, 2008, p. 3)

Additional research evidence indicates that frequent inappropriate use of technology can have negative effects on learning (Odom et al., 2011; Wenglinsky, 2005). Due to technology's rapid evolutionary nature, research has not clearly defined the most effective use of technology in student learning (Fullan, 2013; Pflaum, 2004). As a result, the relationship between technology use and student achievement still remains a topic of

considerable debate (Bailey et al., 2011; Cuban, 2006; Lei, 2010; Schacter, 1999; Wenglinsky, 2006).

Technology and Student Achievement

The purpose of this study is to determine potential relationships between technology use and student achievement based on gender, locale, race, and SES. Because the emphasis of this study was technology use in secondary biology classes, this section focuses on research of instructional technology that analyzed student achievement in science.

Research on the effectiveness of instructional technology and science tends to be inconclusive and often infrequent, making it challenging to conduct research regarding use and achievement (Bebell & Kay, 2010; Patel, Corn, & Halstead, 2011; Lei, 2010). The research is also limited in determining which types of technology have the greatest impact on learning, under which circumstances, and for which students (Education Week, 2007; van Dijk, 2006). Despite these difficulties, a popular consensus among researchers is that within the appropriate pedagogy, technology has great potential to improve student achievement, motivation, learning efficiency, and cognitive skills (Chapman, Masters, & Pedulla, 2010; Fouts, 2000; Kadel, 2008; Wenglinsky, 2005). Several recent studies have identified positive correlations between student achievement in science and technology use (Bertacchini, Bilotta, Pantano, & Tavernise, 2012; Drayton et al., 2010; Karamustafaoglu, 2012; Shapley et al., 2010; Yusuf & Afolabi, 2010).

ISTE published a brief in 2008 that discussed the link between technology and student achievement (Kadel, 2008). Over a 20-year period, ISTE analyzed various technology programs in schools and districts across the United States to determine potential relationships between technology use and student achievement. Common

findings of these evaluations revealed that instructional technology not only influenced student achievement but when effectively utilized, improved student achievement (Kadel, 2008). Many concur that how technology is used has a greater impact than the magnitude of access – quality over quantity (Lei, 2010; Lei & Zhao, 2007; Papanastasiou et al., 2003; Ravitz et al., 2002).

A program study conducted by Meyers and Brandt (2010) evaluated the Enhancing Missouri's Instructional Networked Teaching Strategies (eMINTS) from 1999 to 2009. This program began in 1997 as a grant partnership which formed the Multimedia Interactive Networked Technologies (MINTs) project. Its goal was to deliver high-speed Internet connections to classrooms and place technology in the hands of teachers and students. The purpose of the MINTs project was to determine whether removing technology barriers traditionally experienced by schools could change teaching strategies and improve student performance.

The preliminary results of MINTs were very successful and prompted the Missouri Department of Elementary and Secondary Education in 1999 to launch a statewide initiative known as eMINTS. This program utilizes professional development in interactive group sessions with classroom coaching and mentoring to help teachers integrate technology into their teaching. It incorporates a model that promotes inquiry-based learning, high-quality lesson design, fosters community between students and teachers, and builds technology-rich learning environments (eMINTS National Center, 2013).

Meyers and Brandt's (2010) evaluation revealed that students in eMINTS classrooms outperformed students in non-eMINTS classrooms in both proficiency and mean achievement of science, math, language arts, and social studies. eMINTS students

scored higher in science but with minor significance, producing effect sizes between .11 and .16 (Meyers & Brandt, 2010). However, ISTE reveals that third graders scored significantly higher in science as compared to their peers in statewide assessments (Kadel, 2008). Meyers and Brandt's analysis of student subgroups found gaps between eMINTS and non-eMINTS students – those with individualized education plans (IEP), who qualified for free and reduced lunch (FRL), and minorities (Meyers & Brandt, 2010). These gaps in student subgroups were statistically significant and grew over time, especially students who qualified for FRL. Additionally, students with IEPs and students with limited English proficiency (LEP) in eMINTS schools outscored non-eMINTS peers by approximately one standard deviation in all four subjects (Meyers & Brandt, 2010).

Michigan's Freedom to Learn is a statewide 1:1 laptop program with goals similar to Missouri's eMINT initiative – to improve student achievement and engagement in the context of changing how teachers teach and students learn. Implementation began during the 2004 school year in 199 schools in both rural and urban school districts across the state. Participating schools included elementary, middle, and secondary schools with initial deployment occurring in sixth-grade classrooms. The program created one-to-one learning environments by providing a laptop and wireless connection for each teacher and student. Teachers are immersed in professional development focused around effective technology integration (Kadel, 2008; Ross & Strahl, 2005).

Evaluation of Michigan's Freedom to Learn program has shown success in student achievement within various groups across subjects (Franceschini, Allen, Lowther, & Strahl, 2008; Lowther, Strahl, Inan, & Bates, 2007; Ross & Strahl, 2005). One FTL school witnessed science achievement increase from 68% to 80% in 2003-2004, and math achievement doubled from 31% to 63% the following year (Ross & Strahl, 2005).

These evaluations also reveal that FTL students consistently have significant higher engagement levels regarding technology use as a learning tool compared to national averages (Franceschini et al., 2008; Lowther et al., 2007). Observations of FTL classrooms indicated increased use of technology as learning tools rather than vehicles for more traditional teaching practices such as drill and practice (Lowther et al., 2007). Additionally, evaluators observed FTL teachers more in the role of a coach or facilitator and employing less direct instruction (Ross & Strahl, 2005).

Other studies reveal that technology use has a variable effect or no effect on student achievement in science (Alspaugh, 1999; Fouts, 2000; Lei & Zhao, 2007; Lin, Cheng, Chang, & Hu, 2002; Odom et al., 2011; Shieh, Chang, & Liu, 2011). In some cases, research has shown negative impacts of technology use on achievement (Owusu, Monney, Appiah, & Wilmot, 2010), specifically in observations of low-income households and home computer access (Malamud & Pop-Eleches, 2010; Vigdor & Ladd, 2010). A study conducted by Odom et al. (2011) revealed that computer use resulted in negative impacts when used with traditional, didactic teaching methods. Lei (2010) wrote, “findings from different empirical studies focusing on the effect of technology on learning have been inconsistent and contradictory” (p. 456). Wenglinsky (2006) proclaimed a simplified bottom line of technology success in schools – does using technology raise student achievement? The jury continues its deliberations.

Technology and Student Achievement in North Carolina

There are limited amounts of research that specifically evaluate technology use and student achievement in North Carolina public schools. A majority of this research centers around the evaluation of North Carolina’s IMPACT model and the NC 1:1 Learning Technology Initiative (Corn, Huff, Halstead, & Patel, 2011; Mollette et al.,

2012; Patel et al., 2011). These models were designed to facilitate the incorporation of instructional technology into schools with major components including (1) a full-time technology facilitator and media coordinator, (2) high-quality professional development, (3) access to appropriate educational hardware and software, (4) school-wide flexible access to computer labs, mobile computer carts, and libraries, (5) extensive collaborative planning, and (6) preparing students for work, citizenship, and the 21st century (Bradburn, 2007; The Friday Institute for Educational Innovation, 2012).

NC IMPACT Model. Since its initial implementation in 2003, the IMPACT model has involved 55 high-need schools (as defined by families living below the poverty line) in 32 school districts across the State of North Carolina (Corn et al., 2012). Funding for the seven different IMPACT cohorts was provided through the EETT grant and ended in the 2010-2011 fiscal year. The final IMPACT cohort completed its final activities at the end of its 2-year grant in 2013 (Kimrey, personal communication, 2014).

Several evaluation studies of the IMPACT model have been conducted through the Looking at North Carolina Educational Technology (LANCET) project. This project consisted of a partnership with NCDPI, the Technology in Learning unit of SERVE Center at UNC Greensboro, the Friday Institute for Educational Innovation, and SETDA (NCDPI, 2012).

The evaluation of the IMPACT model was designed and conducted by an evaluation team from the Friday Institute. Its purpose examined various aspects comprised of the attitudes, skills, and behaviors of students, teachers, and administrators. The team used a “quasi-experimental longitudinal evaluation” which utilized matched schools of similar size, type, demographics, and geography (Corn et al., 2012). Using a longitudinal repeated measures approach, the study examined multiple variables which

included student achievement in reading, mathematics, and writing (Mollette, Overbay, & Townsend, 2011).

Results of the evaluation study were positive overall regarding student achievement. These findings confirmed similar results in earlier studies of cohorts I, II, and III (Mollette et al., 2012). In 2007, France Bradburn of NCDPI testified before the Committee on Education and Labor during the ESEA reauthorization hearings and shared early success stories of the IMPACT program (Committee on Education and Labor, 2007).

Looking at student achievement in mathematics, the study showed faster improvement in IMPACT schools as compared to their counterparts. IMPACT students were 37% more likely to increase achievement levels (I – IV) and 25% less likely to drop achievement levels (Mollette, Townsend, & Townsend, 2010). Examining achievement levels as passing or failing (Levels I & II vs. Levels III & IV), the study revealed little difference in the odds of IMPACT students moving from not passing (Level 1 or II) to passing (Level III or IV). However, IMPACT students' odds of shifting from not passing to passing were 42% higher than the comparison students (Mollette et al., 2011; Mollette et al., 2010).

Reading achievement showed similar patterns for IMPACT schools with stronger growth curves or faster improvement. The odds that IMPACT students would increase one or more achievement levels were 6.45 times more likely than comparison groups (Mollette et al., 2010). Study results showed that IMPACT students were less likely to pass the reading end-of-grade (EOG) assessment than comparison students. By the end of the study in year 3, the difference between groups passing the reading EOG was reduced from 11.2% to 1.4%. In the context of this significant improvement, the odds

that IMPACT students would move from achievement levels of I or II (not passing) to levels III or IV (passing) were 55% higher than comparison groups (Mollette et al., 2010).

NCLTI. North Carolina's 1:1 Learning Technology Initiative started in 2008 as collaboration between NCDPI, North Carolina State Board of Education, and Golden LEAF Foundation. The initial pilot group involved approximately 11,500 students and 800 teachers in 12 traditional high schools and seven Early College high schools across 13 LEAs in the state. In each of these schools, teachers and students were provided laptops and wireless broadband Internet access throughout the campuses. The overall goals included improving student achievement through improved teaching practices to better prepare students for the 21st century workforce and citizenship (Corn, Huff, Halstead, & Patel, 2011; Kleiman, 2009).

Although the most visible component of NCLTI was the provision of a wireless laptop for every student and teacher, the initiative also focused on organization, pedagogy, technology policy and infrastructure, professional development, funding, and community engagement as essential parts for a sustainability model to support students for the future (The Friday Institute for Educational Innovation, 2012; Kleiman, 2009).

In 2008, the North Carolina Board of Education contracted the Friday Institute of Educational Innovation to conduct a 3-year evaluation of NCLTI. The Friday Institute issued a series of six reports that provided various perspectives of significant challenges that were revealed during the evaluation process (Corn, Tagsold, & Patel, 2011). The most significant work from this series involved the multi-level examination of student achievement and was presented in 2011 at the Society for Information Technology and Teacher Education International Conference in Chesapeake, Virginia (Patel et al., 2011).

The program evaluation study focused on student achievement, one of three main goals of NCLTI, by reporting analysis results of EOC data for the participating schools. The study's primary research question states, "Do variables associated with a 1:1 initiative predict differences in individual learning outcomes?" (Corn, Huff, Halstead, & Patel, 2011, p. 1635). According to Patel et al. (2011), the study was established on the theoretical framework of using an objective and management-oriented approach to the program evaluation. In this context, the study involved 18 NCLTI pilot schools that represented a wide range of demographic and regional characteristics, including size and school type. A second group of non-1:1 schools with similar demographics, regional characteristics, size, and type were selected to provide comparative data for the study. Student achievement on EOC assessments in the prior school year was also used to match NCLTI schools with non-1:1 schools.

The multi-level analysis model used in the study consisted of school-level and student-level variables. These covariates were included to control for variables that are usually associated with student performance and outcomes. Student-level variables included race, SES, exceptionality, grade, and gender. School-level variables included school type (traditional or early college), ABC distinction, percent of minority, and economically disadvantaged students (Patel et al., 2011).

The study used multi-level modeling (MLM) analyses for three specific reasons: (1) the data was nested – consisting of student data within school data, (2) the MLM model can manage unbalance data due to the different sample sizes in the participating schools, and (3) the research question examined school-level variables and their potential relationship with student-level variables which MLM provides a more appropriate framework for analysis (Bickel, 2007; Patel et al., 2011). The study consisted of two sets

of analyses:

- Compare influence of 1:1 initiative on EOC scores between 1:1 and non-1:1 schools (Patel et al., 2011).
- Determine influence of variables associated with 1:1 environments in on 1:1 schools (Patel et al., 2011).

For both NCLTI schools and comparison schools, these analyses revealed both groups increased proficiency percentages for students on EOC tests. The study concluded there were no significant effects of 1:1 implementation on student's EOC score as compared to non-NCLTI schools. Corn, Huff, Halstead, and Patel (2011) concluded, "Results of multi-level modeling analyses indicated that the best predictor for any of the EOC scale scores was previous achievement as determined by 8th grade EOG scores" (p. 24).

Specifically for biology, the study did reveal several distinctive findings. Comparing length of implementation within the NCLTI schools, the analyses suggested that longer program participation resulted in a slight increase of students passing the biology EOC. Schools with higher percentages of economically disadvantaged students – those who qualified for free or reduced lunch prices – had a lower percentage of passing students. Finally, early college high schools averaged a 10% higher passing rate on the biology EOC than traditional high schools.

Digital Divide

The expression *digital divide* first appeared in a 1999 NTIA report entitled Falling Through the Net. This report defined digital divide as "the divide between those with access to new technologies and those without" (NTIA, 1999, p. 13). The term digital divide has risen to an elevated position in the continuous debates revolving around

technology and its impact in public education (Gunkel, 2003). The term has created a metaphor of separation within society based on differences of computer and Internet access by various groups – essentially utilizing Cervantes' depiction of wealthy and poor segments of society as the *haves* and *have-nots* (van Dijk, 2006). Digital divide rapidly became widespread in literature to describe the differences in computer and Internet accessibility based on various demographic factors such as race, ethnicity, gender, SES, and metropolitan location (Dijk & Hacker, 2003; Jackson et al., 2008). These technology gaps have also been expressed as both a global and national concern that affects education and has been a concern for more than 20 years and still remains in the public spotlight (Waycott et al., 2010).

Early digital divide research examined differences in technology access and opportunities among different populations (Warschauer & Matuchniak, 2010). One possible role in this emphasis was the prevailing idea of technological determinism – the view that everything can be fixed with technology (van Dijk, 2006). However, from 2002 forward, digital divide research began to expand beyond access, examining technology inequalities of social, cultural, and information resources (DiMaggio, Hargittai, Celeste, & Shafer, 2004; van Dijk, 2006).

The evolution of the digital divide is a result of a more informed inquiry into the nature of the problem and additional research in various social groups (Eamon, 2004), moving from an earlier emphasis of computer access and SES to a more extensive focus on race, gender, and ethnicity (Jackson et al., 2008) and on differences in school and home computer access for students (Becker, 2000; McCollum, 2011). Subsequently, research literature describes two distinct digital divides: one identified as the access divide, which describes the differences in technology access; and the second, known as

the utilization divide, recognizes gaps in technology use (Gunkel, 2003; van Dijk, 2006). The access divide has been the focus of most federal policy initiatives and evidence indicates that progress is being made to close the access divide (Hilbert, 2011). The utilization divide is more challenging from a policy perspective because of many factors such as the changing nature of technology; the available content; and the variation in individual technology skills, abilities, and motivation (Attewell, 2001; Ferro et al., 2011; Natriello, 2006).

Others recognize a shift in the access digital divide, moving from technology devices to Internet access (DiMaggio et al., 2004; Zhao, Lu, Huang, & Wang, 2010). This new perspective proposes the concept of *digital inequality* rather than digital divide. The inequality is defined among different Internet users and the extent to which they are able to reap the benefits from their use of technology (Davis, Fuller, Jackson, Pittman, & Sweet, 2007; DiMaggio et al., 2004). Zhao et al. (2010) proposed a model of five dimensions of digital inequality (see Figure 1). In this framework, the four dimensions of technical apparatus, autonomy of use, available social support, and variation of use influence the skill dimension. Digital inequities in these five dimensions would result in different student outcomes, which translate to varying levels of achievement (Zhao et al., 2010).

Measuring the digital divide. Many studies of the digital divide use descriptive measures to show differences in one or more technology variable based on demographics (Cooper, 2006; McGraw et al., 2006; Thomas, 2008). For example, early studies determined the digital divide in access by using student-to-computer ratios to calculate the median ranking in schools (Education Week, 2002; Volman & van Eck, 2001). Schools above the median level would be classified as high-access schools, whereas

schools ranked below the median would be considered low-access schools (Alspaugh, 1999; Morse, 2004). With schools grouped in terms of access, other variables could be examined to determine their effects in these schools (Becker, 2000).

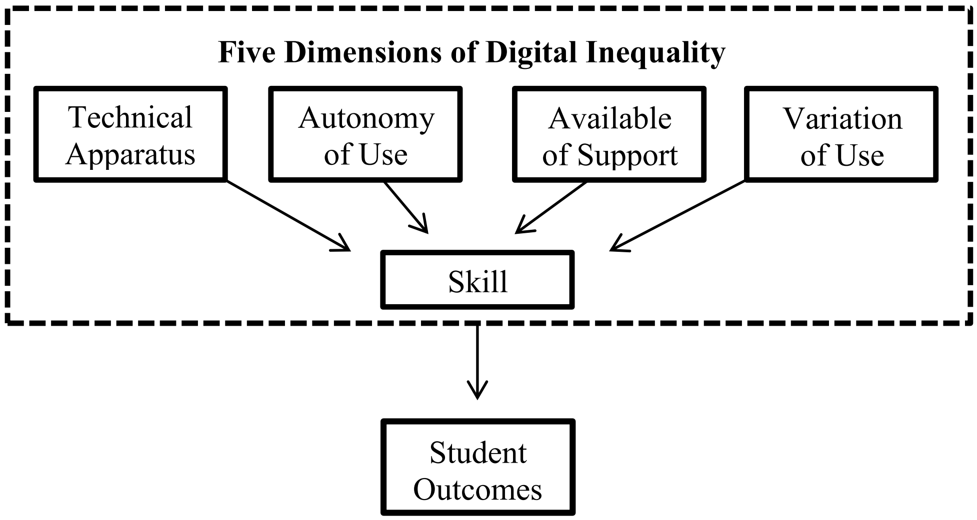

Figure 1. Five Dimensions of Digital Inequality.

Defining the digital divide in the context of technology usage is a more complex effort. For example, one study conducted by Juarez and Slate (2007) analyzed the use of technology in schools. Using enrollment numbers of minority students as independent variables and types of computer usage as the dependent variables, a multivariate analysis of variance (MANOVA) was conducted to determine whether a statistically significant difference in usage between the groups was evident. The analysis revealed a significant difference in types of computer use based on race and ethnicity, suggesting a digital divide in computer use (Juarez & Slate, 2007).

Gunkel (2003) expounded upon another perspective of measuring the digital divide:

The examination of the digital divide needs to develop a sense of self-reflexivity.

> Although empirical studies adequately diagnose and quantify the gap that currently exists, for example, between information haves and have-nots, they do not explicitly recognize how this apparently altruistic endeavor might also entail significant ethical complications. (p. 508)

The digital divide should not be considered as a single event of obtaining specific technologies but defined in terms of the desired impact (Warschauer & Matuchniak, 2010) and recognizing the various causes in technological, as well as, social domains (van Dijk, 2006). Hilbert (2011) cautioned that having a one-size-fits-all perspective of such a multi-layered challenge could be considered harmful in the long run.

Race. The racial divide has been well documented in research literature, which affects African-American, Hispanic, and American Indian students who tend to have less computer and Internet access and use technology in less sophisticated ways when compared to their White and Asian counterparts (Fairlie, 2005; Hacker & Steiner, 2002; Wilson, Wallin, & Reiser, 2003). Just over half of all African-American and Hispanic students have access to a computer at home and only about 40% have Internet access at home (Becker, 2000; Chapman et al., 2010; Fairlie, 2005). Minority students are more likely to use technology for drill and practice, while White students have more experiences designing websites and presentations (Fairlie, 2005; Schofield & Davidson, 2004; Sutton, 1991). While there is not a clear explanation for the racial divide, lack of technology exposure, discrimination, absence of significant content, and low priority for technology use among minority groups are cited as possible explanations for the racial divide (Education Week, 2002).

A study conducted by Jackson et al. (2008) examined technology use among African-American and White middle school students. Results of the study indicated that

African-American males were the least intense users of computers and the Internet. Male students, regardless of race, were more likely to use technology for video games as compared to females according to the study. Student achievement was linked to the amount of time spent working with computers and the Internet; however, video gaming was shown as a negative predictor (Jackson et al., 2008). The research suggested that "educational and community interventions should focus on two related goals: bringing technology to African American males and bringing African American males to technology" (Jackson et al., 2008, p. 443).

SES and poverty. The NCES (2012) defined high-poverty schools as public schools with 76% or more of its students eligible for free or reduced-priced lunch. North Carolina designates a high-poverty school based on the percentage of students identified as economically disadvantaged but does not establish a minimum percentage that separates high-poverty from mid- or low-poverty schools. Economically disadvantaged students (EDS) are students as defined by Child Nutrition Services Section of NCDPI as students who are eligible for free or reduced-price lunch.

A report by Education Week (2007) shows little variation in whether students have used computers in schools based on income. Using 2006 NCES data, 86% of students from families with high incomes ($75,000 and higher) used computers at school compared to 80% of students from families with low incomes (under $20,000) who also used school computers. This data does not indicate the frequency or types of computer use by students, only whether students have used a computer in school (Education Week, 2007).

The gap was significantly greater for home computer use with only 37% of low-income students using computers at home as compared to 86% of students from high-

income families (DeBell & Chapman, 2006; Education Week, 2007). Most differences in access to resources were reflective of the different tax bases between poor and more affluent communities (Ching et al., 2005; Eamon, 2004).

Federal programs such as Title I and e-Rate have helped high-need schools and districts access technology and connectivity (U.S. Department of Education, 2003). Title I is an assistance program which focuses on schools with high percentages of students eligible for free or reduced lunch prices. In order for a school to qualify for school-wide Title I funding, over 50% of their student population must meet this eligibility (Chapman et al., 2010). Title I accounts for approximately 3% of the total national educational expenditures in the United States (U.S. Department of Education, 2003).

E-rate is a federal program which provides subsidies for connectivity and technology in schools and districts across the nation (U.S. Department of Education, 2003). As with Title I funding, these discounts are based on the school and/or district's percentage of students eligible for free or reduced lunch prices. Since its beginning in 1998, this program has witnessed an annual spending budget as high as $2.25 billion (Chapman et al., 2010). The FCC announced in 2014 that an additional $2 billion would be added to e-rate funding in order to increase broadband connectivity over the next 2 years (Cavanagh, 2014b). However, the FCC did indicate it would take time for this additional funding to reach schools and likely not be available until the 2015 fiscal year (Cavanagh, 2014a).

Critics have argued that the digital divide has mostly disappeared as low-income and minority students have greater access to technology due to the infusion of federal dollars. These sources, such as Title I and e-Rate, have served to address technology inequalities between poor and more affluent school districts (Trotter, 2007). By 2003,

national data indicated there were no significant differences in Internet access between high-poverty or high-need schools compared to lower need, more affluent schools (Wells & Lewis, 2006). However, in the same report, data revealed that high-need schools had fewer computers with Internet access per student than lower need schools.

Gender. Research literature is rather conclusive that gender differences in access and computer use in schools have diminished (Cooper, 2006; Mims-Word, 2012). However, recent work by Ferro et al. (2011) discovered that while income and education were positively associated with Internet access, girls on average had fewer numbers of devices to access the Internet as compared to boys.

Regarding attitude towards technology, boys are more positive and confident than girls and perceive more support from parents and peers (Vekiri & Chronaki, 2008). Several studies indicate that boys play more computer games, but girls are apt to use email more frequently (Cooper, 2006; Huang, Hood, & Yoo, 2013; Mims-Word, 2012). In general, girls are more enthusiastic about word processing and graphics (Huang et al., 2013; Jackson, et al., 2008) and prefer applications that promote cooperation rather than competition (Cooper, 2006). Girls also favor programs that appeal to creativity, detailed graphics, and colorful images more than applications requiring dexterity (Huang et al., 2013; Volman & van Eck, 2001).

Municipality. As with race, gender, and SES, municipalities (rural or urban locales) have been linked with the digital divide (Wilson et al., 2003). Geographic location plays a major part in determining who owns a home computer and who has home access to the Internet, therefore impacting student achievement associated with homework (Eamon, 2004). Although the difference between access to home computers in urban and rural municipalities have appeared to stabilize, the gap between

municipalities is growing in many areas of information technology such as broadband and digital media access (Wilson et al., 2003). Ferro et al. (2011) stated that there is a higher concentration of advanced technology users in urban areas as compared to their rural counterparts.

The underachievement of students in urban schools has been well documented and, for the most part, the efforts of the educational community over the past decade to acquire technology and Internet access have been successful (Azzam, 2006; Conceicao & Edyburn, 2005). Others argue that it is easy to promote student-to-computer ratios within school reform efforts (such as vouchers, charter, and magnet schools) with little concern as to how technology is used in the urban classroom (Conceicao & Edyburn, 2005; Pflaum, 2004; van Dijk, 2006).

Hess and Leal (2001) examined 72 urban districts to determine the extent of the digital divide, which they defined as the variations of technology provision to students of different races. In short, the study considered why some urban school districts were more likely to deliver access of a resource that most educators and policymakers consider vital to educational success.

The data examined in the study originated from a national survey of 85 urban school districts conducted by the Council of Urban Boards of Education (CUBE). This information was paired with school- and district-level demographics and finance data from the U.S. Census database. The researchers utilized ordinary least squares and logistic regression analysis to determine potential relationships in the dataset, including technology provision, race, and funding sources (Hess & Leal, 2001). The results indicated the appearance of racial inequities in computer provision. Students in districts with a larger percentage of Black students had less access to classroom computers;

however, there was little evidence to indicate that community education or income affected classroom computer provision. Hess and Leal (2001) concluded in the study that

> Much of the attention paid to educational technology focuses on the gap between suburban and urban districts. We suggest that it is also important to consider variation among urban districts. If significant gaps exist between urban communities, then remedies that do not acknowledge such inequities may reinforce or aggravate them. (p. 775)

The Digital Divide in North Carolina

There has been limited digital divide or digital inequality research conducted specific to the State of North Carolina (Powers et al., 2013; Vigdor & Ladd, 2010; Wilson et al., 2003). The earliest of these was conducted by Wilson et al. (2003) of East Carolina University. In the midst of current research at the time, many argued the digital divide had narrowed or closed altogether (Chapman et al., 2010; van Dijk, 2006). This particular study explored whether social-economic factors revealed potential gender, racial, and geographic divides.

The study collected survey data from 522 interviews that measured public perceptions of the role and purpose of science and technology in North Carolina. The sample distribution, in regards to race and geography, did not significantly vary from the state population and socioeconomic distributions. Also, education, income, age, employment status, marital status, and children in the home were statistically controlled due to the potential influence on the relationship between the dependent variables (computer ownership and Internet access) and independent variables (place of residence, race, and gender). The survey questionnaire contained 56 questions and the total response rate was 53% (Wilson et al., 2003).

The analysis consisted of bivariate logistic regressions between each independent and dependent variables. The results were reported in the context of computer ownership, Internet access, and both variables combined. According to the analyses, African-American, rural, and female respondents were less likely to own a computer and have Internet access. Collectively, African Americans were 50% less likely to own computers and have home Internet access as compared to Whites. Comparison of municipalities revealed a 10% difference in computer ownership and Internet access with urban areas higher than rural areas. When the analyses included the statistically controlled variables, the influence of rural residence and gender were no longer significant.

A second study was published in 2013 from East Carolina University which examined how gaps in technology access were related to *social stratification* (Powers et al., 2013). The social stratification variables identified by the study included race, ethnicity, gender, age, geographic location, household income, education level, and family composition. The study analyzed survey data collected over a 12-year period that created “a longitudinal design that focuses on the same population” (Powers et al., 2013, p. 7).

In 1999, e-NC authority, a division of the North Carolina Department of Commerce, initiated what would become a series of citizen surveys that measured access, attitudes, and perspectives regarding Internet and computer usage (Feser, Horrigan, & Lehr, 2013). Since its implementation, the survey has been conducted on six separate occasions with the most recent in 2011 (e-NC Authority, 2014). The 2013 study reported on the findings from these surveys and concentrated on level of computer ownership and home Internet access in various demographic populations in the state (Powers et al.,

2013).

Data analyses showed in North Carolina, the number of households reporting Internet access more than double during the 12-year span of the conducted surveys. This represents a change from about one of every three households in 1999 to approximately four of five in 2011 (Powers et al., 2013). The largest increase in percentage was observed between the years of 2004 and 2008.

In each survey data set there were significant differences in Internet access between male and female populations. These differences were consistent with previous gender research of the digital divide (Cooper, 2006; Mims-Word, 2012; Vekiri & Chronaki, 2008). The changes in Internet access gradually increased for both gender groups from 1999 to 2011. However, the smallest difference between males and females was witnessed in 2011. This suggests that the Internet access gender gap may be closing in North Carolina (Powers et al., 2013).

The study reported that home Internet access in 1999 was significantly disproportionate between African-American and White respondents. White households were more than twice as likely to have Internet access as compared to African Americans during this time. The divide between African Americans and Whites decreased over a 6-year period ending in 2008 with a 14% difference. This gap has remained unchanged since the last survey in 2011, but both racial groups continue to experience increases in home Internet access (Powers et al., 2013).

The findings for geographic location revealed that gaps remained consistent with urban areas more likely than rural areas to have home Internet access; however, significant progress in acquiring home Internet access for both urban and rural areas was observed through 2010. During this 11-year period, the change in home access increased

188% in rural counties as compared to 95% in urban counties. This indicated that in North Carolina, the growth rate of Internet access was almost twice as fast in rural counties as in urban counties, suggesting that "targeted efforts to increase access to underserved areas have had measurable success" (Powers et al., 2013, p. 11).

In 2011, three of four of homes with annual incomes at or above $25,000 reported having Internet access. The data trends of access and household income gaps have remain consistent over the 12-year period, showing a slight gap increase between the highest and lowest income categories. There still remains a persistent divide between income clusters with lower income populations lagging behind more affluent groups (Powers et al., 2013).

The third noteworthy study of the digital divide in North Carolina was published in June 2010 by Duke University's Sanford School of Public Policy. This report by Vigdor and Ladd (2010) attempted to answer the following questions:

1. Do students' basic academic skills improve when they have access to a computer at home? (p. 3)
2. Has the introduction of high-speed Internet, which expands the set of productive tasks, caused further improvement? (p. 3)

The research analyzed EOG student data from 2000 to 2005, focusing on the reading and math scores, and survey data in Grades 5 through 8. The timespan selected for the study was considered a significant period of expansion for home computer and Internet access. Vidgor and Ladd further explained:

> the longitudinal nature of the data also permit us to address concerns that students with computer access are a non-random sample of the population by comparing the test scores of students before and after they report gaining access to a home

computer, or before and after their local area receives high-speed Internet service. (p. 3)

The student survey is a required section of the EOG assessment that is administered during the last weeks of school (NCDPI, 2010). The focus question asked students about time spent on homework, reading for leisure, watching television, and the frequency of home computer use for schoolwork. According to Vigdor and Ladd (2010), this question was asked to over one million students between 2000 and 2005 which served as the basis for their analysis.

An overall analysis of these student responses indicated that home computer access varies by race and SES. Over 90% of White students reported having a computer at home as compared to 75% of African-American students. The gap between students eligible for free or reduced lunch and nonparticipants was slightly larger with 71% of participants indicating having a home computer contrasted with over 92% of nonparticipants.

Results of the analyses replicated positive outcomes from previous studies of home computer access and achievement; however, this was observed across student comparisons, not in a longitudinal context. When analyzed within student comparisons, the capacity to measure achievement before and after home access, reading and math scores actually declined. These negative effects on reading and math EOG test scores were considered “modest but significant” (Vigdor & Ladd, 2010, p. 8). The report suggested a possible widening of the achievement gap with the greatest impact observed in socioeconomically disadvantaged families who acquired home computers between 2000 and 2005 (Vigdor & Ladd, 2010). These findings were similar to the trends found in study of low-income Romanian households who were provided computers (Malamud

& Pop-Eleches, 2010).

The report concluded with the following:

> Previous studies of home computer use among young adolescents have documented significant disparities in access and use, and have frequently ascribed clear educational benefits to home computer use. Together, these patterns suggest that a policy of broadening home computer access through programs of subsidy or direct provision would narrow achievement gaps. This paper corroborates the existence of sizable socioeconomic gaps in home computer access and use conditional on access, but comes to the opposite conclusion regarding the potential impact of broader access on achievement gaps. (Vigdor & Ladd, 2010, p. 34)

Chapter Summary and Conclusions

Existing research regarding the relationship between technology use and its effects on achievement in various populations communicates a mixed message (Lei, 2010). This mixed message makes it challenging to draw conclusions about the effects of technology and to provide useful suggestions for technology integration in schools and classrooms (Lei, 2010; Ravitz et al., 2002). While research suggests that computer and Internet access are no longer significant issues in public schools, remaining evidence points to lingering digital inequalities within the rapid cycles of technology evolution (Trotter, 2007; Valadez & Duran, 2007; van Dijk, 2006).

Two problems contribute to the contradictory messages over technology use and student achievement. The first is that technology is often studied at a general level which can include various kinds of hardware and software (Cuban, 2006). Wenglinksy (1998) found that many studies “treat technology as an undifferentiated characteristic of schools

and classrooms. No distinction is made between different types of technology" (p. 3). The same technology could be used differently in a variety of contexts and give it different meanings in different settings (Lei & Zhao, 2007). Treating technology as a single entity disguises the unique traits of different technologies, their uses, and different impacts on learning outcomes (Lei, 2010). The key aspect of digital divide research refers to the technology in question (Hilbert, 2011).

The second issue is the emphasis of the research. Most studies focus on *how much* or *how often* technology is used in schools but fail to examine the quality of use or *how* technology is used (Fouts, 2000; Lei, 2010; Lei & Zhao, 2007; Papanastasiou et al., 2003). For example, many studies examine relationships between how much time students spend with computers or how often computers are used and achievement (Karamustafaoglu, 2012; Lei, 2010; Reichstetter, Regan, Lindblad, Overbay, & Dulaney, 2002; Schacter, 1999). However, research also suggests that quality of technology use is more important than the actual quantity (Lei & Zhao, 2007; Ravitz et al., 2002; Wenglinsky, 2005). What really matters is not the use of technology but how it is used.

Odom et al. (2011) pointed out that regardless of how often students use computers in traditional instructional settings, technology integrated with student-centered activities can have a positive effect on student attitudes towards science and should improve student learning. Also, one must consider that not all technological innovations are created equal. Some technologies will have more capacity than others, and their implementations can be significantly influenced by the teacher in the classroom (Hilbert, 2011).

Research Questions

As the literature review of this chapter has shown, there is currently a limited

number of investigations regarding specific technology use, student achievement, and the digital divide in North Carolina public schools. This study was an attempt to add a broader scope to this narrow body of research with a purpose to analyze various aspects of technology use, student achievement, and the digital divide. North Carolina is considered an understudied state in this regard (Powers et al., 2013); and with a significant poverty rate and high percentage of minority groups (Log Into North Carolina, 2014), additional analyses of digital inequalities can add to a restricted body of knowledge.

In this context, the following questions were used to guide and serve as a framework for the analysis model of this study.

1. To what extent do students utilize educational technology in science classrooms and school districts?
2. Are the patterns of technology use equitable in terms of race, gender, municipality, and SES?
3. What is the relationship between types of technology use and student achievement?
4. Does the relationship between the use of technology and student achievement vary by race, gender, municipality, and/or SES?

Chapter 3: Methodology

The quantity of research on instructional technology and its relationship with student achievement is vast (Lei & Zhao, 2007; Lemke et al., 2009; Schroeder et al., 2007). The literature review from Chapter 2 shows that previous research concerning the effects of technology use, student achievement, and the digital divide are relatively mixed (Alspaugh, 1999; Odom et al., 2011). The concept of a digital divide was first introduced in educational research during the late 1990s, and since its inception, the digital divide has been a catalyst for nationwide calls for change regarding access to educational technology for all students (Chapman et al., 2010). Federal and state governments, as well as the private sector, have made intentional strides to address this phenomenon and because of these efforts, current data indicate that access to internet-connected technology in schools has become a ubiquitous reality (Hilbert, 2011; McCollum, 2011).

The digital divide has been examined in a myriad of perspectives as well, with similar results (Ferro et al., 2011; Hilbert, 2011; van Dijk, 2006). Literature reviews reveal consistent trends regarding the digital divide in public schools regarding students in urban and high-poverty settings (Hess & Leal, 2001); however, media reviews indicate that public perception of the digital divide typically resides in the context of computer access (Nagel, 2008; Herold, 2013; Herold, 2014).

There have been few investigations regarding the digital divide in North Carolina public schools beyond access to technology (Vigdor & Ladd, 2010; Wilson et al., 2003). This study was an attempt to add a broader scope to this narrow body of research. The purpose of this study was to describe the extent of technology utilization in high school science classrooms in North Carolina by analyzing various technology uses and their relationship with student achievement. The objectives (1) determined to what extent a

digital divide is present in North Carolina science classrooms and (2) examined its potential relationship to student achievement.

This chapter describes the analysis methods that were used to answer the research questions directing this study. The variables in the data set are presented, as well as the null hypotheses developed to answer the research questions. The research design compares the levels of technology utilization based on gender, race/ethnicity, municipality, and SES/poverty. The specific types of technology and their relationships with student achievement in biology are also examined, and the results of the analyses are presented in Chapter 4.

Analyzing the biology EOC dataset provided an insight to the relationship between various uses of technology and student achievement in specific demographic populations. This quantitative study attempted to determine the relationship between technology use in biology, as reported by students, and their achievement. Specifically, this study endeavored to answer the following questions:

1. To what extent do students utilize educational technology in science classrooms and school districts?
2. Are the patterns of use equitable in terms of race, gender, municipality, and SES?
3. What is the relationship between the use of technology and student achievement?
4. Does the relationship between the use of technology and student achievement vary by race, gender, municipality, and/or SES?

Student Achievement

The ultimate goal of any instructional strategy, curriculum, or education reform initiative is to raise student achievement (Assvedra & Opfer, 2012; Wenglinsky, 1998). Simply defined, student achievement is the increase of individual student knowledge and preparedness for the future (Fullan, 2013). The standards-based education movement has boosted the measuring and reporting of student achievement to a more prominent level of public education. As a result, state and federal accountability systems have raised the bar for school performance and have led to an increased reliance on standardized tests of student achievement (Kadel, 2008).

Analysis of student achievement can bring about significant controversy, as it often reveals different levels of performance between males and females, urban and rural students, and among various racial and poverty groups (Linn et al., 2011). For the purpose of this study, student achievement was examined by means of the developmental scale scores from the North Carolina EOC biology assessment.

Data Set

The data set used in this study was acquired from multiple sources. A letter was submitted to the Accountability Services Division of NCDPI requesting data sets from the 2010-2011 EOC assessment for biology. This data included student demographic information, LEA and school codes, developmental scale scores, achievement levels, and student survey responses. Municipality data (rural or urban) was collected from the online data bank of the North Carolina Rural Economic Development Center.

North Carolina EOC. According to NCDPI (2010), the EOC tests were created in response to the North Carolina Elementary and Secondary Reform Act of 1984 passed by the North Carolina General Assembly. These assessments are used to sample student

content knowledge as outlined in the North Carolina Standard Course of Study. In the 2010-2011 school year, students enrolled in algebra I, biology, and English I were required to take the North Carolina EOC tests. This study analyzed student data from the biology EOC assessment.

Student demographics. The data sets contain student demographic information including gender, race, and SES. Student ethnicity is based on the Department of Education's (U.S. Department of Education, 2010) guidance for federal education data which divides ethnicity into seven categories: American Indian or Alaska Native, Asian, Black or African American, Hispanic, Native Hawaiian or Other Pacific Islander, White, and Two or More Races. Based on the frequency of the racial student groups in the data set, this study examined Black (28.6%), Hispanic (9.8%), and White (54.5%) populations. The remaining four racial subgroups comprise only 7.1% of the study sample.

Students from a family of four are eligible for free school meals if the annual family income is less than $28,665 (at or below 130% of the federal poverty guidelines). Student eligibility for reduced-price meals requires a family's income to be between $28,665 and $40,793 – between 130% and 185% of the poverty level (NCDPI, 2010).

LEA and school codes. In North Carolina, each school district or local education agency (LEA) has a unique two or three digit identification code that is utilized in state and federal reporting. Each individual school located within the LEA also has an individual five to six digit code (NCDPI, 2013b). These codes allow the data set to be disaggregated by school district (LEA) and school regarding student performance and technology use in the classroom.

Developmental scale scores. The 2010-2011 biology EOC assessment consisted

of a total of 80 multiple choice items and an unspecified number of field test items. Each student's raw score was determined by the number of items they answered correctly on the biology EOC assessment. The field test items were excluded from the student raw score calculation. The raw score was then converted to a developmental scale score. Items were assigned a score of 0 if the student did not correctly answer the item, and a score of 1 for a correctly answered item. According to the North Carolina Science Tests Technical Report (NCDPI, 2009),

> Software developed at the L.L. Thurstone Psychometric Laboratory at the University of North Carolina at Chapel Hill converts raw scores (total number of items answered correctly) to scale scores using the three IRT parameters (threshold, slope, and asymptote) for each item. The software implements the algorithm described by Thissen and Orlando (2001, pp. 119-130). Because different items are placed on each form of a subject's test, unique score conversion tables are produced for each form of a test for each grade or subject area. Each scale score has a conditional standard error of measurement associated with it. (p. 28)

Achievement levels. Academic achievement levels range from one (Level I) to four (Level IV) under the North Carolina Testing Program. The procedure of defining cut scores for the different achievement levels is known as academic achievement standard setting. This technique of standard setting involves categorizing students into the four achievement-level groups by professionals who are experts of student achievement in various areas outside of the testing situation and then comparing these judgments to the distributions of students' actual scores (NCDPI, 2009).

For the science EOC assessments, North Carolina teachers were considered expert

professionals with the justification that teachers are able to make informed judgments about student academic achievement because they had observed the wide scope of student work during the school year. Regarding the North Carolina science EOC assessments and their academic achievement standard setting, students were categorized by approximately 1,500 teachers for biology; 1,500 teachers for physical science; and 1,000 teachers for chemistry. They classified students into one of the four achievement levels as described by achievement-level descriptors (NCDPI, 2009).

North Carolina Student Survey (NCSS). The NCSS is a structured student survey conducted by the North Carolina testing program. The purpose of the survey is to produce organized data on the students of North Carolina public schools. These data can be used by educators and instructional leaders to initiate discussions about teaching and instruction. The NCSS contains questions on a set of background, attitudinal, behavioral, and special topic questions that pertain to the learning dimensions of (1) extracurricular participation, (2) instructional participation, (3) educational practices, (4) learning styles, (5) demographic information, and (6) technology usage (NCDPI, 2008).

The design of the NCSS has several important aspects. It is structured to the extent that all students are asked the same questions in the same order. Also, all questions have fixed responses with a limited set of choices. Additionally, several of the question items have been used in previous surveys. Another feature of the NCSS is the student sample is methodically chosen and not given to the student body at large. Finally, the survey is personal since students complete it independently (NCDPI, 2008).

Technology use. The NCSS for the biology EOC assessment has a total of nine questions with two that are specific to the use of technology in the classroom (NCDPI, 2008). Question six in the survey asks, “How do you most frequently use technology in

your science class?" Students have the option to select up to three of the seven provided responses. This study analyzed technology use based on the three most frequent responses as indicated in this student survey question. The identified technology uses for this study include (1) use technology to organize and display data, (2) create presentations and/or web pages, and (3) use the Internet to find information or communicate with other persons.

Municipality. The North Carolina Rural Economic Development Center defined rural as a county with a population density of 250 per square mile or less as of the 2010 census (North Carolina Rural Economic Development Center, 2012). Of the 100 counties in North Carolina, 85 meet this definition with five classified as rural transitional counties. These five counties have higher population densities but retain important rural characteristics, having at least 66% of its land area and a minimum 25% of its population living within the rural definition based on population density (North Carolina Rural Economic Development Center, 2012).

Research Hypotheses

To answer the research questions, this multi-level study tested the following null hypotheses:

$H_0$1: There is no variation of school technology use among race, gender, and socioeconomic student populations.

$H_0$2: There is no variation of technology use in among urban and rural municipalities.

$H_0$3: There is no difference in academic achievement in high school biology classrooms based on technology use, race, gender, and SES.

$H_0$4: There are no differences in student achievement in high school biology

classrooms based on technology use and selected demographic variables within urban and rural municipalities.

The variables and analyses details associated with each null hypothesis are discussed in subsequent sections.

Variables and Analyses

This section describes the applicable independent variables (IV) and dependent variables (DV) for each hypothesis and their associated analysis processes. All statistical tests conducted for the analyses of this study utilized the IBM SPSS Statistics – Version 22 software package.

Figure 2 provides a visual of the framework for the analysis model and how it is viewed on multiple levels. The data set includes variables on the individual student level (gender, race, SES, and achievement) and variables on the district level (municipality).

Technology use and student achievement were analyzed on the individual level in student population groups based on gender, race, and SES. These groups were also analyzed within the broader context of where they reside and its respective municipality and poverty level.

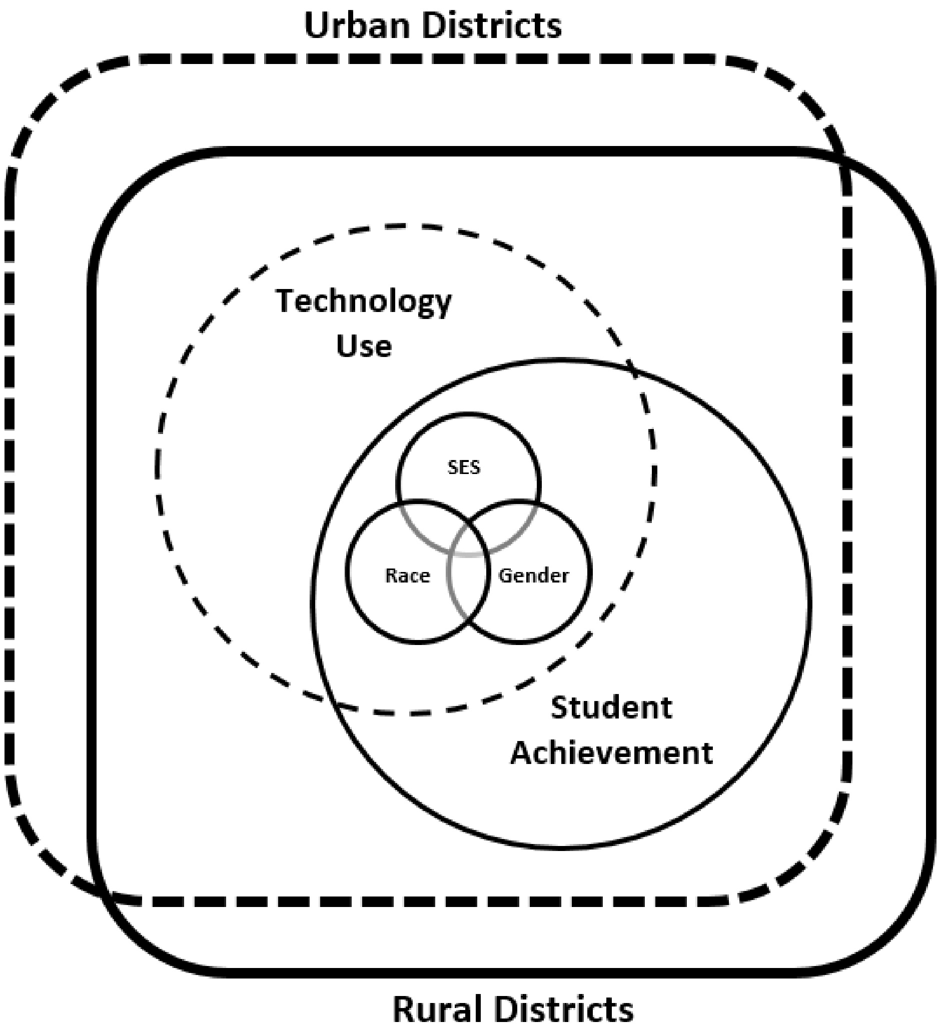

Figure 2. Graphic of Research Variables in Context.

Relationship Analyses

$H_0 1$: There is no variation of school technology use among race, gender, and socioeconomic student populations.

IV(a): Technology Use (Organize & Display Data), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

IV(b): Technology Use (Use Internet), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

IV(c): Technology Use (Create Presentations), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

The first null hypothesis is broken down into four subgroups based on the most frequent technology use identified in the student survey. The study used chi-square tests for potential relationships between four subgroups of identified technology use, gender, race, and socioeconomic student populations. Within each subgroup, three separate tests were used to analyze the relationship between (1) technology use and gender, (2) technology use and race, and (3) technology use and SES.

To further analyze potential relationships within different student population combinations (e.g. Asian females who are eligible for free/reduced lunch) and technology use, the data set were broken down into separate subsets by race and gender. Each of these subsets was grouped by those eligible for free or reduced lunch and those who do not qualify. For each group, a chi-square test was used to determine potential relationships between technology use and the various student population combinations. The results of the analyses provided additional information regarding possible associations between technology use and specific student population groups.

$H_0$2: There is no variation of technology use between urban and rural municipalities.

IV(a): Technology Use (Organize & Display Data), Municipality (Rural vs. Urban)

IV(b): Technology Use (Use Internet), Municipality (Rural vs. Urban)

IV(c): Technology Use (Create Presentations), Municipality (Rural vs. Urban)

This hypothesis was tested using a chi-square analysis of the independent variables technology use and municipality. The data source for technology use was from the student survey responses and municipality classification (rural or urban) from the

North Carolina Rural Economic Development Center. The analysis determined potential relationships between specific technology use and municipality – rural and urban districts. Due to the context of the municipality classification data, city school systems in North Carolina were combined with their respective county school systems.

Factorial Univariate Analyses

$H_0$4: There is no difference in academic achievement based on technology use, race, gender, and SES.

IV(a): Technology Use (Organize & Display Data), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

IV(b): Technology Use (Use Internet), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

IV(c): Technology Use (Create Presentations), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL)

DV: Academic Scale Scores

For the above hypothesis, four separate analysis of variances (ANOVA) were utilized to detect scale score differences among the independent variables. In this multi-factor model, there is a dependent variable (academic scale scores) and four factors or independent variables (technology use, gender, race, and SES). The analysis of variance was used to answer the following questions related to the above null hypothesis:

1. Do any of the independent variables (factors) have a significant effect on student achievement?
2. Which factor can be considered the most important in this context?
3. Can we account for most of the variability in the scale scores?

Multi-Level Analyses

Multilevel models are statistical models that analyze relationships between variables at more than one level. These are particularly suitable for research designs

where data for participants are organized at more than one level – also known as nested data. The units of analysis are at the lower, individual levels (Level 1) which are nested within higher, larger contextual units (Level 2). Multilevel models can be used with data on many levels; however, a two-level model is considered the most common. The possibility of individual-level effects and contextual effects in the same analysis is one of the reasons why multilevel modeling has become so noticeable in the educational research studies (Bickel, 2007).

$H_0$4: *There are no differences in student achievement based on technology use and selected demographic variables within urban and rural municipalities.*

IV(a): Technology Use (Organize & Display Data), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL), Municipality (Rural vs. Urban)

IV(b): Technology Use (Use Internet), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL), Municipality (Rural vs. Urban)

IV(c): Technology Use (Create Presentations), Gender (Male vs. Female), Race (Black, Hispanic, & White), SES (FRL vs. Not FRL), Municipality (Rural vs. Urban)

DV: Academic Scale Scores

Using municipality as a Level 2 variable, the study further analyzed differences in student achievement by technology use and individual level factors (race, gender, and SES) within urban and rural districts. This multi-level analysis design may provide insight to interesting contextual effects and cross-level interactions. Although the data focus of this study was technology use and student achievement, it is important not to disregard the contextual effects of the environment where they reside.

A Factorial Univariate Analysis was used, as in the previous hypothesis, to test the first level independent variables (technology use, gender, race/ethnicity, and SES)

within the context of the second level independent variable (municipality). This model was run twice for each technology use subgroup – once with the level 1 groups which reside in rural counties and again with the level 1 group which are located in urban counties. The results of the analyses were compared for possible contextual effects of municipality.

Chapter Summary

This chapter describes the data set and the variables that were utilized in the framework of analysis for this study. The null hypotheses developed to help answer the research questions have been presented with their respective independent and dependent variables as well as the analysis processes used to test them. These processes have a range from simple relational analyses to more complex factorial univariate and multi-level analyses. The decision to utilize such a large quantitative model was based on the volume of existing research, the context of the study, and the availability of necessary data to complete the data set. Results of this study are presented in Chapter 4, and the implications and recommendations are discussed in Chapter 5.

Chapter 4: Research Findings

This chapter describes the results of the various analyses used to test the hypotheses of this study. The chapter is divided into four sections based on the identified most frequent technology uses in biology classrooms. Each section analyzes the series of null hypotheses within the context of these technology uses.

Relational analyses explore the affiliations between established variables with the focus of looking for meaningful relationships (Tabachnick & Fidell, 2013). The following hypotheses are tested using the relational analysis model:

$H_0 1$: There is no variation of school technology use among race, gender, and socioeconomic student populations.

$H_0 2$: There is no variation of technology use in among urban and rural municipalities.

A Factorial Univariate Analysis examines the effects of multiple independent variables with one dependent variable simultaneously. This allows examinations of interactions – when an independent variable has a different effect on the dependent variable as a function of or grouped with another independent variable. Also, the factorial analysis permits examination beyond the main effects – the effects of one independent variable on a dependent variable without taking into account the independent variable's context (Tabachnick & Fidell, 2013). The following hypotheses were tested using this model:

$H_0 3$ There is no difference in academic achievement in high school biology classrooms based on technology use, race, gender, and SES.

$H_0 4$: There are no differences in student achievement in high school biology classrooms based on technology use and selected demographic variables

within urban and rural municipalities.

Descriptive Analyses

The participants in this study included 97,229 biology students enrolled at 705 public high schools within the 115 school districts in North Carolina during the 2010-2011 school year. Table 1 presents the demographic breakdown of the sample population.

The independent measures include technology use, race, gender, SES, and municipality. The selection of the specific technology use measure is taken from the responses of the student survey in the biology EOC assessment: (SQ6) "How do you frequently use technology in your science class? Mark only three." Based on the student responses to the survey question, the top three choices were identified and selected based on the frequency of "yes" responses. Table 2 shows the breakdown of student responses in the data set by municipality. The specific technology use identified for analysis included use technology to organize and display data, use the Internet to find information or communicate with other persons, and create presentations and/or Web pages.

Table 1

Descriptive Statistics of Data Set Variables

Variable	Description	Category	Range	Frequency	Percent
EOC	Biology standardized test scores		121-179	97229	100.0
Gender	Student gender	Female		48197	49.6
		Male		49032	50.4
Race/Ethnicity	Student race	Black		29973	30.8
		Hispanic		10231	10.5
		White		57025	58.7
SES	Qualify for FRL	No		53793	55.3
		Yes		43436	44.7
SQ6A	Organize & display data	No		46000	47.3
		Yes		51229	52.7
SQ6B	Use simulations	No		75715	77.9
		Yes		21514	22.1
SQ6C	Use the Internet	No		46787	48.1
		Yes		50442	51.9
SQ6D	Use specific programs	No		82886	85.2
		Yes		14343	14.8
SQ6E	Create presentations	No		71876	73.9
		Yes		25353	26.1
SQ6F	Use calculators	No		87611	90.1
		Yes		9618	9.9
SQ6G	Data probes & analysis	No		94349	90.1
		Yes		10371	9.9
SQ9A	Most of the time use technology	No		85635	88.1
		Yes		11594	11.9
MUNC	Student municipality	Rural		51645	53.1
		Urban		45584	46.9

The dependent variable for the third and fourth null hypotheses is the academic

scale score for the biology EOC assessment. The factorial univariate analysis examines variations of scale score within various the independent variable groupings of race, gender, SES, technology use, and municipality.

The data analysis results for this chapter are organized by specific technology use and reported for each hypothesis. This enables all the relevant data to be clustered around the specific technology use identified in the study.

Table 2

Percentage of Technology Use by Municipality (N = 97229)

Technology	Statewide N = 97229	Rural N = 51645	Urban N = 45584
Organize & display data	52.7	52.4	53.0
Use simulations	22.1	22.9	21.3
Use the Internet	51.9	53.6	49.9
Use specific programs	14.8	16.2	13.1
Create presentations	26.1	26.8	25.3
Use calculators	9.9	10.2	9.6
Data probes & analysis	9.9	10.3	9.4

A simple way to interpret an effect is to refer to conventions governing effect size. The best known of these are the thresholds proposed by Cohen (1988). Cohen outlined a number of criteria for gauging small, medium, and large effect sizes estimated using different statistical procedures. Cohen's cut-offs provide a good basis for interpreting effect size and for resolving disputes about the importance of one's results. Table 3 provides the benchmarks for effect size as identified by Cohen that are referenced

throughout this chapter.

Table 3

Cohen's Effect Size Benchmarks

Test	Relevant Effect Size	Effect Size Classes Small	Medium	Large
Crosstabulations	V	.10	.30	.50
ANOVA	n^2	.01	.06	.14
Comparison of Independent Means	d	.20	.50	.80

Use Technology to Organize and Display Data

Data: Relational Analysis

A series of chi-square tests was used to analyze the relationship between (1) technology use and gender, (2) technology use and race, and (3) technology use and SES. Additional analyses also examined potential relationships within different student population combinations (e.g. Asian females who are eligible for free/reduced lunch) and using technology to create presentations. The data set was broken down into separate subsets by race and gender. Each subset was grouped by those eligible for free or reduced lunch and those that did not qualify. For each group, a chi-square test was used to determine potential relationships between technology use and the various student population combinations.

Table 4 summarizes the results of possible relationships between select demographic student groups and the use of technology to organize and display data. The data reveal a relationship between 10 of the 17 population student groups. The three main demographic groups (race/ethnicity, gender, and SES) were statistically significant.

As the subgroups become more specific (White/SES, White/Males/SES, etc.), we

see a trend associated with SES. There is a significant relationship between White/Gender as well as White/SES, which are validated by the significance of the more specific student groups of White/Male/SES and White/Female/SES. The significance of Hispanic/SES, White/SES, and Male/SES groups are also confirmed by the significant groups of Hispanic/Male/SES and White/Male/SES.

Although the pattern of significant groups is evident, the effect size value is less than 0.1 which is considered a very small effect using Cohen's (1988) criteria of .10 for small effect, .30 for medium effect, and .50 for large effect.

Table 4

H_01 (Organize Data): Chi-Square Analysis Summary

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	97229	21.185	2	.000	.015
Gender	97229	8.173	1	.004	.009
SES	97229	14.626	1	.000	.012
Black * Gender	29973	0.021	1	.884	
Hispanic * Gender	10231	1.472	1	.225	
White * Gender	57052	11.251	1	.001	.014
Black * SES	29973	0.437	1	.509	
Hispanic * SES	10231	9.77	1	.002	.031
White * SES	57025	15.76	1	.000	.017
Female * SES	48197	1.217	1	.270	
Male * SES	49032	18.251	1	.000	.019
Black * Female * SES	15144	0.524	1	.496	
Black * Male * SES	14829	2.74	1	.098	
Hispanic * Female * SES	5107	3.053	1	.081	
Hispanic * Male * SES	5124	0.037	1	.007	.037
White * Female * SES	27946	5.958	1	.015	.015
White * Male * SES	29079	10.321	1	.001	.019

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Relational Analysis: Municipality

Chi-square tests were performed to analyze the second null hypothesis (H_02) – potential relationships between select demographic student groups within rural and urban districts and using technology to organize and display data.

The data in Table 5 reveal significant relationships between seven different demographic subgroups in the rural population. The main demographic groups based on gender and SES are statistically significant and also validated by the Hispanic/SES,

White/SES, and Male/SES groups.

Table 5

$H_0$2 (Organize Data): Chi-Square Analysis Summary – Rural Districts

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	51645	18.3	2	.000	.019
Gender	51645	0.1	1	.705	
SES	51645	6.3	1	.012	.011
Black * Gender	13545	0.0	1	.995	
Hispanic * Gender	4688	0.0	1	.992	
White * Gender	33412	0.3	1	.575	
Black * SES	13545	0.5	1	.471	
Hispanic * SES	4688	5.4	1	.020	.034
White * SES	33412	13.3	1	.000	.020
Female * SES	25604	0.2	1	.650	
Male * SES	26041	9.6	1	.002	.019
Black * Female * SES	6901	0.1	1	.801	
Black * Male * SES	6644	1.6	1	.204	
Hispanic * Female * SES	2271	1.1	1	.289	
Hispanic * Male * SES	2417	4.8	1	.028	.045
White * Female * SES	16432	2.8	1	.093	
White * Male * SES	16980	12.0	1	.001	.027

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

White/Male/SES students further qualify the significance of these two-way groups. Regardless of this validation, the Cramer's V value for all are less than 0.1 which indicates little to no effect on the differences in technology use. Based on this context, the null hypothesis ($H_0$2) cannot be rejected.

As shown in Table 6, only six groups were found to be significant in the urban population. Unlike the previous two analyses, the pattern of significant groups is not as

clear. Gender is a significant group and is supported by the significant White/Gender group; however, the Race/Ethnicity and SES groups are only validated by the Hispanic/SES and Male/SES groups. More specified demographic groups (Race/Gender/SES) did not validate the secondary or main effects.

Relational Analysis: Summary

The analysis of the data sets shows a defined pattern of significant variations with race/ethnicity, gender, and SES. More specific patterns emerge as the White and Hispanic student groups are analyzed within SES subsets, especially in rural districts. The variations of significant groups found in the rural and urban analysis are also seen in the whole data set analysis. Despite the number and apparent patterns of the significant groups, the effect size value for all of these statistically significant groups is less than 0.1 and considered a miniscule effect on the variation of technology use. This is generally considered not acceptable (Pallant, 2011), so the second null (H_02) hypothesis is not rejected.

Table 6

$H_0$2 (Organize Data): Chi-Square Analysis Summary – Urban Districts

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	45584	15.5	2	.000	.018
Gender	45584	14.2	1	.000	.018
SES	45584	7.8	1	.005	.013
Black * Gender	16428	0.0	1	.861	
Hispanic * Gender	5543	2.6	1	.105	
White * Gender	23613	20.5	1	.000	.029
Black * SES	16428	0.2	1	.637	
Hispanic * SES	5543	4.8	1	.028	.030
White * SES	23613	1.1	1	.301	
Female * SES	22593	1.3	1	.247	
Male * SES	22991	7.6	1	.006	.018
Black * Female * SES	8243	0.4	1	.550	
Black * Male * SES	8185	1.6	1	.206	
Hispanic * Female * SES	2836	2.3	1	.130	
Hispanic * Male * SES	2707	2.6	1	.108	
White * Female * SES	11514	3.2	1	.073	
White * Male * SES	12099	0.0	1	.830	

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Data: Factorial Univariate Analyses

The third null hypothesis ($H_0$3) was tested using a factorial analysis of variance to test the effects of race/ethnicity, gender, SES, and using technology to create presentations on biology academic scale scores.

Four-way effects. Results from Table 7 show the interaction between race/ethnicity, gender, SES, and technology use (organize data) did not significantly

impact student academic scale scores. The null hypothesis cannot be rejected based solely on the four-way interaction.

Table 7

Analysis Summary of $H_0$3 (Organize Data) – Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	1649028.4	23	71696.9	952.7	.000
Intercept	1077714741.0	1	1077714.0	1432109	.000
Race/Ethnicity	526419.3	2	263209.6	3497.6	.000
Gender	87.7	1	87.7	1.2	.280
SES	208228.3	1	208228.3	2767.0	.000
Technology Use	8908.5	1	8908.5	118.4	.000
R/E * Gender	6154.2	2	3077.1	40.9	.000
R/E * SES	9710.8	2	4855.4	64.5	.000
R/E * Tech Use	873.2	2	436.6	5.8	.000
Gender * SES	25.4	1	25.4	0.3	.560
Gender * Tech Use	515.7	1	515.7	6.9	.010
SES * Tech Use	1.0	1	1.0	0.0	.910
R/E * Gender * SES	408.5	2	204.2	2.7	.070
R/E * Gender * Tech Use	168.7	2	84.3	1.1	.331
R/E * SES * Tech Use	571.3	2	285.6	3.8	.023
Gender * SES * Tech Use	64.6	1	64.6	0.9	.358
R/E * Gender * SES * Tech Use	201.8	2	100.9	1.3	.263
Error	7315032.0	97205	75.254		
Total	2270768082.0	97229			
Corrected Total	8964060.5	97228			

Note. SS = Type III Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Three-way effects. The results also reveal a significant interaction between race/ethnicity, SES, and technology use; however, the effect size of the interaction ($\eta^2 < .01$) is trivial and considered to have no influence on the score variation. This is evident in Table 8 when comparing the mean scale scores of the different demographic groups of the three way interaction.

Table 8

*Comparative Means: (IV) race/ethnicity*SES*technology use and (DV) scale scores*

Race/Ethnicity	EDS	Technology Use	*N*	*M* Scale Score	*SD*
Black	No	No	4269	150.090	.133
		Yes	4960	150.762	.123
	Yes	No	9681	146.077	.088
		Yes	11063	147.084	.083
Hispanic	No	No	1215	152.235	.249
		Yes	1397	153.441	.232
	Yes	No	3814	148.659	.140
		Yes	3805	149.886	.141
White	No	No	19670	156.395	.062
		Yes	22282	157.154	.058
	Yes	No	7351	151.397	.101
		Yes	7722	151.745	.099

Note. N = Sample Size, *M* = Scale Score Mean, *SD* = Standard Deviation.

Three-way effects – secondary analysis. Further analysis of the significant three-way interaction between race/ethnicity, SES, and technology use involves splitting the data set by technology use (no and yes). For each data set, a 2 x 2 (gender x SES) factorial analysis of variance tested the effects of student gender and their SES on biology scale scores.

The data in Tables 9 and 10 reveal a significant two-way interaction with race/ethnicity and SES in both technology use student groups. However, the effect size for these two-way interactions ($\eta^2_{\text{R/E*SES}} < .01$) are considered miniscule with no influence on the scale score variation.

Table 9

Secondary Analysis (Organize Data & Technology Use = NO)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	779332.9	5	155866.6	2034.8	.000
Intercept	508645148.6	1	508645148.6	6640295.9	.000
Race/Ethnicity	263807.9	2	131903.9	1721.9	.000
SES	98119.4	1	98119.4	1280.9	.000
R/E * SES	2865.4	2	1432.7	18.7	.000
Error	3523129.9	45994	76.6		
Total	1068331099.0	46000			
Corrected Total	4302462.8	45999			

Note. *SS* = Type III Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Table 10

Secondary Analysis (Organize Data & Technology Use = YES)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	845236.3	3	169047.3	2278.7	.000
Intercept	573192237.7	1	573192237.7	7726341.5	.000
Race/Ethnicity	265491.7	1	265491.7	1789.3	.000
SES	109995.4	1	109995.4	1482.7	.000
R/E * SES	7728.9	1	7728.9	52.1	.000
Error	3800068.4	51223	74.2		
Total	1202436983.0	51229			
Corrected Total	4645304.7	51228			

Note. *SS* = Type III Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Independently, gender and SES were statistically significant in both data subsets. A comparison of the eta squared values revealed similar effect sizes in both technology use groups as well. For both student subgroups, the effect size values for race/ethnicity ($\eta^2_{\text{Race Tech Use No}} = .070$ and $\eta^2_{\text{Race Tech Use Yes}} = .065$) were more than twice that of SES ($\eta^2_{\text{SES Tech Use No}} = .027$ and $\eta^2_{\text{SES Tech Use Yes}} = .028$). Based on Cohen's (1988) guidelines for effect size, both race/ethnicity and SES have a medium effect on biology scale scores.

The data in Figure 3 display the mean scale score differences between races and

their respective socioeconomic groups within the context of students who used technology to organize and display data. The chart shows the apparent gap between the racial/ethnic and socioeconomic groups with Whites outperforming Hispanics, who scored higher than Black students. The plot lines for Hispanics and Blacks are parallel, which indicate the achievement gap is similar between the respective SES groups. The graph also reveals that for White students using this technology, the students not eligible for free/reduced lunch prices perform higher than their eligible peers by six scale score points ($M_{\text{SES Yes}}$ = 151.2 and $M_{\text{SES No}}$ = 157.2). We also see that the achievement gap between White and Hispanic eligible for free/reduced lunch prices is less than their more affluent peers.

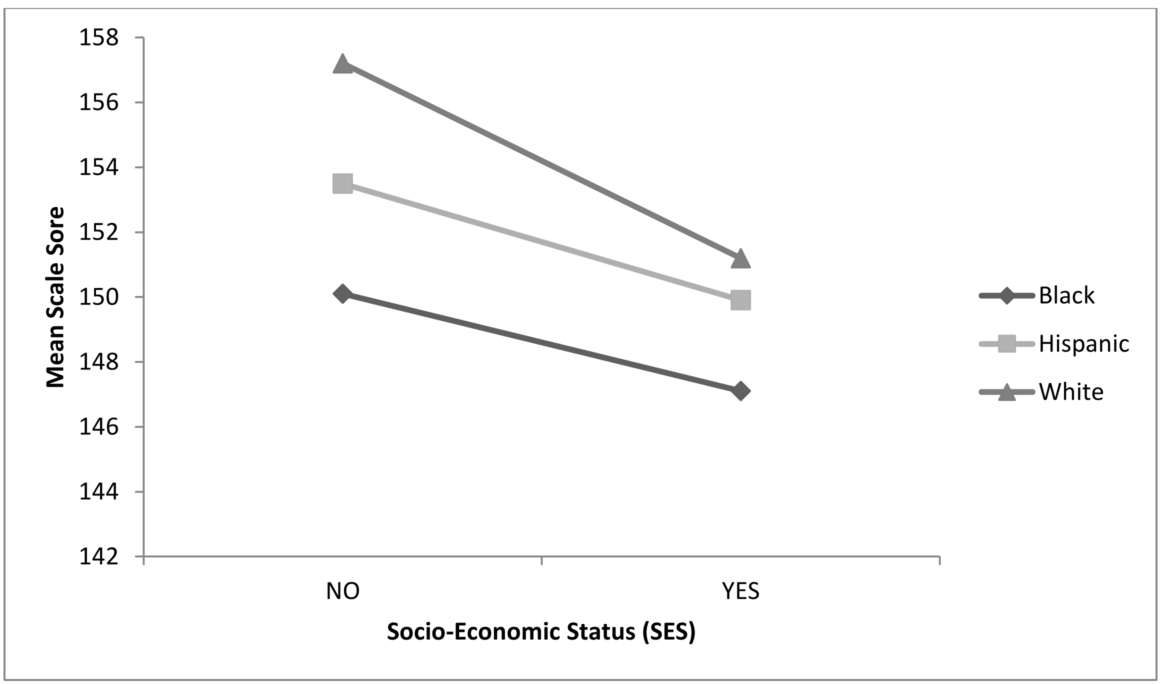

Figure 3. Mean Biology Scale Scores for Students Who Use Technology to Organize and Display Data.

Figure 4 displays the same information as seen in Figure 3, but only for students

who reported not using this specific technology. Similar racial/ethnic achievement gaps are seen, with Whites scoring higher than Hispanics and Black students. Like students who used this technology, Hispanic and Black student performance gaps remain consistent between their respective SES groups. Unlike the previous group that reported using this technology, the slope of the plot line for White students is not as steep, indicating a smaller achievement gap between the SES groups ($M_{\text{SES Yes}} = 151.4$ and $M_{\text{SES No}} = 156.4$). The data in Table 8 also confirms that SES plays a greater role in scale score variation than technology use.

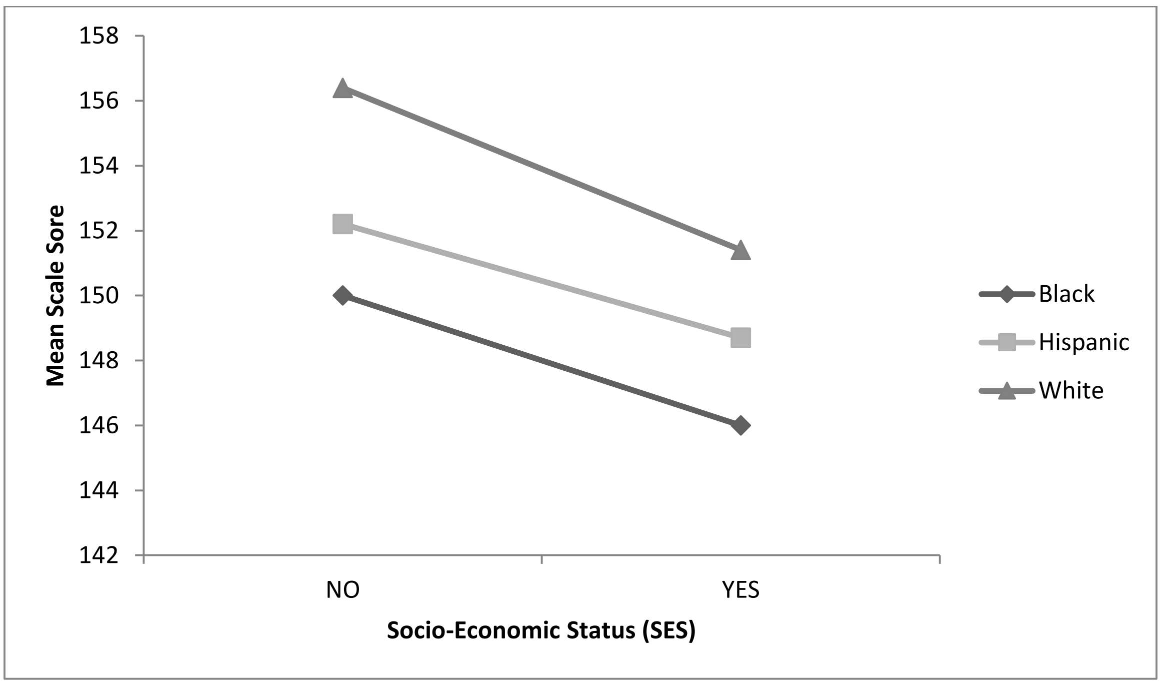

Figure 4. Mean Biology Scale Scores for Students Who Reported Not Using Technology to Organize and Display Data.

Analyzing this three-way interaction from a different perspective separates the data set into its three respective racial/ethnic groups (Black, Hispanic, and White). With the exception of the two-way interactions for Black and Hispanic students, the results from Tables 11-13 show that all the effects for each racial subgroup were significant.

However, the eta squared values reveal that only SES has any influence on the student scale score variation with a medium effect.

Table 11

Secondary Analysis (Organize Data & Black Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	99473.5	3	33157.8	448.7	.000
Intercept	560474565.1	1	560474565.1	7583650.5	.000
SES	93187.8	1	93187.8	1260.9	.000
Tech Use	4412.0	1	4412.0	59.7	.000
SES * Tech Use	187.7	1	187.7	2.5	.111
Error	2214878.2	29969	73.9		
Total	657043019.0	29973			
Corrected Total	2314351.6	29972			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 12

Secondary Analysis (Organize Data & Hispanic Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	29129.8	3	33157.8	119.0	.000
Intercept	17689077.1	1	17689077.1	2168239.6	.000
SES	24593.9	1	24593.9	301.5	.000
Tech Use	2907.5	1	2907.5	35.6	.000
SES * Tech Use	0.0	1	0.0	0.0	.986
Error	834342.7	10227	81.6		
Total	231653253.0	10231			
Corrected Total	863472.5	10230			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 13

Secondary Analysis (Organize Data & White Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	308118.9	3	102706.3	1370.3	.000
Intercept	1052822178.0	1	1052822178.0	14046160.8	.000
SES	298872.5	1	298872.5	3987.4	.000
Tech Use	3560.1	1	3560.1	47.5	.000
SES * Tech Use	422.9	1	422.9	5.6	.018
Error	4273977.4	57021	75.0		
Total	1382071810.0	57025			
Corrected Total	4582096.3	57024			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

The data from Table 14 suggest that effect size is directly related to the magnitude of the mean difference – the greater the mean difference corresponds to a larger effect

size. Within the context of SES, White students have the largest achievement gap, followed by Blacks and then Hispanics. Comparisons of eta squared values also show that SES has more than twice the effect for White students as compared to Hispanic students.

Table 14

Secondary Analysis – Effect Size and Mean Difference Summary for SES

					95% CI for Difference	
Group	N	η^2	*MD*	*SE*	Lower Bound	Upper Bound
Black	29973	.040	3.830	.108	3.618	4.041
Hispanic	10231	.029	3.562	.205	3.160	3.964
White	57025	.065	5.195	.082	5.034	5.357

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval.

Two-way effects. The results from Table 6 indicate significant two-way interactions between race/ethnicity, gender, SES, and technology use. The interactions between race/ethnicity, SES and technology use are qualified by the significant three-way interaction of the variables and have the same effect size ($\eta^2 < .01$), which indicates these combination of factors do not influence the scale score variation.

The remaining significant interactions involve gender, race/ethnicity, and technology use, with the common variable being gender between these two interactions. These effects are not supported by any significant three-way interactions and lack a noteworthy effect size value ($\eta^2 < .01$).

Two-way effects – secondary analyses. Further examination of the significant two-way interactions involving gender separates the data set into its respective female and male subgroups. An ANOVA is used to analyze each set for possible interactions with race/ethnicity and academic scale scores.

The results in Tables 15 and 16 indicate a significant effect for race/ethnicity in both the female and male student groups. The effect size value for the female students population ($\eta^2_{\text{Female Race}} = .13$) is considered a medium influence – approximately 13% of the scale score variation seen between the racial/ethnic groups. In comparison, male students have a similar effect size ($\eta^2_{\text{Male Race}} = .14$), which is considered a large influence based on Cohen's (1988) effect size benchmarks.

Table 15

Secondary Analysis (Organize Data & Female Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	541367.2	2	270683.6	3956.5	.000
Intercept	691128123.1	1	691128123.1	9182801.2	.000
Race/Ethnicity	541367.2	2	270683.6	3596.5	.000
Error	3627240.5	48194	75.3		
Total	1125361058.0	48197			
Corrected Total	4168607.7	48196			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Table 16

Secondary Analysis (Organize Data & Male Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	667392.6	2	333696.3	3963.3	.000
Intercept	691807427.8	1	691807427.8	8216601.7	.000
Race/Ethnicity	667392.6	2	333696.3	3963.3	.000
Error	4128060.2	49029	84.2		
Total	1145407024.0	49032			
Corrected Total	4795452.8	49031			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

The results of the Bonferroni post hoc tests in Tables 17 and 18 reveal that Whites outperformed Hispanics and Black racial groups in average scale score for both female

and male students. Hispanic males and females performed lower than their White counterparts but achieved higher results than Black males and females. Both Black males and females achieved lower mean scale scores than their respective Hispanic and White gender groups.

Table 17

Post Hoc Test – Multiple Comparisons: (IV) Females, Race/Ethnicity, & (DV) Scale Score

Race	Comparison Race	*MD*	*SD*	*p*	95% CI Lower Bound	95% CI Upper Bound
Black *N = 15144*	Hispanic	-1.88	.140	.000	-2.22	-1.55
	White	-7.18	.088	.000	-7.39	-6.97
Hispanic *N = 5107*	Black	1.88	.140	.000	1.55	2.22
	White	-5.30	.132	.000	-5.61	-4.95
White *N = 27946*	Black	7.18	.088	.000	6.97	7.39
	Hispanic	5.30	.132	.000	4.98	5.61

Note. MD = Mean Difference, *SD* = Standard Deviation, *CI* = Confidence Interval; *significance at $p < .05$ level.

Table 18

Post Hoc Test – Multiple Comparisons: (IV) Males, Race/Ethnicity, & (DV) Scale Score

Race	Comparison Race	*MD*	*SD*	*p*	95% CI Lower Bound	95% CI Upper Bound
Black *N = 14829*	Hispanic	-2.92	.149	.000	-3.27	-2.56
	White	-8.07	.093	.000	-8.30	-7.85
Hispanic *N = 5124*	Black	2.92	.149	.000	2.56	3.27
	White	-5.16	.139	.000	-5.49	-4.83
White *N = 29079*	Black	8.07	.093	.000	7.85	8.30
	Hispanic	5.16	.139	.000	4.83	5.49

Note. MD = Mean Difference, *SD* = Standard Deviation, *CI* = Confidence Interval; *significance at $p < .05$ level.

The information in Figure 5 shows the difference between the three racial/ethnic slopes which further suggests achievement gaps between Black, Hispanic, and White students. However, since the profile plot lines do not cross, an interaction between gender and race/ethnicity is indeterminate.

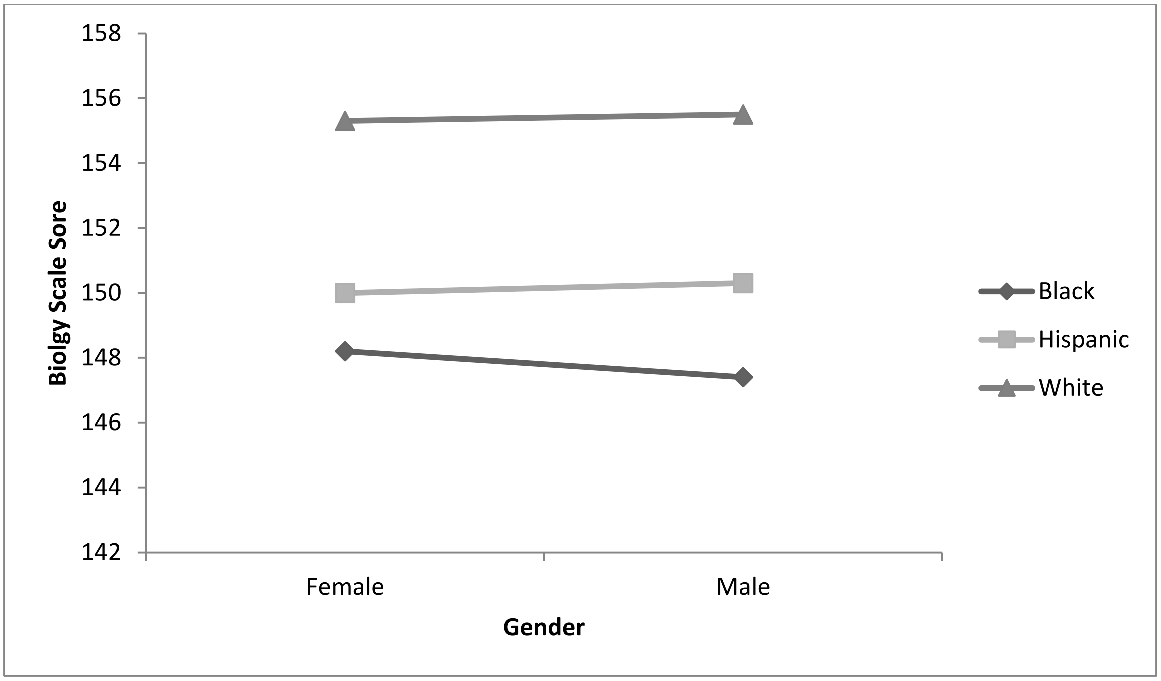

Figure 5. Comparative Means of Biology Scale Scores by Gender.

The information in Figure 6 shows the difference between female and male students of the respective gender groups. Since the profile plot lines cross between Black and Hispanic students, this indicates an interaction between gender and race/ethnicity. Based on the graphical information seen in Figure 6, it can be determined that gender does have an effect on scale scores within the different racial/ethnic student groups.

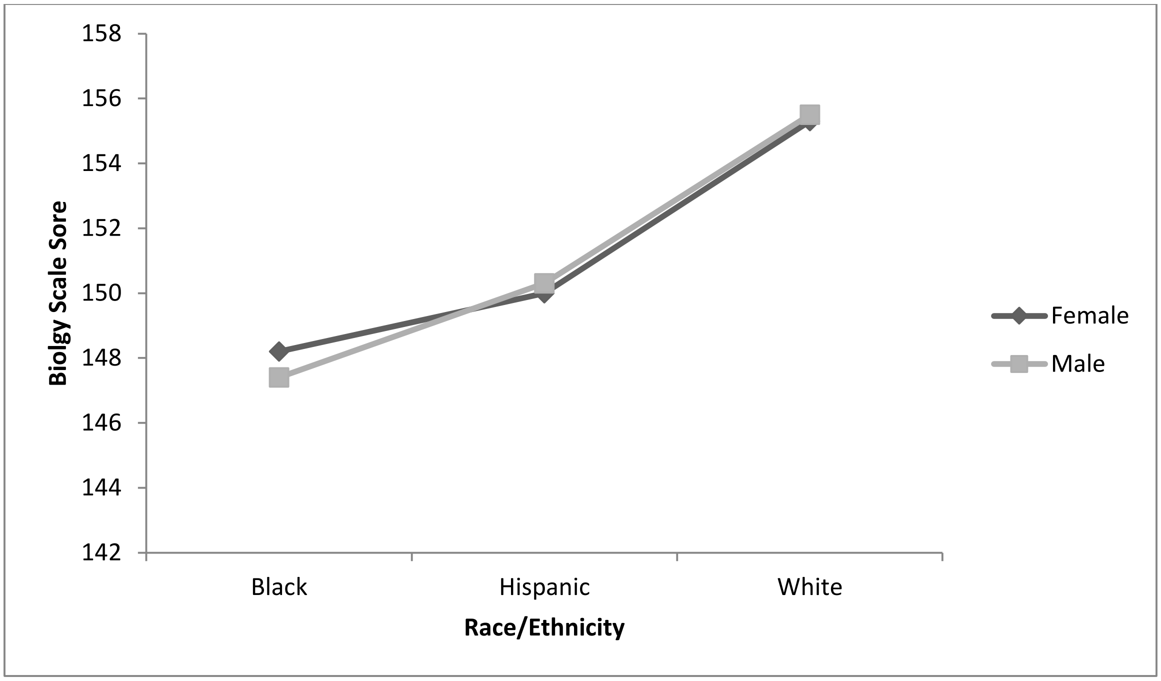

Figure 6. Comparative Means of Biology Scale Scores by Race/Ethnicity.

In further analysis of gender and technology use, an independent sample t test was conducted to compare gender subgroups and using technology to organize and display data. For the female subgroup that used technology, the results of Levene's test, $F(48197) = 1.11$, $p = .291$ indicate that the variances of the two technology use groups are assumed to be approximately equal. Thus, the standard or pooled t-test results are used.

The results of the independent t test were significant, $t(48197) = 6.314$, $p = .000$, $d = 0.54$, indicating that there is a statistically significance difference between the scores of females who use technology ($M = 152.8$, $SD = 9.3$, $n = 25172$) and the scores of females who do not ($M = 152.2$, $SD = 9.3$, $n = 23025$). However, the effect size (Cohen's $d = .058$) was small based on Cohen's scale for d (Cohen, 1988). The 95% confidence interval for the difference between the means is -0.369 to 0.701.

For the male subgroup that used technology, the results of Levene's test, $F(49032) = 11.68$, $p = .001$ indicate that the variances of the two technology use groups are assumed not to be approximately equal and so the Welch t test results are used.

The results of the independent t test was significant, $t(49032) = 12.29$, $p = .000$, $d = 1.10$, indicating that there is a statistically significance difference between the scores of males who use technology ($M = 153.0$, $SD = 9.8$, $n = 26057$) and the scores of males who do not ($M = 151.9$, $SD = 9.9$, $n = 22975$). The effect size (Cohen's $d = .111$) is considered small which indicates that 11.1% of the variation is due to using technology for data organization. The 95% confidence interval for the difference between the means is 0.925 to 1.276. These results suggest that male students who use technology to organize and display data perform better on biology EOC exams.

Main effects. The results indicate statistically significant effects with race/ethnicity, SES, and using technology to organize and display data. The estimated effect size values of race/ethnicity ($\eta^2_{\text{Race}} = .067$) and SES ($\eta^2_{\text{SES}} = .028$) were considered a medium effect on the variability of biology scale scores.

The results from Tukey's post hoc test in Table 19 show the comparisons between the Black, Hispanic, and White students. The data reveal the mean score difference for Black students ($M_{\text{Black}} = 148.5$) was more than two times lower than Hispanic students ($M_{\text{Hispanic}} = 151.1$) as compared to White students ($M_{\text{White}} = 154.2$).

Table 19

Secondary Analysis: Pairwise Comparisons – Race/Ethnicity and Scale Score

Race	Comparison Group	MD	SE	*p*	95% CI for Difference Lower Bound	Upper Bound
Black *N = 29973*	Hispanic	-2.552	.113	.000	-2.751	-2.145
	White	-5.670	.068	.000	-5.780	-5.403
Hispanic *N = 10231*	Black	2.552	.113	.000	2.145	2.751
	White	-3.118	.107	.000	-3.430	-2.858
White *N = 57025*	Black	5.670	.068	.000	5.403	5.780
	Hispanic	3.118	.010	.000	2.858	3.430

Note. MD = Mean Difference, *SE* = Standard Error, *CI* = Confidence Interval; *significance at $p < .05$ level.

The eta squared value ($\eta^2_{\text{Race}} = .067$) indicates that race/ethnicity has a medium effect on the variation of scale scores on the biology EOC assessment. The effect was also evident in the three significant two-way interactions involving race/ethnicity; however, the effect sizes for each were small ($\eta^2 < .01$). The significant three-way interaction between ethnicity, SES, and using technology to organize data also supports the main effect of ethnicity on student biology scale scores.

The main effect of SES was also significant, revealing that students eligible for free and/or reduced lunch were outperformed by their peers who were not classified as SES. This is supported in two-way interactions with ethnicity and technology use individually and also in the three-way interaction between the three variables. However, the partial eta squared value ($\eta^2_{\text{SES}} = .028$) indicates the effect on scale scores is small.

Using technology to organize and display data did have a significant effect on student achievement; however, the mean difference in scale scores was small (yes = 151.6 versus no = 150.8). The significance of this main effect may also be attributed to

the large population size itself rather than the actual mean difference. The effect size of this variable ($\eta^2_{\text{Tech Use}} < .01$) is miniscule and in context does not contribute to a significant achievement gap between users and nonusers.

Summary. The analysis of the data set suggests that individually ethnicity, SES, and using technology to organize and display data have various effects on student achievement in biology EOC assessments. The effect of ethnicity and SES were also evident in more complex interactions with similar outcomes. The specific technology use was a small factor as a main effect and interacting with ethnicity and SES. Further analysis indicates that males who used technology to organize and display data outperformed their male counterparts who reported not using the technology. In this context, we would have to reject the null hypothesis (H_04).

Data: Multi-level Analyses

Factorial Univariate Analysis: Municipality

The fourth null hypothesis (H_04) was tested using a factorial analysis of variance to examine within rural and urban school districts the effects of race/ethnicity, gender, SES, and using technology to organize and display data on biology academic scale scores. The data set was separated into two subsets by municipality (rural and urban) referring to the classification of the student's school district. Table 20 shows the demographic breakdown of the four different factor groups in the rural and urban analysis.

Table 20

Between-Subject Factors for Rural and Urban School Districts

Factor	Group Name	N_{Rural}	N_{Urban}
Race/Ethnicity	Black	13545	16428
	Hispanic	4688	5543
	White	33412	23613
Gender	Female	25604	22593
	Male	26041	22991
SES	No	27596	26197
	Yes	24049	19387
Use Technology to Organize Data	No	24581	34071
	Yes	27064	11513
Totals		516545	45584

Rural Populations

The analysis of rural school districts tested the effects of the factors listed in Table 20 on the student achievement based on academic scale scores in high school biology classes. Table 21 provides a summary of the results from the factor analysis of variance.

Table 21

Analysis Summary of H_03 (Organize and Display Data in Rural Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	756015.7	23	30870.2	454.9	.000
Intercept	457562027.0	1	457562027.0	6333225.0	.000
Race/Ethnicity	254767.3	2	127383.7	1763.1	.000
Gender	776.3	1	776.3	10.7	.001
SES	70684.1	1	70684.1	978.4	.000
Technology Use	3451.2	1	3451.2	47.8	.000
R/E * Gender	2204.7	2	1102.3	15.3	.000
R/E * SES	1505.9	2	752.9	10.4	.000
R/E * Tech Use	850.7	2	425.4	5.9	.003
Gender * SES	98.3	1	98.3	1.4	.243
Gender * Tech Use	152.8	1	152.8	2.1	.146
SES * Tech Use	2.0	1	2.0	0.0	.867
R/E * Gender * SES	12.4	2	6.2	0.1	.918
R/E * Gender * Tech Use	60.1	2	30.1	0.4	.659
R/E * SES * Tech Use	323.3	2	161.7	2.2	.107
Gender * SES * Tech Use	0.0	1	0.0	0.0	.992
R/E * Gender * SES * Tech Use	199.8	2	99.9	1.4	.251
Error	3729507.2	51621	72.2		
Total	119878714.0	51645			
Corrected Total	4485522.9	51644			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 51645; *significance at $p < .05$ level.

Rural: Four-way and three-way effects. Results in Table 21 indicate there are no significant four-way or three-way interactions between race/ethnicity, gender, SES,

and technology use in rural populations. The null hypothesis cannot be rejected based solely on these interactions.

Rural: Two-way effects. Table 21 shows there are three significant two-way interactions between race/ethnicity, gender, SES, and technology use. These effects were not supported by significant three-way interactions, and their respective effect size values were less than .01 with no influence on the scale score variations.

Rural: Two-way effects - secondary analysis. The three significant two-way interactions of the rural population share race/ethnicity as a common variable. Further examination of these interactions involves splitting the rural dataset into the individual racial/ethnic groups and performing an ANOVA to test each subset for interactions with gender, SES, and technology use.

In Table 22, the main effects in the rural Black student population were all significant; however, the scale score mean for technology use was a difference of 1.0 between students who used technology ($M_{\text{Tech Use Yes}} = 148.3$) and those students who did not report using the technology ($M_{\text{Tech Use No}} = 147.3$). This is a marginal scale score increase for Black rural students who used technology to organize and display data, which is supported by its effect size value ($\eta^2_{\text{Tech Use}} = .003$). Using technology to organize and display data has less than a 1.0% effect on the variation of scale scores with this population.

Table 22

Analysis Summary of H_04(Organize Data & Black Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	41344.6	7	5906.4	85.1	.000
Intercept	222616447.0	1	222616447.0	3209468.0	.000
Gender	2315.2	1	2315.2	1763.1	.000
SES	35232.7	1	35232.7	507.9	.000
Technology Use	2530.5	1	2530.5	36.4	.000
Gender * SES	104.7	2	104.7	1.5	.219
Gender * Tech Use	60.6	2	60.6	0.1	.350
SES * Tech Use	12.6	2	12.6	0.2	.670
Gender * SES * Tech Use	21.8	1	21.8	0.3	.575
Error	938958.9	13537	69.3		
Total	293548684.0	13545			
Corrected Total	980303.5	13544			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973;
*significance at $p < .05$ level.

The main effects for SES and technology use in Table 23 were significant; however, the scale score mean difference for technology use was a difference of 1.0 between Hispanic students who used the technology ($M_{\text{Tech Use Yes}} = 151.2$) and those students who indicated not using the technology ($M_{\text{Tech Use No}} = 150.2$). A marginal scale score increase for Hispanic rural students who used technology to organize and display data, which is supported by the small estimated effect size ($\eta^2_{\text{Tech Use}} < .01$).

Table 23

Analysis Summary of H_04(Organize Data & Hispanic Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	10212.1	7	1458.8	18.9	.000
Intercept	72483092.9	1	72483092.9	941831.3	.000
Gender	97.0	1	97.0	1.3	.262
SES	8011.5	1	8011.5	104.1	.000
Technology Use	930.5	1	930.5	12.1	.001
Gender * SES	3.1	2	3.1	0.0	.840
Gender * Tech Use	4.5	2	4.5	0.1	.808
SES * Tech Use	47.6	2	47.6	0.6	.432
Gender * SES * Tech Use	72.9	1	72.9	0.9	.330
Error	360171.6	4680	76.9		
Total	105668662.0	4688			
Corrected Total	370383.7	4687			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, N = 10231; *significance at $p < .05$ level.

In Table 24 we see a significant three-way effect which qualifies the two-way interactions of (1) technology use and SES, and (2) technology use and gender. Although statistically significant, the estimated effect size of the three-way interaction ($\eta^2 < .01$) is small and has a negligible effect on the variation of the academic scale scores.

Table 24

Analysis Summary of H_04 (Organize Data & White Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	139159.6	7	19879.9	273.2	.000
Intercept	670786128.3	1	670786128.3	9219547.3	.000
Gender	110.0	1	110.0	1.5	.219
SES	134560.5	1	134560.5	1849.5	.000
Technology Use	1175.1	1	1175.1	16.1	.000
Gender * SES	168.4	2	168.4	2.3	.128
Gender * Tech Use	610.0	2	610.0	8.4	.004
SES * Tech Use	460.0	2	460.0	6.3	.012
Gender * SES * Tech Use	323.5	1	323.5	4.4	.035
Error	2430376.7	33404	72.7		
Total	799661368.0	33412			
Corrected Total	2569536.4	33411			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, N = 57025; *significance at $p < .05$ level.

The significant two-way interaction in the White population shares a common variable: technology use. A tertiary analysis involves separating the rural White population into its respective technology use subgroups: students who reported using technology to organize and display data and those students who did not use the technology.

A 2 x 2 (gender x SES) analysis of variance tested the effects of gender and SES on academic scale scores of White students in rural school districts who indicated using technology to organize and display data in their biology class. Results indicated significant main effects for gender, $F(1, 17358) = 8.9$, $p = .003$; and SES, $F(1, 17358) =$

1085.8, $p = .000$. A comparison of the estimated effect size values for gender (η^2_{Gender} = .000) and SES (η^2_{SES} = .059) indicates that the medium effect of SES accounts for approximately 5.9% of the variation as compared to 0% for the effect of gender alone.

The two main effects were qualified by a significant interaction between the two factors, $F(1, 17358) = 6.9$, $p = .009$, indicating that the gender effects were not the same for the two different SES conditions. The mean difference between female SES groups ($d = 4.98$) was greater than male SES groups ($d = 4.24$); however, the effect size ($\eta^2 < .01$) is negligible and does not account for the variance of scale scores.

Another 2 x 2 (gender x SES) analysis of variance tested the effects of gender and SES on academic scale scores of White students in rural school districts who reported not using technology to organize and display data in their biology class. Results indicated a significant main effect for SES, $F(1, 16046) = 781.6$, $p = .000$, and not for gender, $F(1, 16046) = 1.3$, $p = .250$; however, the effect size for SES (η^2_{SES} = .046) is small, accounting for approximately 4.6% of the scale score variation. The main effects were not qualified by a significant interaction between the two factors, $F(1, 16046) = .16$, $p = .685$.

The main effects of the secondary analysis for SES and technology use were significant; however, the scale score mean for technology use was a difference of 1.0 between students who reported using the technology ($M = 151.2$) and those who did not ($M = 150.2$). Contextually, this is a marginal scale score increase for White rural students who used technology to organize and display data, which is supported by the effect size for technology ($\eta^2 < .01$) and accounting for essentially none of the scale score variation.

Rural: Main effects. The data from Table 21 shows significance for all four

main variables of the tests of between-subjects effects. The analysis of ethnicity show that White students (M_{White} = 153.7) outperform Hispanic students (M_{Hispanic} = 150.7) and Black students (M_{Black} = 147.8) on biology EOC assessments. Female students (M_{Female} = 150.9) performed slightly higher than male students (M_{Male} = 150.5), while students who were not eligible for free/reduce lunch ($M_{\text{SES No}}$ = 152.6) performed higher than students who were eligible ($M_{\text{SES Yes}}$ = 148.9). Although the four main effects were statistically significant, an examination of the partial eta squared values show that gender, SES, and technology all had small effects ($\eta^2 < .001$). The exception is seen in the race/ethnicity effect, where its partial eta squared value (η^2_{Race} = .064) is considered a medium effect, accounting for approximately 6.4% of the variation.

Rural populations: Summary. The factorial univariate analysis of the rural population data set suggests that separately ethnicity, gender, SES, and using technology to organize and display data have various effects on student achievement in biology EOC assessments. The effect of ethnicity was also evident in more complex interactions with gender, SES, and technology use. Specifically for rural White students, using technology to organize and display data made a greater impact on academic achievement in biology classrooms. In this context, the fourth null hypothesis (H_04) cannot be rejected.

Urban Populations

Table 25 summarizes the analysis of urban school districts tested and the effects of the factors on the student achievement based on academic scale scores in high school biology classes.

Table 25

Analysis Summary of $H_0$3 (Organize and Display Data in Urban Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	935536.2	23	40675.5	526.3	.000
Intercept	583854430.0	1	583854430.0	7554465.0	.000
Race/Ethnicity	265982.3	2	132991.1	1720.7	.000
Gender	187.2	1	187.2	2.4	.120
SES	131241.7	1	131241.7	1698.1	.000
Technology Use	5621.5	1	5621.5	72.7	.000
R/E * Gender	4725.3	2	2362.7	30.6	.000
R/E * SES	12262.4	2	6131.2	79.3	.000
R/E * Tech Use	271.1	2	135.6	1.8	.173
Gender * SES	0.3	1	0.3	0.0	.947
Gender * Tech Use	380.4	1	380.4	4.9	.027
SES * Tech Use	0.2	1	0.2	0.0	.960
R/E * Gender * SES	457.9	2	228.9	2.9	.052
R/E * Gender * Tech Use	116.9	2	58.5	0.8	.469
R/E * SES * Tech Use	180.2	2	90.1	1.2	.312
Gender * SES * Tech Use	112.2	1	112.2	1.5	.228
R/E * Gender * SES * Tech Use	181.1	2	90.5	1.2	.310
Error	3521149.9	45560	77.3		
Total	1071889368.0	45584			
Corrected Total	4456686.2	45583			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, N = 45584; *significance at $p < .05$ level.

Urban: Four-way and three-way effects. Results in Table 25 indicate there are no significant four-way or three-way interactions between race/ethnicity, gender, SES, and technology use in urban populations. The null hypothesis is not rejected based solely on these interactions.

Urban: Two-way effects. Table 25 shows there are three significant two-way interactions between race/ethnicity, gender, SES, and technology use. These effects were not supported by significant three-way interactions and their respective effect size values were less than .01 with no influence on the scale score variations.

Urban: Two-way effects - secondary analysis. One of the significant two-way

interactions of the urban population is between gender and technology use. Further examination of this interaction involves splitting the urban dataset into subgroups of those who used technology to organize and display data and students who did not.

For the subgroup of students who used technology, the results of Levene's test, $F(24165) = 21.86$, $p = .000$, indicate that the variances of the two populations are assumed not to be approximately equal and the Welch t-test results are used.

The results of the independent t test was significant, $t(24165) = -3.5$, $p = .000$, $d = -0.45$, indicating that there is a statistically significance difference between the scores of males ($M = 153.7$, $SD = 10.1$, $n = 12389$) and the scores of females ($M = 153.3$, $SD = 9.7$, $n = 11776$); however, the effect size (Cohen's $d < .01$) was small. The 95% confidence interval for the difference between the means is -0.693 to -0.199.

For the subgroup of students who did not use technology, the results of Levene's test, $F(21419) = 50.35$, $p = .000$, indicate that the variances of the two populations are assumed not to be approximately equal. Thus, the Welch t-test results are used.

The results of the independent t test was not significant, $t(21419) = 1.9$, $p = .064$, $d = 0.25$, indicating that there is not a significant difference between the scores of males ($M = 152.4$, $SD = 10.3$, $n = 10602$) and the scores of females ($M = 152.6$, $SD = 9.6$, $n = 10817$). The 95% confidence interval for the difference between the means is -0.015 to 0.518.

The remaining two significant two-way interactions involve race/ethnicity, SES, and gender – with race/ethnicity as the common variable. Further analyses of these interactions involve splitting the urban data set into its respective racial/ethnic subgroups and analyzing for interactions between gender and SES.

A 2 x 2 (gender x SES) factorial analysis of variance tested the effects of gender

and SES on academic scale scores of Black students in urban school districts. Results indicated significant main effects for gender, $F(1, 16424) = 37.3$, $p = .000$; and SES, $F(1, 16424) = 666.7$, $p = .000$. The two main effects were qualified by a significant interaction between the two factors, $F(1, 16424) = 4.7$, $p = .030$, indicating that the gender effects were not the same for the two different SES conditions. The mean difference between female SES groups ($d = 4.01$) was greater than male SES groups ($d = 3.38$); however, the effect size ($\eta^2_{SES} < .01$) does not account for the variance of scale scores.

A second 2 x 2 (gender x SES) factorial analysis of variance tested the effects of gender and SES on academic scale scores of Hispanic students in urban school districts. Results indicated significant main effects for gender, $F(1, 5539) = 14.0$, $p = .000$; and SES, $F(1, 5539) = 196.1$, $p = .000$. The two main effects were not qualified by a significant interaction between the two factors, $F(1, 5539) = 2.0$, $p = .153$, indicating that the gender effects were approximately the same for the two different SES conditions. Although the main effects were significant, the effect size for gender ($\eta^2_{Gender} < .01$) is small and does not account for the variance of scale scores in the Hispanic subgroup. The effect size for SES ($\eta^2_{SES} = .034$) is small and accounts for approximately 3.4% of the variance of scale scores.

A final 2 x 2 (gender x SES) factorial analysis of variance tested the effects of gender and SES on academic scale scores of White students in urban school districts. Results indicated significant main effects for gender, $F(1, 23609) = 10.2$, $p = .001$; and SES, $F(1, 23609) = 1883.6$, $p = .000$. The two main effects were not qualified by a significant interaction between the two factors, $F(1, 23609) = .600$, $p = .439$, indicating

that the gender effects were the same for the two different SES conditions. Although the main effects were significant, the effect size for gender ($\eta^2_{Gender} < .01$) does not account for the variance of scale scores in the White subgroup; however, the effect size for SES ($\eta^2_{SES} = .074$) is medium and accounts for approximately 7.4% of the variance of scale scores.

Urban: Main effects. Table 25 shows significance for three of the four main effects: race/ethnicity, SES, and technology use. The analysis of race/ethnicity shows that White students ($M_{White} = 154.9$) outperform Hispanic students ($M_{Hispanic} = 151.2$) and Black students ($M_{Black} = 149.0$) on biology EOC assessments. The effect size for race ($\eta^2_{Race} = .070$) is medium and accounts for approximately 7.0% of the variation. Socioeconomic groups were separated by the mean difference of 4.55 scale score points between FRL students ($M_{SES\ Yes} = 149.5$) and non-FRL students ($M_{SES\ No} = 154.0$). The estimated effect size ($\eta^2_{SES} = .036$) is small, accounting for approximately 3.6% of the variation of scale scores. The effects of using technology to organize and display data were separated by a mean difference of 0.942 scale score points between students who use the technology ($M_{Tech\ Use\ Yes} = 152.2$) and students who did not use the technology ($M_{Tech\ Use\ No} = 151.3$) in the biology classroom. The estimated effect size ($\eta^2_{Tech\ Use} = .002$) accounts for less than 1.0% of the scale score variation.

Urban populations: Summary. The univariate analysis of the urban population data set suggests that individually ethnicity, SES, and using technology to organize and display data have various effects on student achievement in biology EOC assessments. The effect of ethnicity was seen in two-way interactions within gender and SES groups. The achievement of Black students was influenced more by SES which reflects similar

trends when looking at SES as a main effect. Students who are eligible for free/reduced lunch do not collectively perform as well as their peers who are not eligible. Looking specifically in the context of technology use, urban gender groups show a negligible variation of mean scale scores between the actual technology use and individual gender groups. In this context, the fourth null hypothesis (H_04) is not rejected.

Use the Technology to Create Presentations

Relational Analysis

A series of chi-square tests was used to analyze the relationship between (1) technology use and gender, (2) technology use and race, and (3) technology use and SES. Additional analyses also examined potential relationships within different student population combinations (e.g. Asian females who are eligible for free/reduced lunch) and using technology to create presentations. The data set was broken down into separate subsets by race and gender. Each subset was grouped by those eligible for free or reduced lunch and those who did not qualify. For each group, a chi-square test was used to determine potential relationships between technology use and the various student population combinations.

Table 26 summarizes the analysis results between the select demographic student groups and using technology to create presentations. The results reveal a significant relationship between 13 of the 17 different population student groups. The three main demographic groups (race/ethnicity, gender, and SES) were statistically significant. In the two-way combinations of race, gender, and SES, the results show seven of the eight groups significant. The data also indicate significant relationships between three of the six three-way combinations of race, gender, and SES.

Specifically, we see significant relationships between White/SES and Black/SES

student groups; however, as the groups become more specific demographically, we see that the White/Female/SES and White/Male/SES significant groups validate the White, gender, and SES main effects. Black/Gender and Black/SES groups are partially validated by the significant Black/Female/SES subgroup. Although there are 13 significant groups, the Cramer's V value for effect size is less than 0.1 which indicates little to no effect on the differences in technology use. Based on this context, the null hypothesis (H_01) cannot be rejected.

Table 26

$H_0$1 (Presentations): Chi-Square Analysis Summary

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	97229	79.1	2	.000	.029
Gender	97229	122.1	1	.000	.035
SES	97229	80.1	1	.000	.029
Black * Gender	29973	80.4	1	.000	.052
Hispanic * Gender	10231	13.7	1	.000	.037
White * Gender	57052	43.3	1	.000	.028
Black * SES	29973	12.6	1	.000	.020
Hispanic * SES	10231	1.8	1	.174	
White * SES	57025	36.7	1	.000	.025
Female * SES	48197	19.4	1	.000	.020
Male * SES	49032	70.9	1	.000	.038
Black * Female * SES	15144	3.6	1	.056	
Black * Male * SES	14829	11.8	1	.001	.028
Hispanic * Female * SES	5107	1.8	1	.180	
Hispanic * Male * SES	5124	0.3	1	.588	
White * Female * SES	27946	8.8	1	.003	.018
White * Male * SES	29079	30.3	1	.000	.032

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Relational Analysis: Municipality

Chi-square tests were performed to analyze the second null hypothesis ($H_0$2) – potential relationships between select demographic student groups within rural and urban districts and using technology to create presentations.

The data in Table 27 reveal significant relationships between 12 different demographic subgroups in the rural population. The main demographic groups are shown to be statistically significant and also validated by the Race/Gender, Race/SES,

and Gender/SES groupings. The significant groups of White/Female/SES and White/Male/SES students further qualify the significance of the White/Gender and White/SES groups. Regardless of the significant groups and their validation of each other, the Cramer's V value for all are less than 0.1 which indicates little to no effect on the differences in technology use. Based on this context, the null hypothesis (H_02) cannot be rejected.

Table 27

H_02 (Presentations): Chi-Square Summary – Rural Municipality

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	51645	70.2	2	.000	.037
Gender	51645	109.5	1	.000	.046
SES	51645	66.9	1	.000	.036
Black * Gender	13545	50.9	1	.000	.061
Hispanic * Gender	4688	14.1	1	.000	.055
White * Gender	33412	53.1	1	.000	.040
Black * SES	13545	4.9	1	.026	.019
Hispanic * SES	4688	1.7	1	.197	
White * SES	33412	45.1	1	.000	.037
Female * SES	25604	22.5	1	.000	.030
Male * SES	26041	48.1	1	.000	.043
Black * Female * SES	6901	3.8	1	.050	
Black * Male * SES	6644	1.9	1	.163	
Hispanic * Female * SES	2271	1.2	1	.276	
Hispanic * Male * SES	2417	0.6	1	.454	
White * Female * SES	16432	14.3	1	.000	.030
White * Male * SES	16980	31.7	1	.000	.043

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

In the urban population, 12 groups were found to be significant in Table 28. The significance pattern is very similar to the rural population (Table 27) with the exception of the Black/SES and Hispanic/SES student groups. The White/Gender and White/SES groups are qualified by the significance of the White/Female/SES and White/Male/SES groups – which is also seen in the previous two analyses for this specific technology use.

We also see the continued small effect size trend of the identified significant groups.

Table 28

$H_0$2 (Presentations): Chi-Square Summary – Urban Municipality

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	45584	15.8	2	.000	.019
Gender	45584	24.5	1	.000	.023
SES	45584	21.7	1	.000	.022
Black * Gender	16428	31.7	1	.000	.044
Hispanic * Gender	5543	2.9	1	.089	
White * Gender	23613	2.2	1	.138	
Black * SES	16428	1.3	1	.253	
Hispanic * SES	5543	0.0	1	.928	
White * SES	23613	3.7	1	.055	
Female * SES	22593	2.8	1	.092	
Male * SES	22991	24.9	1	.000	.033
Black * Female * SES	8243	1.0	1	.312	
Black * Male * SES	8185	9.9	1	.002	.035
Hispanic * Female * SES	2836	1.7	1	.190	
Hispanic * Male * SES	2707	0.7	1	.791	
White * Female * SES	11514	0.8	1	.371	
White * Male * SES	12099	3.2	1	.075	

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Relational Analysis: Summary

The analysis of the data sets shows a defined pattern of significant variations with race/ethnicity, gender, and SES. More specific patterns emerge as the White and Hispanic student groups are analyzed within SES subsets. The variation of significant groups found in the rural and urban analysis can also be seen in the identified significant groups of the complete data set. Despite the number and apparent patterns of the significant groups, the effect size or Cramer's V value for all of the statistically significant groups is less than 0.1 and considered a miniscule effect. This is generally considered not acceptable (Pallant, 2011) and the second null ($H_0$2) hypothesis is not

rejected.

Presentations: Factorial Univariate Analyses

The third null hypothesis ($H_0 3$) was tested using a factorial analysis of variance to test the effects of race/ethnicity, gender, SES, and using technology to create presentations on biology academic scale scores. The analysis summary is shown in Table 29 for students who use technology to create presentations.

Table 29

Analysis Summary of H_03 (Presentations) – Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	1651135.2	23	71788.5	954.2	.000
Intercept	852256342.0	1	852256342.0	11328377.0	.000
Race/Ethnicity	387172.9	2	193586.4	2573.2	.000
Gender	117.4	1	117.4	1.6	.212
SES	171594.9	1	171594.9	2280.8	.000
Technology Use	9056.7	1	9056.7	120.4	.000
R/E * Gender	5419.2	2	2709.6	36.0	.000
R/E * SES	5886.4	2	2943.2	39.1	.000
R/E * Tech Use	174.7	2	87.4	1.2	.313
Gender * SES	23.8	1	23.8	0.3	.574
Gender * Tech Use	910.5	1	910.5	12.1	.001
SES * Tech Use	312.2	1	312.2	4.2	.042
R/E * Gender * SES	374.0	2	187.0	2.5	.083
R/E * Gender * Tech Use	255.5	2	127.8	1.7	.183
R/E * SES * Tech Use	403.9	2	201.9	2.7	.068
Gender * SES * Tech Use	346.0	1	346.0	4.6	.032
R/E * Gender * SES * Tech	211.4	2	105.7	1.4	.245
Error	7312925.3	97205	75.2		
Total	2270768082.0	97229			
Corrected Total	8964060.5	97228			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, N = 97229; *significance at $p < .05$ level.

Four-way effects. Results from Table 29 show the interaction between race/ethnicity, gender, SES, and technology use (create presentations) did not significantly impact student academic scale scores. The null hypothesis cannot be

rejected based solely on the four-way interaction.

Three-way effects. The results reveal a significant interaction between gender, SES, and technology use; however, the effect size of the interaction ($\eta^2 < .01$) is trivial and considered to have no influence on the score variation.

Three-way effects – secondary analysis. Further analysis of the significant three-way interaction between gender, SES, and technology use involves splitting the data set by technology use (no and yes). For each data subset, a 2 x 2 (gender x SES) factorial analysis of variance tested the effects of student gender and their SES on biology scale scores.

The results in Table 30 point toward a significant effect between student gender and SES for the group that used technology to create presentations. This two-way effect validates the significance of each main effect as well; however, the effect size ($\eta^2_{Gender*SES} < .01$) indicates a minimal effect on the variation of biology academic scale scores. The data confirm that both gender groups have similar mean score differences between socioeconomic groups.

Table 30

Comparative Means (Presentations & Technology Use = YES)

					95% CI	
Gender	SES	*N*	*M*	*SE*	Lower Bound	Upper Bound
Female	No	26526	156.0	.102	155.8	156.2
	Yes	21671	149.4	.116	149.1	149.6
Male	No	27267	156.7	.105	156.5	156.9
	Yes	21765	149.6	.126	149.4	149.9

Note. M = Mean Scale Score, *SE* = Standard Error, CI = Confidence Interval.

Figure 7 suggests that both female and male students are likely to perform the

same in their respective SES groups. The plot lines are almost parallel, but since they do not cross, an interaction cannot be determined.

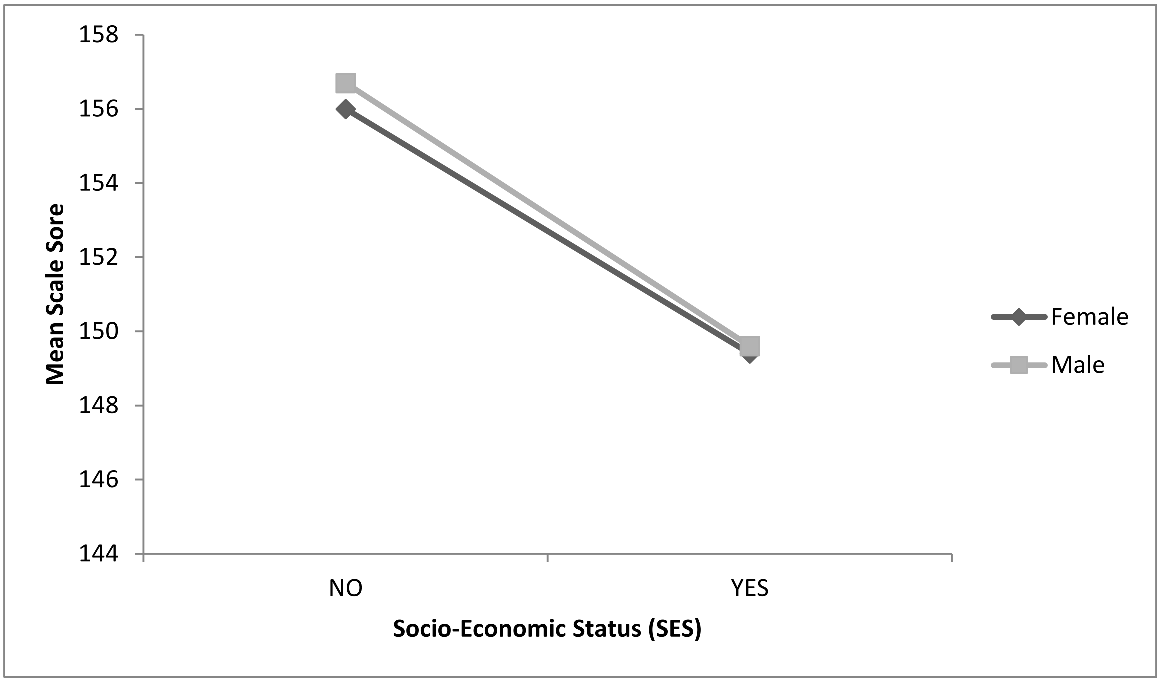

Figure 7. Estimated Marginal Means of Scale Scores between Gender and SES Student Groups Who Use Technology to Create Presentations.

The results of Table 31 indicate significant main effects for each subgroup as well. This suggests that gender and SES influence biology scale scores for both students who use technology to create presentations and those who do not. Examination of effect sizes in both technology subgroups show that gender ($\eta^2_{\text{Gender}} < .01$) has no weight on the score variation according Cohen's scale. However, SES ($\eta^2_{\text{SES}} < .12$) reveals that a student's SES has a medium (almost large) effect on the variation of biology scale scores in both technology groups as well.

Table 31

Secondary Analysis (Presentations & Technology Use = NO)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	784666.9	3	261555.6	3198.0	.000
Intercept	1643713842.0	1	1643713842.0	20097710.0	.000
Gender	667.4	1	667.4	8.2	.004
SES	783876.6	1	783876.6	9584.5	.000
Gender * SES	269.6	1	269.6	3.3	.069
Error	5878132.4	71872	78.1		
Total	1671535803.0	71876			
Corrected Total	6662799.4	71875			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, N = 71876; *significance at $p < .05$ level.

Additional analysis from another perspective comprises of separating the data set by gender (female and male). An additional 2 x 2 (SES x technology use) factorial analysis of variance tested the effects of student SES and their technology use on biology scale scores.

Results indicated a significant main effect for technology use in both gender groups, females: $F_{\text{Females}}(1, 48193) = 57.5$, $p < .001$; and males: $F_{\text{Males}}(1, 49028) = 196.1$, $p < .001$. However, the effect size for both males and females ($\eta^2_{\text{Gender}} < .01$) was trivial and accounts for none of the scale score variation. The analysis results also show a significant effect for SES: females: $F_{\text{Females}}(1, 48193) = 5631.1$, $p < .001$; and Males: $F_{\text{Males}}(1, 49028) = 4726.4$, $p < .001$. Unlike technology use, the effect size for SES ($\eta^2_{\text{Females}} = .105$ and $\eta^2_{\text{Males}} = .088$) is considered of medium size and respectively accounts for approximately 10.5% and 8.8% of the scale score variation.

The secondary analysis reveals in the significant three-way interaction that a

student's SES has the greatest effect on biology achievement scores. In this context with gender and SES, using technology to create presentations did not influence student scores in biology.

Two-way effects. The results reveal significant effects between gender and technology use, as well as SES and technology use. These effects were qualified in the significant three-way interaction between the three variables. Secondary analysis of the three-way interaction reveals that SES has the greatest impact on student achievement scores as compared to technology use and gender.

Additional significant two-way interactions involve race/ethnicity and gender, as well as, race/ethnicity and SES. Although significant, the effect size of each interaction ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Two-way effects – secondary analyses. Additional analysis of the two-way interactions involving race/ethnicity, gender, and SES involves separating the data set into individual racial/ethnic groups (Black, Hispanic, and White) and using an ANOVA to test the interactions between gender and SES.

With the exception of the two-way interactions for Hispanic and White students, the results from Tables 32-34 show that all the effects for each racial subgroup were significant; however, the eta squared values reveal that only SES has any influence on the student scale score variation with a medium effect.

Table 32

Secondary Analysis (Presentations & Black Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	98516.6	3	32838.9	444.1	.000
Intercept	563446808.4	1	563446808.4	7620169.3	.000
Gender	5210.5	1	5210.5	70.1	.000
SES	94145.8	1	94145.8	1273.3	.000
Gender * SES	441.3	1	441.3	6.0	.015
Error	2215835.1	29969	73.9		
Total	657043019.0	29973			
Corrected Total	2314351.6	29972			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 33

Secondary Analysis (Presentations & Hispanic Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	25665.1	3	8555.1	104.4	.000
Intercept	177579168.0	1	177579168.0	2167684.6	.000
Gender	374.5	1	374.5	4.6	.000
SES	25317.2	1	25317.2	309.0	.000
Gender * SES	125.9	1	125.9	1.5	.215
Error	837807.4	10227	81.9		
Total	231653253.0	10231			
Corrected Total	863472.5	10230			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 34

Secondary Analysis (Presentations & White Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	302296.1	3	100765.4	444.1	.000
Intercept	1053394234.0	1	1053394234.0	14034672.2	.000
Gender	768.1	1	768.1	10.2	.001
SES	301886.1	1	301886.1	4022.1	.000
Gender * SES	135.7	1	135.7	1.8	.179
Error	4279800.2	57201	75.1		
Total	1382071810.0	57025			
Corrected Total	4582096.3	57024			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

The data from Table 35 suggest that effect size is directly related to the magnitude of the mean difference – the greater the mean difference corresponds to a larger effect size. Within the context of SES, White students have the largest achievement gap, followed by Blacks and then Hispanics. Comparisons of eta squared values also show that SES has more than twice the effect for White students as compared to Hispanic students.

Table 35

Secondary Analysis – Effect Size and Mean Difference Summary for SES

Group	*N*	η^2	*MD*	*SE*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Black	29973	.041	3.840	.108	3.629	4.051
Hispanic	10231	.029	3.608	.205	3.205	4.010
White	57025	.066	5.220	.082	5.382	5.059

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval.

Main effects. The results indicate statistically significant effects with race/ethnicity, SES, and using technology to create presentations. The estimated effect size values of race/ethnicity ($\eta^2_{\text{Race}} = .050$) and SES ($\eta^2_{\text{SES}} = .023$) were considered a medium effect on the variability of biology scale scores.

Table 36 shows that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. The eta squared value ($\eta^2_{\text{Race}} = .050$) indicates that race/ethnicity has a medium effect on the variation of scale scores. This variation was also qualified in two-way interactions involving race/ethnicity, gender, and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

Table 36

Secondary Analysis: Pairwise Comparisons – Race/Ethnicity and Scale Score

Race	Comparison Group	MD	SE	*p*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Black *N = 29973*	Hispanic	-2.448	.127	.000	-2.751	-2.145
	White	-5.592	.079	.000	-5.780	-5.403
Hispanic *N = 10231*	Black	2.448	.127	.000	2.145	2.751
	White	-3.144	.119	.000	-3.430	-2.858
White *N = 57025*	Black	5.592	.079	.000	5.403	5.780
	Hispanic	3.144	.119	.000	2.858	3.430

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch ($M_{\text{Yes}} = 149.4$) were outperformed by their peers who were not classified as SES ($M_{\text{No}} = 153.7$). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students who used the technology ($M_{\text{Technology Yes}} = 152.0$) and students who did not ($M_{\text{Technology No}} = 151.0$). Although statistically significant, the context of the effect size ($\eta 2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Summary. The analysis of this data set suggests that individually race/ethnicity and student SES have various effects on student achievement in biology EOC assessments. These main effects were also justified in more complex interactions with

each other, as well as with gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results point to the rejection of the third null hypothesis (H_03).

Multilevel Factorial Analysis: Municipality

The fourth null hypothesis (H_04) was tested using a factorial analysis of variance to examine within rural and urban school districts, the effects of various student groups, and using technology to create presentations on biology academic scale scores. Table 37 shows the breakdown of the four different factor groups in the rural and urban analysis.

Table 37

Between-Subject Factors for Rural and Urban School Districts

Factor	Group Name	N_{Rural}	N_{Urban}
Race/Ethnicity	Black	13545	16428
	Hispanic	4688	5543
	White	33412	23613
Gender	Female	25604	22593
	Male	26041	22991
SES	No	27596	26197
	Yes	24049	19387
Use Technology to Create Presentations	No	37805	34071
	Yes	13840	11513
Totals		516545	45584

Municipality: Rural

Table 38 summarizes the analysis of rural school districts tested and the effects of the factors on the student achievement based on academic scale scores in high school biology classes.

Table 38

Analysis Summary of H_03 (Use of Presentations in Rural Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	765703.8	23	33291.5	461.9	.000
Intercept	377296117.0	1	377296117.0	5235846.0	.000
Race/Ethnicity	183487.8	2	91743.9	1273.2	.000
Gender	121.7	1	121.7	1.7	.194
SES	62405.5	1	62405.5	866.0	.000
Technology Use	6600.6	1	6600.6	91.6	.000
R/E * Gender	1811.5	2	905.7	12.6	.000
R/E * SES	1001.6	2	500.8	6.9	.001
R/E * Tech Use	290.2	2	145.1	2.0	.133
Gender * SES	0.5	1	0.5	0.0	.936
Gender * Tech Use	462.4	1	462.4	6.4	.011
SES * Tech Use	320.1	1	320.1	4.4	.035
R/E * Gender * SES	119.4	2	59.7	0.8	.437
R/E * Gender * Tech Use	65.1	2	32.6	0.5	.637
R/E * SES * Tech Use	171.4	2	85.7	1.2	.304
Gender * SES * Tech Use	354.8	1	354.8	4.9	.026
R/E * Gender * SES * Tech Use	385.6	2	192.8	2.7	.069
Error	3719819.1	51621	75.0		
Total	1198878714.0	51645			
Corrected Total	4485522.9	51644			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Rural: Four-way effects. Results from Table 38 show the interaction between race/ethnicity, gender, SES, and technology use did not significantly impact student academic scale scores. The null hypothesis cannot be rejected based solely on the four-way interaction.

Rural: Three-way effects. The results reveal a significant interaction between gender, SES, and technology use; however, the effect size of the interaction ($\eta^2 < .01$) is trivial and considered to have no influence on the score variation.

Rural: Three-way effects – secondary analysis. Further analysis of the

significant three-way interaction between gender, SES, and technology use involves splitting the data set by technology use (no and yes). For each data subset, a 2 x 2 (gender x SES) factorial analysis of variance tested the effects of student gender and their SES on biology scale scores.

The results in Table 39 show significance for both main effects which are not qualified in the two-way interaction. Examination of the effect size values clearly show that gender ($\eta^2_{Gender} < .01$) has no effect on scale score variations in this population group; however, the effect of student SES ($\eta^2_{SES} = .101$) on scale score variation was significant based on Cohen's rating of effect size.

Table 39

Secondary Analysis (Presentations & Technology Use = YES)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	332800.2	3	110933.4	1424.0	.000
Intercept	864803473.0	1	316279848.8	11101320.7	.000
Gender	625.4	1	470.8	8.0	.005
SES	332121.9	1	138526.3	4263.4	.000
Gender * SES	253.7	1	181.6	3.3	.071
Error	2944733.9	37801	77.9		
Total	872676331.0	37805			
Corrected Total	3277534.2	37804			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 25353;
*significance at $p < .05$ level.

The results of Table 40 indicate significant main effects as well. This suggests that gender and SES influence biology scale scores for both students who use technology to create presentations and those who do not. An examination of effect size in the nontechnology use subgroup shows that gender ($\eta^2_{Gender} < .01$) has no weight on scale score variation; however, SES ($\eta^2_{SES} = .117$) reveals that a student's SES has a medium effect on the variation of biology scale scores. A similar pattern is seen in both

technology subgroups.

Table 40

Secondary Analysis (Presentations & Technology Use = NO)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	139617.5	3	46539.2	617.7	.000
Intercept	316279848.8	1	316279848.8	4197637.2	.000
Gender	470.8	1	470.8	6.2	.012
SES	138526.3	1	138526.3	1838.5	.000
Gender * SES	181.6	1	181.6	2.4	.121
Error	1042502.7	13836	75.3		
Total	326202383.0	13840			
Corrected Total	1182120.2	13839			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 71876; *significance at $p < .05$ level.

Analysis from a different perspective involves separating the data set by gender (female and male). A 2 x 2 (SES x technology use) factorial analysis of variance tested the effects of student SES and their technology use on biology scale scores for each gender group.

Results indicated a significant main effect for technology use in both gender groups, females: $F_{\text{Tech Use}}(1, 25600) = 75.3$, $p < .001$; and males: $F_{\text{Tech Use}}(1, 26037) = 157.5$, $p < .001$; however, the effect size for both males and females ($\eta^2 < .01$) was trivial and accounts for none of the scale score variation.

The analysis results also show a significant effect for SES, females: $F_{\text{SES}}(1, 25600) = 2726.1$, $p < .001$; and males: $F_{\text{SES}}(1, 26037) = 2225.1$, $p < .001$. Unlike technology use, the effect size for SES ($\eta^2_{\text{Females}} = .096$ and $\eta^2_{\text{Males}} = .079$) is considered of medium size and respectfully accounts for approximately 9.6% and 7.9% of the scale

score variation.

The secondary analysis reveals in the significant three-way interaction that a student's SES has the greatest effect on biology achievement scores. In this context with gender and SES, using technology to create presentations did not influence student scores in biology.

Rural: Two-way effects. The results reveal significant effects between gender and technology use, as well as SES and technology use. These effects were qualified in the significant three-way interaction between the three variables. Secondary analysis of the three-way interaction reveals that SES has the greatest impact on student achievement scores as compared to technology use and gender.

There are additional significant two-way interactions involving race/ethnicity, gender, and, SES. Although each of the two-way interactions were significant, the effect size of each ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Rural: Two-way effects – secondary analyses. Additional analysis of the two-way interactions involving race/ethnicity, gender, and SES separated the data set into individual racial/ethnic groups (Black, Hispanic, and White) and using an ANOVA to test the interactions between gender and SES.

The results from Tables 41-43 did not point out statistically significant two-way interactions for the three racial/ethnic subgroups; however, effect size data indicate that SES again played a significant role in the scale score variation for all three groups ($\eta^2_{\text{Black SES}} = .036$, $\eta^2_{\text{Hispanic SES}} = .022$, and $\eta^2_{\text{White SES}} = .053$).

Table 41

Secondary Analysis of Rural Districts (Presentations & Black Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	37634.5	3	32838.9	180.2	.000
Intercept	224416154.0	1	224416154.0	3223633.1	.000
Gender	2253.9	1	2253.9	32.4	.000
SES	35544.6	1	35544.6	510.6	.000
Gender * SES	101.6	1	101.6	1.5	.227
Error	942669.1	13541	224416154.0		
Total	293548684.0	13545			
Corrected Total	980303.5	13544			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 42

Secondary Analysis of Rural Districts (Presentations & Hispanic Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	8356.3	3	2785.4	36.0	.000
Intercept	72943178.6	1	72943178.6	943756.9	.000
Gender	86.4	1	86.4	1.1	.290
SES	8244.1	1	8244.1	106.7	.000
Gender * SES	0.885	1	0.885	0.011	.915
Error	362027.4	4684	77.3		
Total	105668662.0	4688			
Corrected Total	370383.7	4687			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 43

Secondary Analysis of Rural Districts (Presentations & White Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	135867.2	3	45289.1	621.7	.000
Intercept	67150654.7	1	67150654.7	9218055.4	.000
Gender	122.0	1	122.0	1.7	.196
SES	135846.5	1	135846.5	1864.4	.000
Gender * SES	162.6	1	162.6	2.2	.135
Error	2433669.2	33408	72.8		
Total	799661368.0	33412			
Corrected Total	2569536.4	33411			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 27025; *significance at $p < .05$ level.

Rural: Main effects. The data show statistically significant effects with race/ethnicity, SES, and using technology to create presentations. The effect size values of race/ethnicity ($\eta^2_{\text{Race}} = .047$) and SES ($\eta^2_{\text{SES}} = .016$) are considered a medium effect on the variability of biology scale scores.

The data in Table 44 show that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. This variation was also qualified in two-way interactions involving race/ethnicity, gender, and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

Table 44

Secondary Analysis: Pairwise Comparisons – Race/Ethnicity and Scale Score

Race	Comparison Group	*MD*	*SE*	*p*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Black	Hispanic	-2.703	.190	.000	-3.157	-2.249
	White	-5.609	.113	.000	-5.879	-5.339
Hispanic	Black	2.703	.190	.000	2.249	3.157
	White	-2.906	.173	.000	-3.319	-2.492
White	Black	5.609	.113	.000	5.339	5.879
	Hispanic	2.906	.173	.000	2.492	3.319

Note. *MD* = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch ($M_{\text{Yes}} = 149.1$) were outperformed by their peers who were not classified as SES ($M_{\text{No}} = 153.0$). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students who used the technology ($M_{\text{Technology Yes}} = 151.7$) and students who did not ($M_{\text{Technology No}} = 150.4$). Although statistically significant, the context of the effect size ($\eta^2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Rural: Summary. The analysis of the rural data set suggests that individually race/ethnicity and student SES have various effects on student achievement in biology EOC assessments. These main effects were also justified in more complex interactions

with each other, as well as gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results support the rejection the fourth null hypothesis ($H_0$4).

Municipality: Urban

Urban: Four-way and three-way effects. Results from Table 45 show there is not a statistically significant four-way or three-way interaction between race/ethnicity, gender, SES, technology use (organize and display data). The null hypothesis cannot be rejected based solely on these interactions.

Table 45

Analysis Summary of H_03 (Presentations in Urban Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	931064.5	23	40481.1	523.1	.000
Intercept	446722979.0	1	446722979.0	5772797.0	.000
Race/Ethnicity	197634.6	2	98817.3	1277.0	.000
Gender	680.4	1	680.4	8.8	.003
SES	103412.1	1	103412.1	1336.3	.000
Technology Use	2851.9	1	2851.9	36.9	.000
R/E * Gender	4151.4	2	2075.7	26.8	.000
R/E * SES	7319.3	2	3659.6	47.3	.000
R/E * Tech Use	36.4	2	18.2	0.2	.790
Gender * SES	13.3	1	13.3	0.2	.678
Gender * Tech Use	488.5	1	488.5	6.3	.012
SES * Tech Use	100.7	1	100.7	1.3	.254
R/E * Gender * SES	375.8	2	187.9	2.4	.088
R/E * Gender * Tech Use	124.3	2	62.2	0.8	.448
R/E * SES * Tech Use	444.3	2	222.2	2.8	.057
Gender * SES * Tech Use	76.4	1	76.4	1.0	.320
R/E * Gender * SES * Tech Use	8.1	2	4.1	0.1	.949
Error	352561.7	45560	77.4		
Total	1071889368.0	45584			
Corrected Total	4456686.2	45583			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 45584; *significance at $p < .05$ level.

Urban: Two-way effects. The results reveal a significant effect between gender and technology use in urban school districts. Table 46 displays the comparative means of females and males who use technology to create presentations and those who do not use the technology in their Biology class. The data do indicate that both female and male students who use technology to create presentations score slightly higher than those students who do not use the technology; however, the context of the score variation does not suggest a significant difference which is reflected in the effect size value ($\eta^2_{\text{Tech Use *}}$

$_{\text{Gender}} < .01$).

Table 46

Pairwise Comparisons – Gender, Technology Use & Mean Scale Scores

Gender	*N*	Technology Use	*M*	*SE*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Female	26526	No	151.5	.091	151.4	151.7
	21671	Yes	152.0	.150	151.7	152.3
Male	27267	No	151.6	.090	151.4	151.8
	21765	Yes	152.7	.159	152.4	153.0

Note. M = Mean Scale Score, *SE* = Standard Error, CI = Confidence Interval.

The data reveal additional significant two-way interactions involving race/ethnicity, gender, and SES. Although each of the two-way interactions were significant, the effect size of each ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Urban: Two-way effects – secondary analyses. Additional analysis of the two-way interactions involving race/ethnicity, gender, and SES involves separating the data set into individual racial/ethnic groups (Black, Hispanic, and White) and using an ANOVA to test the interactions between gender and SES.

The results shown in Tables 47-49 did not indicate a statistically significant two-way interaction for the Hispanic and White racial/ethnic subgroups; however, effect size data for the significant two-way interaction in the Black student population ($\eta^2_{\text{Black Gender*SES}} < .01$) points out that the interaction between the factors did not influence the scale score variation. Examination of the effect size for the main effects indicates that SES again played a significant role in the scale score variation for all three groups (η^2_{Black} SES = .039, η^2_{Hispanic} SES = .034, and η^2_{White} = .074). The effect of SES on the

achievement in the White student population was double the Hispanic and Black student populations in urban districts.

Table 47

Secondary Analysis of Urban Districts (Presentations & Black Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	53715.8	3	17905.3	232.8	.000
Intercept	332901342.9	1	332901342.9	4327772.1	.000
Gender	2872.4	1	2872.4	37.3	.000
SES	51283.8	1	51283.8	666.7	.000
Gender * SES	362.8	1	362.8	4.7	.030
Error	1263369.7	16424	76.9		
Total	363494335.0	16428			
Corrected Total	1317084.5	16427			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 48

Secondary Analysis of Rural Districts (Presentations & Hispanic Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	17862.9	3	5954.3	69.5	.000
Intercept	103470093.3	1	103470093.3	1208279.3	.000
Gender	1200.9	1	1200.9	14.0	.290
SES	16789.6	1	16789.6	196.1	.000
Gender * SES	175.3	1	175.3	2.0	.153
Error	474328.1	5539	85.6		
Total	125984591.0	5543			
Corrected Total	492191.1	5542			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 49

Secondary Analysis of Rural Districts (Presentations & White Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	143806.7	3	47935.61	631.0	.000
Intercept	365881634.8	1	365881634.8	4816581.5	.000
Gender	777.0	1	777.0	10.2	.001
SES	143085.5	1	143085.5	1883.6	.000
Gender * SES	45.6	1	45.6	0.6	.439
Error	1793408.8	23609	76.0		
Total	582410442.0	23613			
Corrected Total	1937215.4	23612			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

Urban: Main effects. The results from Table 50 reveal statistically significant effects with race/ethnicity, SES, and using technology to create presentations. The effect size values of race/ethnicity ($\eta^2_{\text{Race}} = .053$) and SES ($\eta^2_{\text{SES}} = .028$) were considered a medium effect on the variability of biology scale scores.

Table 50

Secondary Analysis: Pairwise Comparisons for Urban Districts Race/Ethnicity and Scale Score

Race	Comparison Group	*MD*	*SE*	*p*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Black *N = 29973*	Hispanic	-2.243	.171	.000	-2.653	-1.834
	White	-5.890	.117	.000	-6.171	-5.610
Hispanic *N = 10231*	Black	2.243	.171	.000	1.834	2.653
	White	-3.647	.170	.000	-4.055	-3.239
White *N = 57025*	Black	5.890	.117	.000	5.610	6.171
	Hispanic	3.647	.170	.000	3.239	4.055

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

Table 50 shows that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. This variation was also qualified in two-way interactions involving race/ethnicity, gender, and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch (M_{Yes} = 149.6) were outperformed by their peers who were not classified as SES (M_{No} = 154.3). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students

who used the technology ($M_{\text{Technology Yes}} = 152.3$) and students who did not ($M_{\text{Technology No}} = 151.6$). Although statistically significant, the context of the effect size ($\eta^2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Urban: Summary. The analysis of the urban data set suggests that individually race/ethnicity and student SES also have various effects on student achievement in biology EOC assessments. As seen in the rural analysis, these main effects were justified in more complex interactions with one another along with gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results further confirm the rejection the fourth null hypothesis (H_04).

Use the Internet to Find Information

Relational Analysis

A series of chi-square tests was used to analyze the relationship between (1) technology use and gender, (2) technology use and race, and (3) technology use and SES. Additional analyses also examined potential relationships within different student population combinations (e.g., Asian females who are eligible for free/reduced lunch) and using technology to create presentations. The data set was broken down into separate subsets by race and gender. Each subset was grouped by those eligible for free or reduced lunch and those who did not qualify. For each group, a chi-square test was used to determine potential relationships between technology use and the various student population combinations.

Table 51 summarizes the analysis results between the select demographic student groups and using technology to create presentations. The results reveal a significant relationship between 13 of the 17 different population student groups. The three main

demographic groups (race/ethnicity, gender, and SES) were statistically significant. In the two-way combinations of race, gender, and SES, the results show seven of the eight groups significant. The data also indicate significant relationships between three of the six three-way combinations of race, gender, and SES.

Specifically, we see significant relationships between White/SES and Black/SES student groups. However, as the groups become more specific demographically, we see that the White/Female/SES and White/Male/SES significant groups validate the White, gender, and SES main effects. Black/Gender and Black/SES groups are partially validated by the significant Black/Female/SES subgroup. Although there are 13 significant groups, the Cramer's V value for effect size is less than 0.1 which indicates little to no effect on the differences in technology use. Based on this context, the null hypothesis ($H_0 1$) cannot be rejected.

Table 51

$H_0$1 (Internet): Chi-Square Analysis Summary

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	97229	98.9	2	.000	.032
Gender	97229	72.1	1	.000	.027
SES	97229	89.4	1	.000	.030
Black * Gender	29973	26.7	1	.000	.030
Hispanic * Gender	10231	4.9	1	.026	.022
White * Gender	57052	43.4	1	.000	.028
Black * SES	29973	8.1	1	.004	.016
Hispanic * SES	10231	1.5	1	.215	
White * SES	57025	26.1	1	.000	.021
Female * SES	48197	48.7	1	.000	.032
Male * SES	49032	41.9	1	.000	.029
Black * Female * SES	15144	7.9	1	.005	.029
Black * Male * SES	14829	1.8	1	.175	
Hispanic * Female * SES	5107	0.1	1	.892	
Hispanic * Male * SES	5124	2.6	1	.108	
White * Female * SES	27946	12.9	1	.000	.022
White * Male * SES	29079	12.7	1	.000	.021

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Relational Analysis: Municipality

Chi-square tests were performed to analyze the second null hypothesis ($H_0$2) – potential relationships between select demographic student groups within rural and urban districts and using technology to create presentations. The data in Table 52 reveal significant relationships between 12 different demographic subgroups in the rural population. The main demographic groups are shown to be statistically significant and

are also validated by the Race/Gender, Race/SES, and Gender/SES groupings. The significant groups of White/Female/SES and White/Male/SES student further qualify the significance of the White/Gender and White/SES groups. Regardless of the significant groups and their validation of each other, the Cramer's V value for all are less than 0.1 which indicates little to no effect on the differences in technology use. Based on this context, the null hypothesis (H_02) cannot be rejected.

Table 52

H_02 (Internet): Chi-Square Summary – Rural Municipality

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	51645	16.6	2	.000	.018
Gender	51645	58.3	1	.000	.034
SES	51645	42.1	1	.000	.029
Black * Gender	13545	14.4	1	.000	.033
Hispanic * Gender	4688	9.8	1	.002	.046
White * Gender	33412	35.6	1	.000	.033
Black * SES	13545	3.7	1	.055	
Hispanic * SES	4688	5.0	1	.026	.033
White * SES	33412	20.5	1	.000	.025
Female * SES	25604	21.1	1	.000	.029
Male * SES	26041	21.4	1	.000	.029
Black * Female * SES	6901	2.6	1	.107	
Black * Male * SES	6644	1.5	1	.221	
Hispanic * Female * SES	2271	1.9	1	.173	
Hispanic * Male * SES	2417	3.2	1	.072	
White * Female * SES	16432	10.4	1	.001	.025
White * Male * SES	16980	9.5	1	.002	.024

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

In the urban population, 12 groups were found to be significant in Table 53. The significance pattern is very similar to the rural population (Table 52) with the exception of the Black/SES and Hispanic/SES student groups. The White/Gender and White/SES groups are qualified by the significance of the White/Female/SES and White/Male/SES groups – which is also seen in the previous two analyses for this specific technology use.

We also see the continued small effect size trend of the identified significant groups.

Table 53

$H_0$2 (Internet): Chi-Square Summary – Urban Municipality

Subgroup	*N*	χ^2	*df*	*p*	*V*
Race/Ethnicity	45584	65.1	2	.000	.038
Gender	45584	18.4	1	.000	.020
SES	45584	57.8	1	.000	.036
Black * Gender	16428	12.0	1	.001	.027
Hispanic * Gender	5543	0.8	1	.783	
White * Gender	23613	9.6	1	.002	.020
Black * SES	16428	10.5	1	.001	.025
Hispanic * SES	5543	0.0	1	.929	
White * SES	23613	14.0	1	.000	.024
Female * SES	22593	34.3	1	.000	.039
Male * SES	22991	24.6	1	.000	.033
Black * Female * SES	8243	10.3	1	.001	.035
Black * Male * SES	8185	2.2	1	.140	
Hispanic * Female * SES	2836	0.3	1	.600	
Hispanic * Male * SES	2707	0.4	1	.506	
White * Female * SES	11514	7.8	1	.005	.026
White * Male * SES	12099	6.0	1	.014	.022

Note. V = Cramer's V (effect size); *significance at $p < .05$ level.

Relational Analysis: Summary

The analysis of the data sets shows a defined pattern of significant variations with race/ethnicity, gender, and SES. More specific patterns emerge as the White and Hispanic student groups are analyzed within SES subsets. The variation of significant groups found in the rural and urban analysis can also be seen in the identified significant groups of the complete data set. Despite the number and apparent patterns of the significant groups, the effect size or Cramer's V value for all of the statistically significant groups is less than 0.1 and considered a miniscule effect. This is generally considered not acceptable (Pallant, 2011) and the second null ($H_0$2) hypothesis is not rejected.

Presentations: Factorial Univariate Analyses

The third null hypothesis ($H_0 3$) was tested using a factorial analysis of variance to test the effects of race/ethnicity, gender, SES, and using technology to create presentations on biology academic scale scores.

Four-way effects. Results from Table 54 show the interaction between race/ethnicity, gender, SES, and technology use (Internet) did not significantly impact student academic scale scores. The null hypothesis cannot be rejected based solely on the four-way interaction.

Three-way effects. The results did not reveal a significant interaction between race/ethnicity, gender, SES, and technology use. The null hypothesis cannot be rejected based solely on the three-way interaction.

Table 54

Analysis Summary of $H_0 3$ (Internet) – Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	1652086.4	23	71829.8	954.9	.000
Intercept	1080365841.0	1	1080365841.0	14362725.8	.000
Race/Ethnicity	520189.6	2	260094.8	3457.7	.000
Gender	30.2	1	30.2	0.4	.526
SES	208488.1	1	208488.1	2771.6	.000
Technology Use	11628.6	1	11628.6	154.6	.000
R/E * Gender	6039.1	2	3019.5	40.1	.000
R/E * SES	9713.2	2	4858.6	64.6	.000
R/E * Tech Use	440.0	2	440.0	2.9	.054
Gender * SES	23.4	1	23.4	0.3	.577
Gender * Tech Use	496.1	1	496.1	6.6	.010
SES * Tech Use	219.2	1	219.2	2.9	.088
R/E * Gender * SES	379.3	2	189.7	2.5	.080
R/E * Gender * Tech Use	8.6	2	4.3	0.1	.945
R/E * SES * Tech Use	72.4	2	36.2	0.5	.618
Gender * SES * Tech Use	22.3	1	22.3	0.3	.583
R/E * Gender * SES * Tech	73.6	2	36.8	0.5	.613
Error	7311974.0	97205	75.2		
Total	2270768082.0	97229			
Corrected Total	8964060.5	97228			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 97229; *significance at $p < .05$ level.

Two-way effects. The results reveal a significant effect between gender and technology use. Table 55 displays the comparative means of females and males who use technology to create presentations and those who do not use the technology in their

biology class. The data does indicate that both female and male students who use technology to create presentations score slightly higher than those students who do not use the technology; however, the context of the score variation does not suggest a significant difference which is reflected in the effect size value ($\eta^2_{\text{Tech Use * Gender}} < .01$).

Table 55

Pairwise Comparisons – Gender, Technology Use & Mean Scale Scores

Gender	N	Technology Use	*M*	*SE*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Female	23025	No	150.9	.082	150.7	151.0
	25172	Yes	151.7	.078	151.5	151.8
Male	22975	No	150.6	.080	150.4	150.8
	26057	Yes	151.8	.079	151.7	152.0

Note. M = Mean Scale Score, *SE* = Standard Error, CI = Confidence Interval.

The data reveal additional significant two-way interactions involving race/ethnicity, gender, and SES. Although each of the two-way interactions were significant, the effect size of each ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Two-way effects – secondary analyses. Additional analysis of the two-way interactions involving race/ethnicity, gender, and SES involves separating the data set into individual racial/ethnic groups (Black, Hispanic, and White) and using an ANOVA to test the interactions between gender and SES.

The results in Tables 56-58 do not indicate a statistically significant two-way interaction for the Hispanic and White racial/ethnic subgroups; however, effect size data for the significant two-way interaction in the Black student population ($\eta^2_{\text{Black Gender*SES}} < .01$) point out that the interaction between the factors did not influence the scale score

variation. Examination of the effect size for the main effects indicates that SES again played a significant role in the scale score variation for all three groups (η^2_{Black} SES = .041, η^2_{Hispanic} SES = .029, and η^2_{White} = .066). The effect of SES on the achievement in the White student population was double of the Hispanic population and 62% greater than Black student populations.

Table 56

Secondary Analysis (Internet & Black Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	98516.6	3	32838.9	444.1	.000
Intercept	563416808.4	1	563416808.4	7620169.3	.000
Gender	5210.5	1	5210.5	70.1	.000
SES	94145.8	1	94145.8	1273.3	.000
Gender * SES	441.3	1	441.3	6.0	.015
Error	2215835.1	29969	76.9		
Total	657043019.0	29973			
Corrected Total	2314351.6	29972			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 57

Secondary Analysis (Internet & Hispanic Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	25665.1	3	8555.1	104.4	.000
Intercept	177579168.0	1	177579168.0	2167684.6	.000
Gender	374.5	1	374.5	4.6	.033
SES	25317.3	1	25317.3	309.0	.000
Gender * SES	125.9	1	125.9	1.5	.215
Error	837807.4	10227	81.9		
Total	231653253.0	10231			
Corrected Total	863472.5	10230			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 58

Secondary Analysis (Internet & White Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	302296.1	3	100765.4	1342.5	.000
Intercept	1053394234.0	1	1053394234.0	14034672.2	.000
Gender	768.1	1	768.1	10.2	.001
SES	301886.1	1	301886.1	4022.1	.000
Gender * SES	135.7	1	135.7	1.8	.179
Error	4279800.2	23609	75.1		
Total	1382071810.0	23613			
Corrected Total	4582096.3	23612			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

Main effects. The results indicate statistically significant effects with race/ethnicity, SES, and using the Internet to find information. The estimated effect size

values of race/ethnicity (η^2_{Race} = .066) and SES (η^2_{SES} = .028) were considered a medium effect on the variability of biology scale scores.

Table 59 shows that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. The eta squared value (η^2_{Race} = .066) indicates that race/ethnicity has a medium effect on the variation of scale scores. This variation was also qualified in two-way interactions involving race/ethnicity, gender, and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

Table 59

Secondary Analysis: Pairwise Comparisons – Race/Ethnicity and Scale Score

					95% CI for Difference	
Race	Comparison Group	MD	SE	*p*	Lower Bound	Upper Bound
Black *N = 29973*	Hispanic	-2.523	.112	.000	-2.792	-2.253
	White	-5.631	.068	.000	-5.794	-5.467
Hispanic *N = 10231*	Black	2.523	.112	.000	2.253	2.792
	White	-3.108	.107	.000	-3.364	-2.853
White *N = 27025*	Black	5.631	.068	.000	5.467	5.794
	Hispanic	3.108	.107	.000	2.853	3.364

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch (M_{Yes} = 149.2) were outperformed by their peers who were not classified as SES (M_{No} = 153.4). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score

variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students who used the technology ($M_{\text{Technology Yes}} = 151.8$) and students who did not ($M_{\text{Technology No}} = 151.0$). Although statistically significant, the context of the effect size ($\eta 2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Summary. The analysis of this data set suggests that individually race/ethnicity and student SES have various effects on student achievement in biology EOC assessments. These main effects were also justified in more complex interactions with each other, as well as with gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results point to the rejection of the third null hypothesis ($H_0 3$).

Multilevel Factorial Analysis: Municipality

The fourth null hypothesis ($H_0 4$) was tested using a factorial analysis of variance to examine within rural and urban school districts the effects of race/ethnicity, gender, SES, and using technology to create presentations on biology academic scale scores. The data set was separated into two subsets by municipality (rural and urban) referring to the classification of the student's school district. Table 60 shows the demographic breakdown of the four different factor groups in the rural and urban analysis.

Table 60

Between-Subject Factors for Rural and Urban School Districts

Factor	Group Name	N_{Rural}	N_{Urban}
Race/Ethnicity	Black	13545	16428
	Hispanic	4688	5543
	White	33412	23613
Gender	Female	25604	22593
	Male	26041	22991
SES	No	27596	26197
	Yes	24049	19387
Use Technology to Create Presentations	No	37805	34071
	Yes	13840	11513
Totals		516545	45584

Municipality: Rural

The analysis of rural school districts tested the effects of the factors listed in Table 60 on the student achievement based on academic scale scores in high school Biology classes. Table 61 provides a summary of the results from the factor analysis of variance.

Table 61

Analysis Summary of H_03 (Internet in Rural Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	764113.5	23	33222.3	460.8	.000
Intercept	455024927.9	1	377296117.0	6311813.5	.000
Race/Ethnicity	250716.0	2	125358.0	1738.9	.000
Gender	622.9	1	622.9	8.6	.003
SES	68873.3	1	68873.3	955.4	.000
Technology Use	7275.2	1	7275.2	100.9	.000
R/E * Gender	2110.2	2	1055.1	14.6	.000
R/E * SES	1591.6	2	795.8	11.0	.000
R/E * Tech Use	446.8	2	223.4	3.1	.045
Gender * SES	87.5	1	87.5	1.2	.270
Gender * Tech Use	196.4	1	196.4	2.7	.099
SES * Tech Use	473.2	1	473.2	6.6	.010
R/E * Gender * SES	14.5	2	7.2	0.1	.905
R/E * Gender * Tech Use	221.7	2	110.8	1.5	.215
R/E * SES * Tech Use	160.0	2	79.8	1.1	.330
Gender * SES * Tech Use	54.2	1	54.2	0.7	.386
R/E * Gender * SES * Tech Use	18.0	2	9.0	0.1	.883
Error	3721409.4	51621	72.1		
Total	1198878714.0	51645			
Corrected Total	4485522.9	51644			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 51645; *significance at $p < .05$ level.

Rural: Four-way effects. Results from Table 61 show the interaction between race/ethnicity, gender, SES, and technology use did not significantly impact student academic scale scores. The null hypothesis cannot be rejected based solely on the four-

way interaction.

Rural: Three-way effects. The results did not reveal a significant interaction between race/ethnicity, gender, SES, and technology use. The null hypothesis cannot be rejected based solely on the three-way interaction.

Rural: Two-way effects. The results reveal a significant effect between gender and technology use. Table 62 displays the comparative means of females and males who use technology to create presentations and those who do not use the technology in their biology class. The data do indicate that both female and male students who use technology to create presentations score slightly higher than those students who do not use the technology; however, the context of the score variation does not suggest a significant difference which is reflected in the effect size value ($\eta^2_{\text{Tech Use * Gender}} < .01$).

Table 62

Pairwise Comparisons – Gender, Technology Use & Mean Scale Scores

					95% CI	
Gender	N	Technology Use	*M*	*SE*	Lower Bound	Upper Bound
Female	23025	No	150.4	.130	150.1	150.6
	25172	Yes	151.4	.114	151.2	151.6
Male	22975	No	149.8	.121	149.6	150.1
	26057	Yes	151.2	.115	151.0	152.1

Note. M = Mean Scale Score, *SE* = Standard Error, CI = Confidence Interval.

The data reveal additional significant two-way interactions involving race/ethnicity, gender, and SES. Although each of the two-way interactions were significant, the effect size of each ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Rural: Two-way effects – secondary analyses. The results shown in Tables 63-

65 did not indicate a statistically significant two-way interaction for the Hispanic and White racial/ethnic subgroups; however, effect size data for the significant two-way interaction in the Black student population ($\eta^2_{\text{Black Gender*SES}} < .01$) points out that the interaction between the factors did not influence the scale score variation. Examination of the effect size for the main effects indicates that SES again played a significant role in the scale score variation for all three groups (η^2_{Black} SES = .036, η^2_{Hispanic} SES = .022, and $\eta^2_{\text{White}} = .053$). The effect of SES on the achievement in the White student population was double of the Hispanic population and 68% greater than Black student populations.

Table 63

Secondary Analysis of Rural Districts (Internet & Black Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	37634.5	3	12544.8	180.2	.000
Intercept	224416154.0	1	224416154.0	3223633.1	.000
Gender	2253.9	1	2253.9	32.4	.000
SES	35544.6	1	35544.6	510.6	.000
Gender * SES	101.6	1	101.6	1.5	.227
Error	942669.1	13541	69.6		
Total	293548684.0	13545			
Corrected Total	980303.5	13544			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 64

Secondary Analysis of Rural Districts (Internet & Hispanic Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	8356.3	3	2785.4	36.0	.000
Intercept	72943178.6	1	72943178.6	943756.9	.000
Gender	86.4	1	86.4	1.1	.290
SES	8244.1	1	8244.1	106.7	.000
Gender * SES	0.1	1	0.1	0.0	.915
Error	362027.4	4684	77.3		
Total	105668662.0	4688			
Corrected Total	370383.7	4687			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 65

Secondary Analysis of Rural Districts (Internet & White Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	135867.2	3	45289.1	621.7	.000
Intercept	671506754.7	1	671506754.7	9218055.4	.000
Gender	122.0	1	122.0	1.7	.196
SES	135846.5	1	135846.5	1864.8	.000
Gender * SES	162.6	1	162.6	2.2	.135
Error	2433669.2	33408	72.8		
Total	799661368.0	33412			
Corrected Total	2569536.4	33411			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

Main effects. The results indicate statistically significant effects with race/ethnicity, SES, and using the Internet to find information. The estimated effect size

values of race/ethnicity (η^2_{Race} = .063) and SES (η^2_{SES} = .018) were considered a medium effect on the variability of biology scale scores.

Table 66 shows that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. The eta squared value (η^2_{Race} = .063) indicates that race/ethnicity has a medium effect on the variation of scale scores. This variation was also qualified in two-way interactions involving race/ethnicity, gender, and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

Table 66

Secondary Analysis: Pairwise Comparisons – Race/Ethnicity and Scale Score

Race	Comparison Group	MD	SE	*p*	95% CI for Difference Lower Bound	Upper Bound
Black *N = 29973*	Hispanic	-2.853	.173	.000	-3.267	-2.440
	White	-5.720	.098	.000	-5.955	-5.486
Hispanic *N = 10231*	Black	2.853	.173	.000	2.440	3.267
	White	-2.867	.159	.000	-3.248	-2.486
White *N = 57025*	Black	5.720	.098	.000	5.486	5.955
	Hispanic	2.867	.159	.000	2.486	3.248

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch (M_{Yes} = 148.9) were outperformed by their peers who were not classified as SES (M_{No} = 152.6). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score

variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students who used the technology ($M_{\text{Technology Yes}} = 151.3$) and students who did not ($M_{\text{Technology No}} = 150.1$). Although statistically significant, the context of the effect size ($\eta^2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Rural: Summary. The analysis of the rural data set suggests that individually race/ethnicity and student SES have various effects on student achievement in biology EOC assessments. These main effects were also justified in more complex interactions with each other, as well as gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results support the rejection the fourth null hypothesis (H_04).

Municipality: Urban

Urban: Four-way and three-way effects. Results from Table 67 show there is not a statistically significant four-way or three-way interaction between race/ethnicity, gender, SES, and technology use (Internet). The null hypothesis cannot be rejected based solely on these interactions.

Table 67

Analysis Summary of H_03 (Internet in Urban Districts)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	933977.0	23	40607.7	525.2	.000
Intercept	585791920.4	1	585791920.4	7576180.2	.000
Race/Ethnicity	265073.2	2	132536.6	1714.1	.000
Gender	304.1	1	304.1	3.9	.047
SES	131520.8	1	131520.8	1701.0	.000
Technology Use	4748.8	1	4748.8	61.4	.000
R/E * Gender	4627.5	2	2313.7	29.9	.000
R/E * SES	12134.5	2	6067.3	78.5	.000
R/E * Tech Use	171.8	2	85.9	1.1	.329
Gender * SES	1.2	1	1.2	0.0	.900
Gender * Tech Use	351.6	1	351.6	4.5	.033
SES * Tech Use	13.6	1	13.6	0.2	.675
R/E * Gender * SES	412.6	2	206.3	2.7	.069
R/E * Gender * Tech Use	164.8	2	82.4	1.1	.344
R/E * SES * Tech Use	12.3	2	6.1	0.1	.924
Gender * SES * Tech Use	12.5	1	12.5	0.2	.687
R/E * Gender * SES * Tech Use	179.9	2	90.0	1.2	.312
Error	3522709.2	45560	77.3		
Total	1071889368.0	45584			
Corrected Total	4456686.2	45583			

Note. SS = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 45584; *significance at $p < .05$ level.

Urban: Two-way effects. The results reveal a significant effect between gender and technology use. Table 68 displays the comparative means of females and males who use technology to create presentations and those who do not use the technology in their biology class. The data do indicate that both female and male students who use technology to create presentations score slightly higher than those students who do not use the technology; however, the context of the score variation does not suggest a significant difference which is reflected in the effect size value ($\eta^2_{\text{Tech Use * Gender}} < .01$).

Table 68

Pairwise Comparisons - Gender, Technology Use & Mean Scale Scores

				95% CI for Difference	
Gender	Technology Use	*M*	*SE*	Lower Bound	Upper Bound
Female	No	151.3	.109	151.1	151.6
	Yes	152.0	.110	151.8	152.2
Male	No	151.3	.110	151.1	151.5
	Yes	152.4	.112	152.2	152.7

Note. M = Mean Scale Score, *SE* = Standard Error, CI = Confidence Interval.

The data reveal additional significant two-way interactions involving race/ethnicity, gender, and SES. Although each of the two-way interactions were significant, the effect size of each ($\eta^2 < .01$) was minimal, accounting for little or none of the scale score variation.

Urban: Two-way effects – secondary analyses. Additional analysis of the two-way interactions involving race/ethnicity, gender, and SES involves separating the data set into individual racial/ethnic groups (Black, Hispanic, and White) and using an ANOVA to test the interactions between gender and SES.

The results shown in Tables 69-71 did not indicate a statistically significant two-way interaction for the Hispanic and White racial/ethnic subgroups; however, effect size data for the significant two-way interaction in the Black student population ($\eta^2_{\text{Black Gender*SES}} < .01$) points out that the interaction between the factors did not influence the scale score variation. Examination of the effect size for the main effects indicates that SES again played a significant role in the scale score variation for all three groups (η^2_{Black} SES = .039, η^2_{Hispanic} SES = .034, and η^2_{White} = .074). The effect of SES on the achievement in the White student population was double the Hispanic and Black student

populations.

Table 69

Secondary Analysis of Urban Districts (Internet & Black Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	53715.8	3	17905.3	232.8	.000
Intercept	332901342.9	1	332901342.9	4327772.1	.000
Gender	2872.4	1	2872.4	37.3	.000
SES	51283.8	1	51283.8	666.7	.000
Gender * SES	362.8	1	362.8	4.7	.030
Error	1263368.7	16484	76.9		
Total	363494335.0	16428			
Corrected Total	1317084.5	16427			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 29973; *significance at $p < .05$ level.

Table 70

Secondary Analysis of Urban Districts (Internet & Hispanic Student Population)
Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	17862.9	3	5954.3	69.5	.000
Intercept	103470093.3	1	103470093.3	1208279.3	.000
Gender	1200.9	1	1200.9	14.0	.000
SES	16789.6	1	16789.6	196.1	.000
Gender * SES	175.3	1	175.3	2.0	.153
Error	474328.1	5539	85.6		
Total	125984591.0	5543			
Corrected Total	492191.1	5542			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 10231; *significance at $p < .05$ level.

Table 71

Secondary Analysis of Urban Districts (Internet & White Student Population) Tests of Between-Subjects Effects

Source	*SS*	*df*	*MS*	*F*	*p*
Corrected Model	143806.7	3	47935.6	631.0	.000
Intercept	365881634.8	1	365881634.8	4816581.5	.000
Gender	777.0	1	777.0	10.2	.001
SES	143085.5	1	143085.5	1883.6	.000
Gender * SES	45.6	1	45.6	0.6	.439
Error	1793408.8	33408	76.0		
Total	582410442.0	33412			
Corrected Total	1937215.4	33411			

Note. *SS* = Sum of Squares, *df* = Degrees of Freedom, *MS* = Mean Square, *F* = F Ratios, *N* = 57025; *significance at $p < .05$ level.

Main effects. The results indicate statistically significant effects with race/ethnicity, SES, and using the Internet to find information. The estimated effect size values of race/ethnicity ($\eta^2_{\text{Race}} = .070$) and SES ($\eta^2_{\text{SES}} = .036$) were considered a medium effect on the variability of biology scale scores.

Table 72 shows that White students outperformed Hispanic students, who scored higher than Black students on the biology EOC assessment. The eta squared value ($\eta^2_{\text{Race}} = .070$) indicates that race/ethnicity has a medium effect on the variation of scale scores. This variation was also qualified in two-way interactions involving race/ethnicity, gender and SES; however, the effect sizes for these two-way interactions ($\eta^2 < .01$) were considered trivial with no effect on score variation.

Table 72

Secondary Analysis: Pairwise Comparisons – race/ethnicity and scale score

Race	Comparison Group	MD	SE	*p*	95% CI for Difference Lower Bound	95% CI for Difference Upper Bound
Black *N = 29973*	Hispanic	-2.258	.149	.000	-2.615	-1.900
	White	-5.906	.101	.000	-6.148	-5.663
Hispanic *N = 10231*	Black	2.258	.149	.000	1.900	2.615
	White	-3.648	.149	.000	-4.005	-3.291
White *N = 57025*	Black	5.906	.101	.000	5.663	6.148
	Hispanic	3.648	.149	.000	3.291	4.005

Note. MD = Mean Difference, *SE* = Standard Error, CI = Confidence Interval; *significance at $p < .05$ level.

The main effect of SES was also significant with the results revealing that students eligible for free and/or reduced lunch ($M_{\text{Yes}} = 149.5$) were outperformed by their peers who were not classified as SES ($M_{\text{No}} = 154.0$). The effect of SES is qualified in the two-way interaction with technology use and the three-way interaction with gender and technology use. In both interactions, SES had the strongest influence on scale score variation.

Using technology to create presentations did have a significant effect on student achievement; however, the mean difference in scale scores was small between students who used the technology ($M_{\text{Technology Yes}} = 152.2$) and students who did not ($M_{\text{Technology No}} = 151.3$). Although statistically significant, the context of the effect size ($\eta^2_{\text{Tech Use}} < .01$) was insignificant in the small scale score variation.

Urban: Summary. The analysis of the urban data set suggests that individually race/ethnicity and student SES also have various effects on student achievement in

biology EOC assessments. As seen in the rural analysis, these main effects were justified in more complex interactions with one another along with gender and technology use. In these more complex interactions, SES was the stronger influence on scale score variation. The data results further confirm the rejection the fourth null hypothesis ($H_0 4$).

Research Question 1

To what extent do students utilize educational technology in science classrooms and school districts? Based on the frequency response from question 9 of the student survey, only 11.9% of biology students reported, "using computer, calculators, or other educational technology to learn science" (North Carolina Department of Public Instruction, 2008). The question asked, "Which of the following do you spend the most time during science class," and students can select up to three different answer selections. The nature of the question does not exclude the use of technology in biology classrooms for the students who did not select using computers. The low frequency of reported technology use must be taken in the proper context since it is not likely that only 11.9% of student sample used technology in class.

Using the responses from survey question 9, the frequency percentages of the various technologies used in biology classrooms were compared in Table 2. The most commonly used technologies selected for this study included using technology to organize and display data, using technology to create presentations, and using the Internet to find information. These technologies were the top selections across the state's school districts, as well as in both rural and urban school districts.

In questions with long category lists, it is well-known that categories near the top and bottom will be selected more often. This is order-bias, where the presentation order of the categories affects the likelihood of response (Serenko & Bontis, 2013). Using

technology to organize and display data could be a result of order-bias due to its position as the first option of the survey answers. The solution to order-bias is randomization. By randomizing the order in which categories are presented, the likelihood of bias is reduced (Perreault, Jr., 1979).

Research Question 2

Are the patterns of use equitable in terms of race, gender, municipality and SES? There were slight variations between student groups indicating technology was used as a major instructional tool in the classroom. The difference in the percentages of race/ethnicity, gender, and municipality varied within 0.3 points of the mean and between groups. Socioeconomic groups varied slightly higher (SES_{Yes} = 12.6% and SES_{No} = 11.4%) with students who qualified reporting a higher use than their peers.

The patterns of specific technology use were significant in the primary effects of race/ethnicity, gender, and SES within both rural and urban school districts. The same pattern was seen in the primary effects of the most commonly used technologies identified in Table 2. Although the primary effects were statistically significant based on chi-square calculations, the Cramer's V values were all less than 0.10 indicating a very weak association based on Cohen's scale (Ellis, 2010).

Examination of secondary effects reveled more complex patterns that varied within the gender, race/ethnicity, and SES combinations. Using technology to organize and display data revealed the smallest pattern variation compared to using technology for presentations and using the Internet. The analyses revealed significant variations in White*gender and White*SES groups in both statewide and rural school districts. The only other secondary groups to show significant variations were within the Hispanic*SES and male*SES combinations across all three populations.

Using technology to create presentations showed greater variation among the secondary effects including the three different racial/ethnic*gender groups. These groups were statistically significant in both statewide and rural school districts with the exception of the Black*gender populations; they were also significant in urban districts. The analyses also revealed significant variations in Black*SES, White*SES, female*SES, and male*SES populations across statewide and rural school districts. The male*SES population also was statistically significant within urban school districts.

The most complex patterns were seen in student groups using the Internet with all three racial/ethnic*gender populations showing significance in statewide, rural, and urban school districts. Black*SES groups were significant in statewide and urban districts as well as White*SES groups. Hispanic*SES groups along with White*SES groups were also significant in rural school districts. Among female*SES and male*SES groups, they were all statistically significant across state, rural, and urban school districts. Although the above secondary effects were statistically significant based on chi-square calculations, the Cramer's V values were all less than 0.10, indicating a very weak association based on Cohen's scale (Ellis, 2010).

Looking at tertiary effects showed very little variation among the various combinations; however, some of the significant groups did validate the significance of some of the secondary groups. For example, in groups using technology to organize and display data, the significance of Hispanic males and SES groups validated the secondary significant groups of Hispanic*SES and male*SES. This was seen in both statewide and rural school districts. Both White females and males showed significant variations within their respective socioeconomic groups in both statewide and rural school districts. These validated the White*SES, male*SES, female*SES, and White*gender groups in

statewide and rural districts as well. The pattern was evident for all three specific technology uses. Black females and their respective socioeconomic were significant for Internet use in statewide and urban school districts. This supported the secondary groups of Black*gender, Black*SES, and female*SES within the same districts.

Like the primary and secondary effects, the Cramer's V values were all less than 0.10, indicating a very weak association based on Cohen's scale (Ellis, 2010). When examining the percentages of use within the different significant groups, we see the range of variation between 0.2 and 3.1 percentage points. The only exception is between male Hispanics and their respective socioeconomic groups in school districts that use technology to organize and display data. The usage gap was 4.3 percentage points with 50.4% of male Hispanics eligible for free/reduce lunch prices using the technology as compared to the 54.7% usages of their noneligible peers.

Research Question 3

What is the relationship between the use of technology and student achievement? An initial examination of the mean difference between the responses of survey question 9 shows a 0.6 point mean difference between students who selected technology use ($M_{Yes} = 152.0$) and those who did not ($M_{No} = 152.6$). Further analysis reveals a significant effect between academic scale scores at the $p < 0.5$ level for the two groups [$F(1, 97446) = 44.7$, $p < .01$]. Although statistically significant, the eta squared value ($\eta^2 < .001$) is considered trivial based on Cohen's effect scale (Ellis, 2010). This is reflected in the mean difference between the groups which in context is very little difference in scale scores.

Additional analysis of the specific technology use revealed a slightly higher mean

difference between students who used technology and those who did not. The variation of mean differences ranged between 0.7 and 1.2 points between the most used technologies as identified in Table 2. Although statistically significant as main effects, the effect size of each specific technology use was considered trivial ($\eta^2 < .01$) based on Cohen's scale (Ellis, 2010). In context of academic scale scores for biology, the variation range is not very great. The significance of technology use is attributed to the large sample size of the tested population (N = 97229) where a slight variation of mean difference will show as significance in most statistical tests (Vacha-Hasse & Thompson, 2004).

Research Question 4

Does the relationship between the use of technology and student achievement vary by race, gender, municipality, and/or SES? A deeper analysis of the relationship between technology and student achievement (scale scores) by race/ethnic, gender, municipal, and SES groups revealed minimal variation outside of groups involving race/ethnicity and SES. As main effects, race/ethnicity, SES, and technology use were all statistically significant in statewide, rural, and urban school districts. The mean effect size values for these main variables was highest for race/ethnicity ($\eta^2 = .061$), followed by SES ($\eta^2 = .026$), and technology use ($\eta^2 < .01$). In regards to student achievement, race/ethnicity had a medium effect on scale score variation, while SES had a small effect. The effect of technology use on scale scores across statewide, rural, and urban school districts was less than 0.01 and considered to have minimal to no influence on the variation.

Further disaggregation at the secondary level reveals significant two-way

interactions between technology, race, gender, and SES. Though statistically significant, the eta squared values for effect size indicate minimal influence on academic scale scores. The consistency of significant interactions involving race/ethnicity and SES validate their significance as main effects and their influence when analyzed with technology status.

Gender did not play a significant role as a main effect when examining its influence with academic scale scores; however, when involved with technology use in the two-way interactions was significant. Like the other significant two-way interactions involving race/ethnicity and SES, the effect size values ($\eta^2 < .01$) indicate minimal influence of scale score variation. Comparison of mean differences for gender and technology use interactions was less than 1.0 scale score point between gender groups which is not a major variation within the context of biology scale scores.

Three-way interactions involving technology were significant in three scenarios: (1) statewide involving race, SES, and technology, (2) statewide involving gender, SES, and technology, and (3) rural municipalities involving gender, SES, and technology. While statistically significant, the effect size values ($\eta^2 < .01$) mirrored those of the two-way interactions considered to have minimal effect on scale score variation.

Chapter Summary

This chapter began with an analysis of variations of technology use within various demographic populations. The descriptive analysis found that approximately 11% of students reported using technology the majority of time in their biology class. When analyzing specific technology uses, the three most frequent uses selected by students were using technology to organize and display data, using the Internet, and using

technology to create presentations.

The relational analyses did indicate several statistically significant variations of use within different population groups; however, due to the large population sample size, it was important to examine the effect size calculations to gain a better understanding and context of the significance. The analysis revealed that despite being statistically significant, the relevance of the association in the variations were minimal at best, based on the effect scale established by Cohen (1988).

Additional factorial univariate analyses were employed to determine potential relationships between technology use and student achievement. The data revealed that technology use did not influence the variation of student achievement scale scores as much as race/ethnicity and SES. White students outperformed Hispanic students by an average of three scale score points and Black students by an average of six scale score points. Technology use alone averaged less than a one point difference in mean scale scores and only when interacting with race, gender, and/or SES did the mean difference increase; however, this increase within the context of the biology scale score range was negligible.

The following chapter discusses the implications of these findings as well as the limitations of this study and the need for additional research.

Chapter 5: Discussion

Chapter 5 presents a summary of the key findings in this study. The limitations of the study are shared with a focus on factors that may have affected the outcome of the analyses. This chapter concludes with a discussion of the need for additional research regarding the role of technology and its use in science classrooms.

Key Findings

The analyses discussed in Chapter 4 identified several statistically significant variations of use within different population groups. It was important to examine the effect size calculations to gain a better understanding and context of the significance due to the exceptionally large sample size. The analyses revealed that despite being statistically significant, the relevance of the association in the variations were minimal at best.

The factorial univariate analyses employed to determine potential relationships between technology use and student achievement revealed that technology use had minimal influence on the variation of student achievement scale scores. In comparison, student race/ethnicity and SES had a greater impact on scale score variation in biology classrooms. White students outperformed Hispanic students by an average of three scale score points and Black students by an average of six scale score points. These patterns were also consistent within rural and urban school districts.

Alone, technology use averaged less than a one point difference in mean scale scores. When interacting with race, gender, and/or SES, the mean difference slightly increased; however, the extent of technology influence on student achievement was marginal at best.

Implications

Technology Use in Schools

Technology has been the center of curriculum reform efforts and school budget deliberations in school districts across the nation (Fullan, 2013). Over the last 3 decades, computer and Internet technologies have emerged into significant roles in the evolution of science instruction (Lei & Zhao, 2007; Osborne & Hennessy, 2003). Fullan (2013) asserted that technology, change, and pedagogy are all connected collectively and make an invincible combination.

In many cases, research proposes that technology is not used to its potential and mainly is utilized in ways to support existing instructional practices (Cuban, 1998; Cuban et al., 2001; Fouts, 2000; Lei, 2010; Lei & Zhao, 2007; Odom et al., 2011). Science teachers can be challenged to integrate technology into instruction if lesson plans are not aligned with or do not complement technological components. The rapid evolution of technology and tech-savvy students may also present an additional hurdle for teachers who struggle to maintain the technology status quo (Wenglinsky, 2005). Despite this rapidly evolving environment, a U.S. Department of Education (2003) report indicated that 85% of teachers felt somewhat well-prepared to use technology in classroom instruction.

Technology's complex nature lends itself to a variety of uses, which include individual and group learning, information processing and sharing, communications, instructional management, distance learning, and assessment (Lee & Spires, 2009; Muir-Herzig, 2004; Wenglinsky, 2005). Laboratory experiences are also an important component of the biology curriculum which should not be supplanted by technology. Instead, computers and software can allow students to conduct specific laboratory

exercises that would not otherwise be available due to lack of time, equipment, and/or resources (Bull & Bell, 2008). In these situations for example, computer simulations can provide an accessible medium to conduct experiments and collect and analyze data in a more conventional environment (Matray & Proulx, 1995). Students also can visualize important ideas in biology that occur on a microscopic level which are often difficult to comprehend (Davis, 2008; Wenglinsky, 2005).

The reported low use of technology in biology classrooms in this study is consistent with present literature (Alspaugh, 1999; Bain, 2004; Cuban, 2001; Muir-Herzig, 2004; Odom et al., 2011; Shapley et al., 2010). Despite the reported low use in this study, there is tremendous potential for technology implementation and integration across the entire science curriculum (Bell & Smetana, 2008; Berk, 2010; Bull & Bell, 2008; Gabric, Hovance, Comstock, & Harnisch, 2005; Hakverdi-Can & Dana, 2012; Park, 2008).

The higher frequency of students who qualified for free/reduced lunch using technology than their nonqualifying peers contradicts previous research which found that schools with smaller SES populations were typically more frequent users of technology due to greater exposure (Eamon, 2004; Ferro et al., 2011; Swain & Pearson, 2003; Valadez & Duran, 2007; Vigdor & Ladd, 2010). In conjunction with other research, this study suggests that technology use in schools is no longer exclusive to schools with low SES populations (Thomas, 2008; van Dijk, 2006; Warschauer & Matuchniak, 2010).

The lack of variation in technology use between demographic groups found in this study also parallels more recent research regarding the digital divide (Ferro et al., 2011; Galperin, 2010; Hilbert, 2011; van Dijk, 2006). These findings add to the continuous debate over the digital divide and how it is defined and quantified (Trotter, 2007). Larger

questions loom regarding the quality of instruction using technology rather than the quantity or access to the technology itself (Chapman et al., 2010).

Technology and Student Achievement

As seen in this study and other research, higher technology use does not automatically ensure positive outcomes in the context of student achievement (Corn, Huff, Halstead, & Patel, 2011; Schroeder et al., 2007; Shieh et al., 2011). Existing research regarding the relationship between technology and student achievement has revealed positive, negative, and indeterminate outcomes (Bebell & O'Dwyer, 2010; Lin et al., 2002; Patel et al., 2011). The findings of this study add to the body of research which indicates that technology use does not meaningfully affect student achievement in science classrooms.

Several studies propose that the use of technology has a variable relationship with student achievement in science based on the manner in which it is used in the classroom (Lei, 2010; Odom et al., 2011; Papanastasiou et al., 2003; Schacter, 1999; Schroeder et al., 2007; Tamim et al., 2011; Wenglinsky, 2005). Examining specific technology uses did not reveal further noteworthy outcomes regarding student achievement. This supports current research by Lei (2010) which suggests that how technology is used has a greater impact than access to different technologies. The findings determined that various technology uses had various effects on student outcomes but collectively did not significantly influence student achievement.

Other research proposes that technology is primarily utilized to reinforce current instructional methods in the classroom. The method of technology utilization has been referred to as *uninspired* (Odom et al., 2011; Wenglinsky, 1998). While the findings of this study were not negative in relation to student achievement, the indifferent effects

could be attributed to utilization of lower order tasks that may be neither engaging nor challenging to students (Wenglinsky, 2005).

Contrastingly, the study findings reveal the potential of technology's positive influence as well. When taken as a component of and not the solution to increasing student achievement, technology can clearly affect student outcomes (Reichstetter et al., 2002). The findings also confirm research that positive relationships are possible between technology and student achievement when utilized in constructive and student-centered ways (Bebell & Kay, 2010; Noeth & Volkov, 2004; Odom et al., 2011).

Digital Divide

A particular interest for this study was the extent of the digital divide within North Carolina science classrooms. Limited digital divide research in the state served as a motivator to explore social-economic, gender, racial/ethnic, and municipal factors and their potential role with technology use and its influence on student achievement. The study findings reveal minimal variation of technology use based on the student survey responses. This supports Wilson et al.'s (2003) research findings regarding public perceptions of the purpose of science and technology in North Carolina and Powers et al.'s (2013) study findings suggesting the reduction of technology access across numerous demographic variables including race, ethnicity, gender, age, geographic location, household income, education level, and family composition.

A third study conducted in North Carolina by Vigdor and Ladd (2010) attempted to answer questions surrounding home computer access and student achievement. Their findings indicated that home computer access varied by race and SES. Over 90% of White students reported having a computer at home as compared to 75% of African-American students. Additionally, the gap between students eligible for free or reduced

lunch and nonparticipants was slightly larger with 71% of participants indicating having a home computer contrasted with over 92% of nonparticipants. These results contradict the findings of this study; however, it is important to understand the different contexts. Vigdor and Ladd’s work focused on home computer access as compared to school technology use for this particular research.

The lack of variation in technology use in this study does support digital divide research outside of North Carolina (Chapman et al., 2010; Galperin, 2010; Hess & Leal, 2001; Mims-Word, 2012). These studies concurred that gaps in technology access within schools and districts are not as evident as seen in the earliest years of technology integration; however, the complex identity of the digital divide still leaves ample room for controversy within educational spheres (Galperin, 2010; Hilbert, 2011).

Study Limitations

Advances in technology have brought us the ability to collect, transfer, and store massive datasets (Herland, Khoshgoftaar, & Wald, 2014). These developments have allowed an increasing number of research studies to now rely on very large samples. For example, Pavlou and Dimoka (2006) used over 10,000 public feedback comments from eBay; Overby and Jap’s (2009) research included over 108,333 data points from used car sales; and Herland et al.’s (2014) work discussed how the medical industries now employs big data sets which includes up to several million records.

With a very large sample, the standard error becomes extremely small, even so that minuscule variances become statistically significant. Ellis (2010) explained that in the context of comparing groups A and B, the effects of A and B are always different at some decimal place. Cohen (1988) proposed that literally a null hypothesis is always false in the real world. Even false to a tiny degree, a large enough sample will produce a

significant result and lead to its rejection. In any given context, there is not always an assurance of a large enough sample to produce statistically significant outcomes (Gigerenzer, 2004).

Large samples also provide opportunities to conduct more powerful data analysis and inferences compared to smaller samples. One advantage with larger data sets is the detection and examination of small effects. Large samples enable researchers to incorporate many control variables in the study model without sacrificing sample power (Gigerenzer, 2004).

Because the subjects of this study differ in grade level, outside generalizations of the results are limited. Research shows that relationships between technology use and student achievement vary between grade level and subject (Bebell & O'Dwyer, 2010; Corn, Huff, Halstead, & Patel, 2011; Kadel, 2008; Kara I. , 2008; Meyers & Brandt, 2010; Wenglinsky, 2006). In this context, the finding of this study may not apply to students in other subjects and grade levels.

Another study limitation is the use of standardized testing as a measure of student achievement. Standardized testing, such as the biology EOC assessment, is supported by three fundamental assumptions: (1) standardized tests are designed objectively, (2) are unbiased, and (3) accurately measure a student's understanding of content standards. Convinced by these assumptions, school officials use test data as the main criteria in determining a student's academic proficiency. Also, because legislators believe test data is a reliable indicator of student achievement, standardized tests have become an essential part of the education process, often used in education policy and reform.

The primary function of a standardized test is to provide specific information to assist decision making for legislators, school officials, and other educational leaders.

Assessments that are valid, reliable, and norm-referenced make it rather easy for policymakers to collect data on students. This is interesting since the third key assumption regarding standardized testing is that its primary function is to measure a student's academic status; however, test data is certainly more useful to educators than students since a competent teacher can ascertain a student's proficiency level based on homework, quizzes, and classroom participation.

Since standardized tests can only measure, not determine, a student's academic status, the argument is made that it is precarious for policymakers to mainly rely on data provided by these tests (Linn et al., 2011). The price and efficiency of standardized testing and the vast amounts of information they provide are quite attractive to administrators, who rely on such information for educational policy decisions. A great assumption is that newer standardized tests have overcome the flaws of past tests and are able to accurately measure important data (Kadel, 2008); however, this argument grossly ignores real-world limitations as to what standardized tests actually measure. Standardized tests are created to assess a student's level of knowledge which means the results are not a complete representation of the student's total academic picture (Rainie & Hitlin, 2005; Wenglinsky, 2006). A goal of education is to help prepare students for real-world success. It is important to be certain of the methodology used in measuring this goal.

The nature of the student survey questions limited the ability to fully interpret the results of the analysis. The question responses only indicated the presence of technology use rather than frequency. It is possible that differences in student achievement exist between students who use technology for daily tasks and those who use technology infrequently. This aligns with studies that suggest that the quality of technology use has a

greater impact over the quantity of technology itself (Swain & Pearson, 2003; Tamim et al., 2011).

Finally, the data set analyzed in this study incorporates information regarding student achievement, technology use, and specific technology applications from the 2010-2011 school year. Technology is a rapidly evolving tool with continuous investments of money, time, and effort in its integration. It is likely with these swift technology changes and the advancements of its applications that more current data can provide different results; however, the findings of this study confirm current research (Corn, Huff, Halstead, & Patel, 2011; Lee & Tsai, 2013; Patel et al., 2011) that technology use makes a marginal difference in student achievement. Although technology has changed over the past several years, it appears that its use and application in education has not. We will not be able to establish more current trends until updated data sets regarding technology use in schools are available.

Recommendations for Future Research

Due to the emphasis of accountability in schools and the significant cost of technology integration, the need to better understand technology's impact is necessary. The relevance of technology in education is unquestionable. In order for our students to successfully compete in a global workforce, effective integration of technology into education is required (Friedman, 2005; Wenglinsky, 2006).

The limitations of this study reveal the need for additional research on the topic of technology use in schools to help provide a deeper understanding of its potential influence on student achievement. Additional research can clarify the relationship between technology application and other factors that contribute to the digital divide debate. Suggestions for future research should include

- survey questions that measure not only technology use, but the frequency in which it is utilized,
- data regarding teacher professional development specifically focused on technology integration and implementation,
- qualitative approaches that provide greater insights to social contexts of potential digital divides in schools and how students use technology, and
- data that identifi2es constructivist instructional methods that incorporate technology.

Additional research that involves a broader scope to include teacher and student perceptions of technology integration would be beneficial on many levels. Technology should be more than just a series of educational bandwagons that lack proper foundations for sustained implementation.

Chapter Summary

This study adds to the existing body of research investigating relationships between technology use, student achievement, and the digital divide. Existing research reveals a variety of interpretations of technology use and the digital divide (Ferro et al., 2011; Galperin, 2010; Hess & Leal, 2001; Hilbert, 2011; van Dijk, 2006). This study found minimal effects on the variations of technology use between various demographic groups. This supports the idea that the digital divide is no longer a relevant issue in education (Galperin, 2010; Pflaum, 2004; Valadez & Duran, 2007); however, this study was limited by the nature of the student survey questions regarding the frequency of technology use.

Technology use in the classroom was found to be a minimal influence on student

achievement in biology. Analysis of specific technology applications found little to no effect on student scale scores from the biology EOC assessment. This analysis was partially limited, due to the nature of the survey which only identified application use and not frequency. The study also identified, to an extent, a low use of technology in classroom instruction which confirms existing research (Berk, 2010; Cuban, 2001; Hakverdi-Can & Dana, 2012; Pflaum, 2004; Shapley et al., 2010).

Prensky (2012) concluded that we should all support technological experimentation and innovation in education. Instead of spending and often wasting billions of dollars to create things that are new, we should try harder to fix what is already in place. Properly motivated students are far more capable and creative than we give them credit for. Technology can give them the motivation they need to work, create, and succeed.

Believers of educational technology have research to confirm their support. Fullan (2013) summarized technology in education best:

> Technology is not a panacea. Not all technology is good for pedagogy. And great pedagogy can and will exist without technology. We have, however, greatly miscast and underutilized technology's power. When we enlist technology in the service of exploratory learning for all, watch out! On the other hand, if we plod along with standards and assessment using technology only as a prop, we will get what we deserve: a higher level of tedium. It is time to take the lid off learning. (p. 78)

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