Analyzing the Use of Technological/Engineering Design-Based Biotechnical Learning Pedagogical Approaches to Promote Change in Concept Knowledge of Eighth Grade Mathematics Students

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Abstract

The purpose of this research was to document the ways in which the pedagogical approaches of technology/engineering design-based learning (T/E DBL) were shown to promote change in concept knowledge of eighth grade mathematics students. A mixed method, sequential explanatory multiple embedded case study was used to determine the significance between the T/E DBL intervention and bivariate measurement data concept knowledge.

Whole Group quantitative data analysis indicated a statistical significance between pretest and posttest scores. Qualitative data (Interactive Engineering Journals and semi-structured interviews) analyses for the Sub-Group confirmed that students did possess the bivariate data concept knowledge as documented through quantitative results and those gains were directly related to experiences students had while engaged in the T/E DBL intervention.

This research demonstrated that the utilization of T/E DBL in an eighth-grade mathematics classroom has the potential to foster a change in concept knowledge of bivariate measurement data through informed design decision-making in a 21st century problem context. This study can be used as a guide for mathematics educators and curriculum developers implementing T/E DBL pedagogy allowing students to learn through contextual experiences. Future research should explore the utilization of T/E DBL to teach additional mathematical concepts at different grade levels.

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General Audience Abstract

This research demonstrated that the utilization of technology/engineering design-based learning (T/E DBL) in an eighth-grade mathematics classroom has the potential to increase mathematical concept knowledge through informed design decision-making in a 21st century problem context. Participants were asked to design a solution to a real-world problem which required mathematics concept knowledge in order for students to make decisions about their design. Participants also kept an Interactive Engineering Journal (IEJ) throughout the design challenge.

The results of the mathematics pre/posttest taken before and after the design challenge indicated that students increased their mathematical concept knowledge through their experiences during the design challenge. A small group of participants were selected to participate in IEJ analysis and individual interviews. These data confirmed that students did gain mathematical concept knowledge in connection to their experiences during the design challenge.

This study can be used as a guide for mathematics educators and curriculum developers implementing T/E DBL pedagogy allowing students to learn through contextual experiences. Future research should explore the utilization of T/E DBL to teach additional mathematical concepts at different grade levels.

Dedication

This dissertation is dedicated to:

my dad, David M. Feldes, who instilled in me the perseverance to complete this degree,

my mom, Susan M. Feldes, who has consistently been my biggest cheerleader,

my husband, Brandon W. Reed, who has supported my every endeavor, and

my daughter, Coralynn M. Reed. I hope you fulfill every dream you have, my darling.

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To my family and friends who have provided words of encouragement, praise, and a listening ear throughout this process, I am so appreciative. Your inspiring words have meant more than you know.

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CHAPTER ONE: INTRODUCTION

Overview

The goal of the public education system is the "development of literate individuals with the capacity to think critically and utilize acquired knowledge as a tool for solving complex 21st century problems" for themselves, their community, their country, and their world (Wells, 2017, p. 325). It is the intention of educators to prepare students for whatever paths they choose and equip them with the 21st century skills they will need to problem-solve down those paths. Over the past century, technology education and engineering education have evolved into recognized individual disciplines. The combined utilization of the content and practices of technology education and engineering education with the content and practices of science education and mathematics education forms the foundation for Integrative STEM Education (I-STEM ED) (Wells, 2008). Over the past few decades, I-STEM ED has helped to answer the call for educators in all four disciplines to work collaboratively to prepare students for life ((ITEA, 2001/2007, renamed the International Technology & Engineering Educators Association, ITEEA)).

I-STEM ED is defined as "the application of technological/engineering-design-based approaches to intentionally teach content and practices of science and mathematics education concurrently with content and practices of technology/engineering education." (Wells & Ernst, 2012/2015). The difference between commonly known science, technology, engineering, and mathematics (STEM) and I-STEM ED lies in the "I" or "Integrative" pedagogy which utilizes the collaboration between the STEM disciplines in an ongoing, learner-centered context (Wells, 2013). Technology/engineering design-based learning (T/E DBL) is a pedagogical approach which combines the content and practices of the four I-STEM ED disciplines to design a solution to solve real-world problems (Wells, 2019). Educators intentionally guide instruction so students experience a need for specific disciplinary content and skills to make decisions regarding their designed solution.

Mathematics is the conceptual language for science, technology, and engineering (ITEA, 2001/2007). In the *Standards for Technological Literacy*, ITEA specifically addresses the importance of mathematical concept knowledge and designerly skills stating that, “mathematical concepts, such as the use of measurement, symbols, estimation, accuracy, and the idea of scaling and proportion are key to developing a product or system and being able to communicate design dimensions and proper function” (2001/2007, p. 50). Proficiency in mathematical concept knowledge is vital for the communication of ideas between STEM disciplines. Mathematical literacy, including statistical literacy, is needed to analyze data to make informed design decisions (English, 2015).

Several studies have analyzed the connections between variations of design-based learning and specific science content knowledge (Wells, 2016a; Kolodner, Camp, Crismond, Fasse, & Gray, 2003; Holbrook, Gray, Fasse, Camp, & Kolodner, 2001; Fortus, Dershimer, Krajcik, Marx, & Mamlok-Naaman, 2004; Doppelt, Mahalik, Schunn, & Krisinski, 2008; Mehalik, Doppelt, & Schunn, 2008; Schnittka and Bell, 2010). A few studies have analyzed the relationships between engineering design, mathematical thinking, and science content knowledge (Kelly and Sung, 2017), engineering design and mathematical and science concepts (Akins and Burghardt, 2006), and mathematics infusion into engineering/technology education and mathematics content knowledge (Burghardt, Hecht, Russo, Lauckhardt, & Hacker, 2010). However, there is a limited amount of research analyzing the relationships between technology/engineering design-based learning and concept knowledge of specific mathematics content.

Nature of the Problem

Problem-solving in the 21st century will require students to use skills to solve problems that have not yet been introduced or even imagined. For students to be prepared for their unknown future, they must be able to make informed decisions about their world (Wells, 2016b). Technology/engineering design-based learning provides a context through which educators can give students experiences designing solutions for the real world to build those 21st century problem solving skills. Because mathematics is a communication tool for science, technology, and engineering, students need to be proficient in mathematical concept knowledge (ITEA, 2001/2007). Regular mathematics assessment internationally and nationally through the Programme for International Student Assessment's (PISA), the Trends in International Mathematics and Science Study (TIMSS), and National Assessment of Educational Progress (NAEP) indicates a global emphasis on the importance of mathematics education (The Organisation for Economic Co-operation and Development's (OECD), 2020; The National Center for Education Statistics (NCES), 2022e). However, most eighth-grade students in the U.S. either do not demonstrate proficiency or score lower than average in mathematical knowledge on international, national, and many state assessments.

The PISA, administered every three years, measures how well 15-year-old students internationally use knowledge in reading, mathematics, and science to face real-world challenges (NCES, 2022e). Specifically on the mathematics portion of the PISA, students are asked to "employ and interpret mathematics in a variety of contexts to describe, predict and explain phenomena, recognizing the role that mathematics plays in the world" (OECD, 2022, para. 2).

On the most recent 2018 PISA, students in the U.S. scored below 24 out of 36 other OECD educational system members. The TIMSS measures trends in scientific and mathematical proficiency internationally every four years in grades four and eight (NCES, 2022g). The NCES reports that there were no significant changes to eight grade scores in mathematics between the 2015 TIMSS and the 2019 TIMSS (2022b). Eighth graders in the Unites States ranked eleventh out of the 46 education systems participating internationally. These two international assessments indicate that the majority of eight grade students cannot use mathematical concepts and skills to solve real-world problems. National assessments, such as the NAEP, further support these findings.

The NAEP, also known as “The Nation’s Report Card”, is used to assess samples of students nationally biyearly in reading, math, science, writing, arts, civics, geography, economics, US history, and technology and engineering literacy (TEL) in the crucial academic periods of grades four, eight, and twelve (National Assessment Governing Board, 2022). The results of the 2019 Mathematics NAEP, given to approximately 147,400 eighth-grade students, indicate that only 34% of students in the United States were at or above proficiency in mathematics conceptual and procedural knowledge. This percentage has remained the same since 2009 (NCES, 2022d) again indicating that need to examine best practices in the mathematics classroom to increase students’ mathematics concept knowledge.

Even at the state level, the majority of eighth grade students are not demonstrating proficiency in mathematics. High stakes testing in states, such as West Virginia, focuses on priority disciplines, such as reading and mathematics, in grades three through eight (West Virginia Department of Education, 2019). Over the past five years on the West Virginia General Summative Assessment (WVGSA), the number of students reaching mathematical proficiency has not exceeded 39 percent (West Virginia Department of Education, 2022), further supporting the need for investigation into pedagogical approaches which foster increased mathematical concept knowledge.

The TEL NAEP, measuring real-life application of technology and engineering, was given for the first time to eighth graders in 2014, but most recently in grade eight in 2018 to approximately 15,400 students. The inclusion of the TEL NAEP demonstrates the growing importance of technological and engineering literacy in the United States (NCES, 2022h). On the 2018 TEL NAEP, 46% of eighth-grade students were proficient in technological and engineering literacy. Although awareness of the educational benefits of technological literacy for teaching STEM disciplinary content and practice has risen, the pedagogical approaches K-12 educators should take to promote such literacy is not yet well established.

Rationale for the Study

Technology and engineering educators have long promoted mathematics integration into technology, engineering, and science education curricula (ITEA, 2001; Wells, 2008; Flowers, 2014). The National Council of Teachers of Mathematics (NCTM) (2000) emphasizes the importance of learning mathematics in context. In Standard 3 of the *Standards for Technological Literacy,* ITEA recognizes the close relationship between technology, science, and mathematics in technology education (2001/2007). T/E DBL provides a contextual experience within technology and engineering education that emphasizes a need to have mathematical concept knowledge to solve a problem.

When students are asked to design a T/E DBL solution to a real-world problem, they are engaged in the design process and recognize the need to communicate their concept knowledge for the sake of the success of their design. Students with higher levels of conceptual understanding know the importance of mathematical ideas and the appropriate contextual application for those ideas. Conceptual understanding can be demonstrated through the ability to make and justify design decisions based on mathematical reasoning described by the student (Mahalik, Doppelt, & Schuun, 2008).

Standard 3 of the *Standards for Technological Literacy* (ITEA, 2001/2007) states that students benefit from learning through the relationships between technology and other fields of study. Specifically, in relation to mathematics, technological ideas and skills “may be used to build a representation of data collected during mathematics instruction” (ITEA, 2001/2007, p. 46). The *Principals and Standards for School Mathematics* provide that “students should learn how to collect data, organize their own or others’ data, and display the data in graphs and charts that will be useful in answering their questions” (NCTM, 2000, p. 50). These two national standards demonstrate the necessity in teaching the mathematical concepts of patterns of association between bivariate measurement data and lines of best fit through T/E DBL in the eighth-grade mathematics classroom. T/E DBL gives students a context though which to learn the usefulness of data collection and analysis relative to science, technology, and engineering.

Middle school mathematics concept knowledge provides a foundation for higher level mathematics (Iuculano & Menon, 2018). According to the NCTM (2000), students in middle grades, specifically, must understand concepts related to bivariate data so they can better understand later concepts. However, recent data from international, national, and state assessments indicate that most students are not proficient in mathematics. Within the growing body of research documenting the benefits of an integrative STEM education pedagogy (ITEA, 2001/2007; NCTM, 2000; Wells, 2008) for teaching disciplinary content and practice, there remains a gap in the research investigating the ways in which T/E DBL promotes change in mathematical concept knowledge of eight grade mathematics students as they learn to make informed 21st century decisions to solve problems. Specifically, because eighth grade students nationally continue to demonstrate a lack of proficiency in mathematics, research is necessary to examine “which integrative approaches put mathematics most effectively to the forefront of learning experiences” (Fitzallen, 2015, p. 243). Studies are needed to investigate this gap in the research examining the relationships between T/E DBL and change in mathematical concept knowledge.

Purpose of the Study

The goal of I-STEM ED is to develop students into citizens who are scientifically, technologically, engineering, and mathematically literate. A mathematically literate individual can “formulate, employ, and interpret” mathematics (OECD (2010) as cited in Jablonka & Niss, 2014, p. 391). As indicated through state, national, and international assessments reflecting the status of students’ mathematical knowledge, there is a clear need in the United States for increased proficiency in mathematics. T/E DBL provides an avenue through which mathematics educators can increase mathematics proficiency by engaging students in an environment where grade-level mathematics concept knowledge is needed to design a solution to a real-world problem. By intentionally teaching mathematical concepts through experience, T/E DBL provides a context for students to use their eighth-grade mathematical concept knowledge to solve problems in the 21st century.

The purpose of this research is to document the ways in which the pedagogical approaches of T/E DBL are shown to promote change in concept knowledge of eighth grade mathematics students. Specifically, this research seeks to demonstrate how the utilization of T/E DBL in an eighth-grade mathematics classroom has the potential to foster a change in concept knowledge of patterns of association between bivariate measurement data and lines of best fit used to model relationships between two quantitative variables on a scatter plot through informed design decision-making in a 21st century problem context.

Research Questions and Sub-Questions

The following research questions were developed from the problem statement and will be used to guide this research.

RQ1 – What evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) documents a change in concept knowledge of:

a) patterns of association between bivariate measurement data on a scatter plot, and
b) lines of best fit used to model predictive relationships among two quantitative variables on a scatter plot

Definition of Terms

Assessment

The analysis of what learners know (De Giacomo et al., 2012).

Bivariate Data

A type of data involving two variables (NCTM, 2000).

Conception

A mental representation of an interpretation, or perspective, of information. (Simon, 2017; Henze & DeVries, 2021)

Concept Knowledge

A cluster of related generalizations derived from knowledge, including procedural, declarative, and conceptual knowledge (Sierpinska, 1994; Henze & DeVries, 2021)

Conceptual Knowledge

Knowing why; an understanding of the relationships between information that a person knows. (Scheffler, 1965).

Conceptual Understanding

The abstract process of connecting one piece of knowledge to another (Sierpinska, 1994).

Declarative Knowledge

Knowing that (Ryle, 1949).

Design

A distinct form of problem solving including the "process of forming plans and developing products to solve a problem or address an opportunity to meet human needs or desires" (Daugherty, Mentzer, Kelley, 2011, p.50).

Design-Based Learning

An educational approach providing learning opportunities utilizing inquiry and reasoning through the design of a solution to an open-ended problem (Gómez Puente, Van Eijck, & Jochems, 2012).

Design-Based Biotechnical Learning

An educational approach providing learning opportunities utilizing inquiry and reasoning through the design of a solution to an open-ended problem requiring biological and technological knowledge and skills (Gómez Puente, Van Eijck, & Jochems, 2012; Wells & Van de Velde, 2020).

Engineering

An application of science to the design of objects in the real world (Feibleman, 1961).

Engineering Design

An iterative process in which an open-ended problem is solved through a clearly communicated design (Daugherty, Mentzer, Kelley, 2011).

Habits of Mind

Mental habits that help students develop a repertoire of approaches to be applied in a variety of situations as needed to solve problems (Cuoco, Goldenburg, & Mark, 1996).

Instruction

The instructor's manipulation of the learning environment to foster learning (De Giacomo et al., 2012).

Integrative STEM Education

“the application of technological/engineering-design-based approaches to intentionally teach content and practices of science and mathematics education concurrently with content and practices of technology/engineering education.” (Wells & Ernst, 2012/2015).

Knowledge

“an individual’s personal stock of information, skills, experiences, beliefs, and memories” (Alexander, Schallert, Hare, 1991, p. 317).

Learning

The process of increasing knowledge (Greeno, Collins, & Resnick, 1996).

Learning Theory

An educator’s view of learning, knowledge, and the learning process (Tolman, 1948; Piaget, 1971; Bruner, 1960; Dewey, 1938).

Mathematical Concept

A cluster of related generalizations derived from various types of knowledge typically grouped under one name or phrase (Sierpinska, 1994; Henze & DeVries, 2021).

Mathematical Concept Knowledge

A researcher’s articulation of a student’s generalizations, derived from procedural, declarative, and/or conceptual knowledge, that are the result of reflective abstraction (Henze & DeVries, 2021; Sierpinska, 1994; Simon, 2017; Star & Stylianides, 2013).

Mathematical Conceptual Knowledge

What is known (knowledge of concepts and principles) and how it is known (general and abstract principles and connections) (Hiebert and Lefevre, 1986; Crooks and Alibali, 2014; Rittle-Johnson & Schneider, 2014; Rittle-Johnson, ,Schneider, & Star, 2015)

Mathematical Conceptual Understanding

"comprehension of mathematical concepts, operations, and relations" connecting mathematical conceptual knowledge and strategic knowledge (Kilpatrick, Swafford, Findell, 2001, p. 5).

Mathematical Habits of Mind

"specialized ways of approaching mathematical problems and thinking about mathematical concepts that resemble the ways employed by mathematicians" (Sword, Matsuura, Cuoco, Kang, Gates, 2018, p.257).

Mathematical Procedural Knowledge

Knowledge of skill, formal language, symbols, and algorithms used to solve problems (Hiebert & Lefevre, 1986; ; Rittle-Johnson & Schneider, 2014).

Mathematical Literacy

"an individual's capacity to formulate, employ, and interpret mathematics in a variety of contexts. It includes reasoning mathematically and using mathematical concepts, procedures, facts, and tools to describe, explain, and predict phenomena" (OECD (2010) as cited in Jablonka & Niss, 2014, p. 391).

Procedural Knowledge

Knowing how (Ryle, 1949).

Technology

The "knowledge, skills, and practices" which include designing, making, and using technology that is driven by human will and need (Kelley & Knowles, 2016, p. 6).

Technology Design

An iterative process in which an open-ended problem is solved through a form of technology clearly communicated through a constructed prototype (Daugherty, Mentzer, Kelley, 2011).

Technology/Engineering Design-Based Learning

The primary pedagogical approach used to teach Integrative STEM Education which strategically combines the content and practices of the four I-STEM ED disciplines, collaboratively using technology and engineering design to help students develop higher order thinking skills used by experts to design solutions to real world problems (Wells, 2013).

Technological Literacy

The ability to use, manage, assess, and understand technology (ITEA/ITEEA, 2007, p. 9).

Skills

The application of knowledge (Bialik & Fadel, 2015).

Statistical Literacy

“the ability to understand and make use of statistical information including methods” (Grant, 2017, p. 17).

Strategic Knowledge

The knowledge of processes to utilize other types of knowledge that a person has (Alexander, Schallert, & Hare, 1991).

21st Century Skills

Those skills, including academic, critical thinking, communication, collaboration, and creativity, which can be used to increase the success of students in the 21st century (NEA, 2012).

CHAPTER TWO: LITERATURE REVIEW

Overview

The research problem required thorough review of literature related to the theoretical framework for this study, Integrative STEM Education, and research intentionally structuring design-based learning to teach disciplinary content. The information gathered from the literature review supports the research design chosen by the researcher. First, language associated with learning is defined, and theories of learning are compared to build a theoretical framework for this study. Second, the development and use of technology/engineering design-based biotechnical learning (T/E DBL) in the mathematics classroom is discussed. Third, the research methodologies of previous studies utilizing DBL in the science and mathematics classrooms which influenced the research design of this study are presented.

Theoretical Framework

Over the past several decades, researchers have provided a variety of definitions for learning. Washburne (1936) states that learning is “an increase, through experience, of problem-solving ability” (p. 610). The works of Skinner (1938, 1953) influenced views on learning, such as that of De Houwer, Barnes-Holmes, and Moors (2013) who define learning as “an effect of experience on behavior.” Posner, Strike, Hewson, and Gertzog (1982) state that learning is a “rational activity” occurring when students fundamentally “comprehend and accept ideas because they are seen as intelligible and rational” (p. 212). These definitions provide a broad scope of what learning encompasses. They range from learning as an increase in mental ability to learning as a change in behavior. However, learning cannot affect behavior, problem solving, or rationalization unless there is an initial gain of some knowledge which inspired the change in behavior or ability. Changes in problem-solving ability, rationalization, and behavior are observable outcomes of learning. These observable changes do not address the process of learning itself. An early definition by Woodworth (1929) describes learning as a process through which mental traits are acquired. His thoughts are echoed in the later definition of learning by Greeno, Collins, and Resnick (1996) that “learning is the process by which knowledge is increased or modified” (p.20). Learning is a mental process observable in many forms. However, the observable effects of learning are initiated by a gain in some type of knowledge. Thus, a definition for the term knowledge is necessary.

Knowledge

Learning is the process of increasing knowledge (Greeno et al., 1996). In broad terms, knowledge can be described as “an individual's personal stock of information, skills, experiences, beliefs, and memories” (Alexander, Schallert, & Hare, 1991, p. 317). However, decades of relevant literature have continued to narrow the scope of *knowledge* into several knowledge types. Among those, two knowledge types have consistently resonated and developed over time. Ryle (1949) described two early categories of knowledge - “knowing how” and “knowing that” (p.17). “Knowing how” is associated with knowing steps and skills for doing. “Knowing that” refers to the factual beliefs and understandings that one has. Similarly, Bruner (1960) discussed knowledge in terms of skills and general ideas. He emphasized the role of education on increasing both types of knowledge so that they are useful to students futuristically. Scheffler (1965) later accentuated the complexity of the concept of knowledge, providing the more detailed description of what it entails:

> “… the range of the everyday concept of knowing is very wide, including familiarity with things, places, persons, and subjects, competence in a variety of learned performances,

and possession of ostensible truths on matters of fact as well as faith, the fallible items of science and everyday experience, as well as the alleged certainties of mathematics and metaphysics" (p.2).

Scheffler (1965) contributed to the further development of knowledge types by introducing knowledge as a concept. He stated that the "concept of knowing is related in important ways to other fundamental and difficult ideas" (p. 2). He described the acquisition of an understanding of information, better known today as conceptual knowledge. In 1983, Anderson's cognitive psychology work provided empirical evidence for the existence of two additional knowledge types: procedural knowledge and declarative knowledge.

In mathematics education specifically, mathematical knowledge is widely recognized and categorized into procedural and conceptual knowledge (Hiebert & Lefevre, 1986; Rittle-Johnson, Siegler, & Alibali, 2001; McCormick, 2004; Star & Stylianides, 2013). In relation to mathematics, Hiebert and Lefevre (1986) distinguish between procedural and conceptual knowledge as the knowledges of skill and understanding, respectively. They more specifically define procedural knowledge as the composition of formal language and algorithms used in mathematics and conceptual knowledge as "knowledge that is rich in relationships" (p.3).

Thus far, three types of knowledge have resonated through many years of research - procedural (knowledge of skills), declarative (knowing that), and conceptual knowledge (knowing why). However, Li (2002) recognizes four types of knowledge declarative (knowing that), procedural (knowing how), schematic (knowing why), and strategic (knowing when, where, why, how). Her description of schematic knowledge as knowledge of principles and mental models of related concepts mirrors the description of conceptual knowledge within much research in mathematics (Hiebert & Lefevre, 1986; Rittle-Johnson et al., 2001; McCormick, 2004; Star & Stylianides, 2013). Also similar to Li (2002), Alexander, Schallert, and Hare (1991) discuss strategic knowledge as the knowledge of processes to utilize other types of knowledge that a person has. The several decades of research presented allude to the breakdown of conceptual knowledge into the two categories of schematic knowledge (knowing why) and strategic knowledge (knowing when, where, why, and how to use all other knowledge types). Figure 1 shows the relationships between knowledge types.

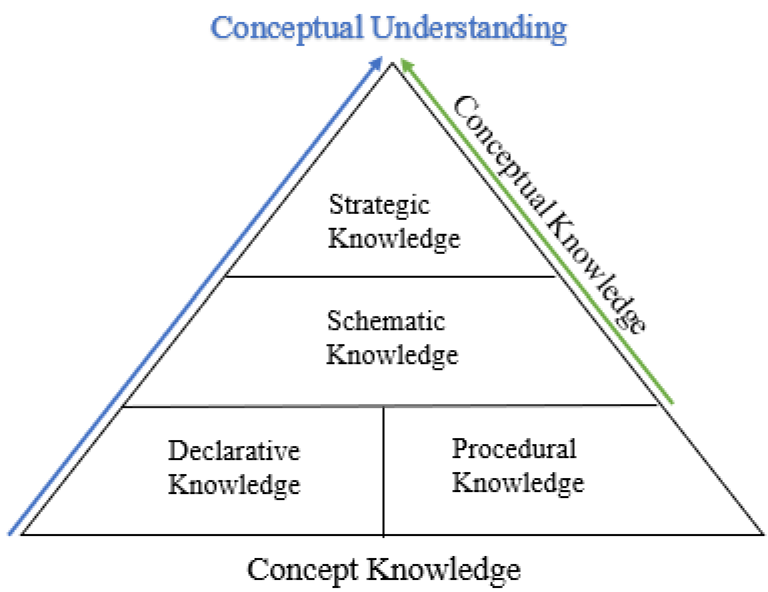


Figure 1. Relationships between knowledge types.

Through the process of learning, students gain various types of knowledge about a concept. Students gather information and synthesize it so that it can that can be accessed as needed. Through experience, they learn when, where, why, and how to use their knowledge, ultimately reaching a level of conceptual understanding of the concept. It is imperative that educators understand the process of learning to create ample opportunities for students to learn.

Conceptual Language

Concept Knowledge

Concept knowledge describes a cluster of related generalizations derived from various types of knowledge, including procedural, declarative, and conceptual (including schematic, and strategic knowledge) (Li, 2002; Henze & DeVries, 2021). These generalizations are typically grouped under one concept name or phrase. For example, the concept of multiplication is an umbrella for the knowledge of procedures to solve a multiplication problem, the symbols related to multiplication, the understanding of what happens as something multiplies, where and when multiplication is useful, and other knowledge related to multiplication.

Conceptual Knowledge

Conceptual knowledge is knowing why; more specifically, conceptual knowledge is *an* understanding of the relationships between information that a person knows (Scheffler, 1965). The specification of "an" understanding instead of "the" understanding is based on the premise of conceptions and preconceptions. A conception is a student's mental representation of their interpretation, or perspective, of information (Simon, 2017; Henze & DeVries, 2021). Students come into the classroom with pre-conceptions, their conceptions prior to instruction, of conceptual knowledge that may be scientifically correct or incorrect (Henze & DeVries, 2021). Students may have "an" understanding that is scientifically incorrect but makes sense to them based on the context in which the knowledge was gained. Conceptual knowledge exists within the spectrum of conceptual understanding. Students have lower (schematic) or higher (strategic) levels of conceptual knowledge based on their understandings.

Mathematical Conceptual and Procedural Knowledge

In mathematics, conceptual knowledge has been thoroughly studied to encompass specific mathematics-focused elements. In 1903, Bertrand Russell stated in his book, *The Principles of Mathematics*, "The fact that all Mathematics is Symbolic Logic is one of the greatest discoveries of our age; and when this fact has been established, the remainder of the principles of mathematics consists in the analysis of Symbolic Logic itself" (p.5). In this discussion of pure mathematics, Russell reveals the two categories of mathematical knowledge that are most prevalent in studies of mathematics today and that Hiebert and Lefevre (1986) distinguish between - procedural knowledge and conceptual knowledge. Mathematical procedural knowledge refers to knowledge of skill, formal language, symbols, and algorithms used to solve problems (Hiebert and Lefevre, 1986; Rittle-Johnson &Schneider, 2014). A connection can be made between mathematical procedural knowledge and Russell's (1903) reference to mathematics as a knowledge of symbols. Mathematical conceptual knowledge is defined by Hiebert and Lefevre (1986) as "knowledge that is rich in relationships" (p.3). However, conceptual knowledge is more recently described by what is known (knowledge of concepts and principles) and how it is known (general and abstract principles and connections) (Hiebert and Lefevre, 1986; Crooks and Alibali, 2014; Rittle-Johnson &Schneider, 2014; Rittle-Johnson, Schneider, & Star, 2015). A connection can be made between conceptual knowledge and Russell's (1903) reference to mathematical logic. In synthesis, mathematics knowledge consists of a knowledge of procedures, symbols, skills, and algorithms and the knowledge of their derivation, rationality, use, and the connections between them.

Procedural knowledge is used to calculate solutions but does not require logical connections or an understanding of the rationalization behind the knowledge. Conceptual knowledge connects procedures and mathematics principles to logic. Gaining conceptual knowledge leads students to an understanding of where the procedure originated, how it is used, when and where to use it, and how it applies or connects to other types of knowledge. Conceptual knowledge also correlates to an understanding of the connections between mathematics and other disciplines, such as science, technology, and engineering.

Mathematical Conceptual Understanding

A feature of conceptual knowledge is the increase of understanding of underlying connections that comes with expertise (Rittle-Johnson &Schneider, 2014). Conceptual understanding is the abstract process of connecting one piece of knowledge (procedural, declarative, schematic, strategic) to another (Sierpinska, 1994). The National Research Council (NRC) defines mathematical conceptual understanding, one of the five features of mathematical proficiency, as the "comprehension of mathematical concepts, operations, and relations" (Kilpatrick, Swafford, & Findell, 2001, p. 5). To gain mathematical conceptual understanding, students must have the ability to rationalize the mathematics knowledge they gain. Mathematical conceptual understanding is based on student recognition of patterns and outcomes, but students with higher levels of conceptual understanding know the importance of those patterns and the appropriate contextual application for those outcomes.

In the *Curriculum and Evaluation Standards for School Mathematics*, NCTM (1989) emphasizes the focus on "mathematical concepts and understanding" in mathematics curriculum. Particularly middle school students' formal operational stage of cognitive development allows them the ability to rationalize and think abstractly (Piaget & Inhelder, 1969). Through reflective abstraction of mathematical experiences and outcomes, learners recognize relationships between prior conceptions (Simon, 2017). The stability and reliability of these relationships builds mathematical conceptual understanding.

Learning Theories

An educator's view of learning, knowledge, and the learning process affects their instruction and the learning that happens in their classroom. To increase their own understandings and clarify their views, educators often turn to the works of educational psychologists, such as Tolman (1948), Piaget (1971), Bruner (1960), and Dewey (1938), who have studied aspects of the learning process and contributed to the development of learning theories. Learning theories begin as knowledge that is verified by scientific methods. That knowledge is then expressed as learning principles which, through rationalized patterns, may contribute to conceptual models of the learning process. When predictions made by the models are verified, elaborations and variations of the models become learning theories (Gagne & Driscoll, 1988). A learning theory is "a theory that describes what takes place while learning is going on and after learning has taken place" (Bruner, 1963). Learning theories provide educators with research-based information about the learning process that can be used to guide pedagogical decisions in the classroom.

A learning theory serves to provide an explanation of how the learning process takes place, including how students process information and increase knowledge. The learning process encompasses every phase of learning from internal sensory input to external environmental interactions. By analyzing the learning process through the theories that explain them, educators can choose pedagogical practices which best affect learning. Cognitivist learning theories serve to explain the internal process of learning. Constructivist learning theories contribute to the understanding of how students connect the knowledge they have internalized to new knowledge.

Experiential learning theory describes the effects of the external world on the learning process. Together, these theories contribute to a fuller description of the learning process than any learning theory alone. With an understanding of these processes, educators can effectively facilitate experiences that result in student learning.

Cognitivist Learning Theory

"Humans are processors of information" (Mayer, 2012, p. 85). Humans begin learning by processing information in the brain (Gagne & Driscoll, 1988). Significant amounts of research have contributed to the understandings of the cognitive processes which occur during learning. Kohler's (2013) experiments cognitively challenging apes contributed to the ideas of Gestalt theory of perspective and problem solving as a cognitive process. According to Gestalt theory, the learner looks at the whole of the problem, then proceeds to find a way to solve it. Tolman (1948), while working at University of California, Berkley, conducted experiments analyzing rats while they were navigating through mazes with and without rewards. Through variations of the experiments, the rats demonstrated complex mental processes through the formation of what Tolman (1948) called "cognitive maps" - mental configurations of the physical world (p. 193). Tolman expanded on the ideas of latent learning, originated by Blodgett (1929), that learning can occur without the use of rewards. Later, Miller, Galanter, and Pribram (1960) provided details about information processing and the effects of cognitive perceptions of inputs and outputs. The contributions of these researchers lay the groundwork for cognitivist learning theory.

Cognitivism relates to the cognitive progressions that occur when a learner experiences mental stimulation and processes the information received from that stimulus. The brain processes information in the five stages of: sensory sensation, perception, attention, encoding, and memory (Jordan, Carlile, & Stack, 2008). Cognitive stimulation begins with the perception of sensory input, leading to an attentive focus on the source of the sensory input. When sensory stimuli are perceived and attended to, the student begins to encode the information received into mental representation, or schema (Jordan, Carlile, & Stack, 2008). Schema, introduced by Bartlett (1932), is the term for the representations through which information is organized in the mind. When information is received, it is encoded, or organized, into schema. Schemata are then used as references to process other information in the form of short-term and long-term memory. Building on Miller's (1967) work with memory, Marton and Saljo (1976) describe two types of information processing: surface-level and deep-level processing. When learners partake in surface level processing, they are often using their short-term memory to reference information they have received. Students who experience deep-level processing seek to understand the intended content, activating their long-term memory. Cognitivist learning theory supports the effective use of organization and processing of information leading to an increase in knowledge - learning.

Constructivist Learning Theory

As students learn, they construct knowledge and understanding by building on what they already know and integrating it with new information. This is the foundation for constructivist learning theory. Piaget and Inhelder (1969) contributed to the understanding of a child's cognitive abilities at progressive stages of development as they grow physically and mentally. According to Piaget and Inhelder (1969), the cognitive development of children happens in four stages: sensory motor stage (0 - 2 years), preoperational stage (2 - 7 years), concrete operations stage (7 - 11 years), and formal operational stage (11 - 15 years). All children progress through each stage in their own time - some children remain in one stage longer than others. As children move through these stages their cognitive ability transforms from reliance on concrete representations to an ability to reason more abstractly and logically. This abstract cognitive ability reached in the formal operational stage aligns with the views of Posner et al. (1982) on cognitive conceptual change as learners are able to rationalize ideas. It is the responsibility of educators to present developmentally appropriate content to their students (Ojose, 2008).

Bruner (1960) references these four stages of development when discussing a child's conceptual development. Bruner (1960) states that "what is most important for teaching basic concepts is that the child be helped to pass progressively from concrete thinking to the utilization of more conceptually adequate modes of thought" (p.38). As children grow cognitively, their ability to rationalize increases. When introducing new knowledge (cognitive learning theory), young children relate best to sensory input and concrete modeling of ideas. As they gain knowledge, they build on the knowledge they already have, increasing their understanding of the connections between knowledge and the ability to think abstractly about those concepts. The abstract thought processes of a child strengthen with each stage of development. Bruner (1960) also states that any child can learn any subject as long as the material is presented in a developmentally appropriate manner. He calls for educators to introduce knowledge early so that children may build upon that knowledge as they continue to develop physically and intellectually.

Constructivist learning theory can be segmented into three perspectives. Trivial constructivism emphasizes the role of the individual in acquiring knowledge. Social constructivism examines knowledge affected by the learner's perception and environment. Critical constructivism utilizes reflection as an important part of the learning process (Jordan, Carlile, & Stack, 2008). Bruner (1961) found that children construct new knowledge based on their existing knowledge in an active learning process of discovery. During this process, the learner “selects and transforms information, constructs hypotheses, and makes decisions, relying on a cognitive structure” (Clabaugh, 2010, p. 398). Bruner (1961) was an advocate for student participation in discovery learning to promote life-long learning and effective memory retrieval. He emphasized that those students who are active participants in their education are better able to discover information for themselves and recollect what they have learned.

Experiential Learning Theory

Experiential learning theory encompasses learning which occurs through experiences. An experience is an “active engagement with the environment” by the learner (Boud, Cohen, & Walker, 1997, p.6). Kolb’s (1984) definition of learning as “the process whereby knowledge is created through the transformation of experience” supports experiential learning theory (p. 38). In the early twentieth century, Dewey (1938) encouraged the transformation of education from a teacher-centered traditional setting where students are provided factual information to a student-centered setting where students learn through interactions with the world. The basis for this transformation was the preparation of students to use knowledge to help them face current and future issues. Although Dewey’s (1938) ideas called for educational reform almost a century ago, his reasons for doing so are still relevant in today’s educational system and society. The goal of education today remains the development of individuals who can utilize knowledge to solve problems in their world (Wells, 2017).

Dewey (1938) stresses the importance of meaningful experiences by providing criteria for such - an educational experience must be engaging and promote continuity. Educational experiences that promote continuity influence later experiences and stimulate intellectual and moral development. It is the role of the teacher to provide experiences that stimulate this growth and continuity. By articulating specifically these intended learning outcomes, teachers can intentionally drive instruction through experience (Cross, 1982). The decisions educators make in the classroom influence the learning that happens inside and outside of the classroom.

Comparing and Contrasting Learning Theories

Many constructivists understand the influence of experiences on the construction of knowledge and learning (Cottrill, 2003). Piaget's (1973) views on understanding and invention support the views of experiential learning theorists, such as Dewey (1938), that children are investigators of their environment and learn from their first-hand experiences with the world. Bruner (1960) also discusses the importance of a child's environment to their development and education. Cognitive psychologists have used participant experiences in problem solving to investigate the cognitive process involved in learning (Kohler, 1925; Tolman, 1948). The major differences between these theories relate to the initial influence on the increase of knowledge. In cognitive learning theory, information is processed in the brain when a learner receives sensory (sight, smell, taste, touch, sound) input that heightens their focus on that source of information. The brain then categorizes the information into schema, and it is stored as either short-term or long-term memory to be accessed later. Constructivist learning theory builds on this theory in the sense that humans cognitively develop and mentally process different types of information as they grow. Constructivists examine the difference in information processing and perception between humans at different developmental stages, emphasizing the need for concrete representations of information at a younger age when abstraction is minimal. There is a difference in the need for physical sensory perceptions for younger learners and the abilities of learners to learn more abstractly as they grow. Experiential learning theory also focuses on the sensory perception of the learner but does not focus on the internal cognitive processes which help develop meaning for these experiences. Instead, focus is on the environment through which students learn. Figure 2 highlights the connections and differences between these three learning theories.

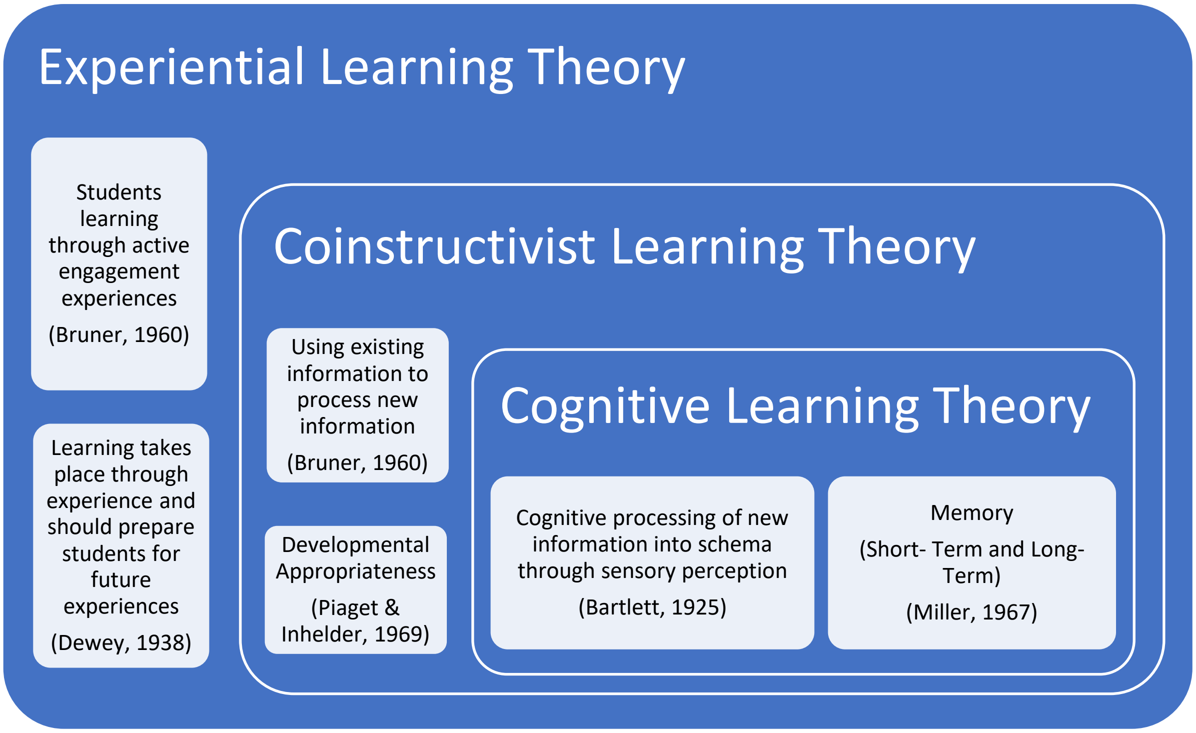


Figure 2. The relationships between learning theories.

In Figure 2, cognitive learning theory is in the inner most section of the graphic because it explains the most internal processes of learning, from sensory perception to the storage of information into memory, taking place in the mind. Constructivist learning theory is in the center of the graphic because it builds on cognitive theory of processing to build new information from existing information – making connections between the two. Constructivist learning theory also connects with experiential learning theory through the developmentally appropriate experiences that students need in order to learn. Experiential learning theory is on the outer layer of the graphic because it focuses on the influences of external environmental experiences students have while gaining knowledge. However, cognitive learning theory is still needed to process information gained by these experiences, leaving cognitive learning theory still within the shape of experiential learning theory. Individually, these learning theories focus on learning through three different lenses, but together, they explain the process of learning as an entity from an internal to external perspective.

Technology/engineering design-based learning (T/E DBL) allows students to explore and learn disciplinary content as they are independently and developmentally ready. By keeping in mind the cognitivist, constructivist, and experiential learning theories, educators can provide engaging experiences of interest to students that promote continuity in a way that is developmentally appropriate for the child's cognitive ability. T/E DBL exemplifies a natural combination of these theories through student engagement in real world problems that require a designed solution. Students are interested in the solution to an authentic problem (cognitive learning theory), students analyze the problem and design a solution based on their individual interests (experiential learning theory) and cognitive abilities while seeking the subject matter which helps them complete their design solution (constructive learning theory). Educators intentionally design these experiences to teach specific subject matter (Wells, 2019). Throughout these learning experiences, students collaborate to design their solution.

Summary of Theoretical Framework

A theoretical framework serves to discuss the feasibility of a researcher's approach to answering a research question (Lederman & Lederman, 2015). The researcher reviews literature about the phenomenon they wish to study, including theories and previous studies on similar topics. The literature provides guidance and support for the lens through which the research is conducted.

Cognitivist, constructivist, and experiential learning theories describe the internal processes and external influences involved in learning, forming the theoretical framework for this study. Learning is the process of increasing knowledge (Greeno et al., 1996). Knowledge can be categorized into several types including declarative, procedural, schematic, and strategic knowledge. (Ryle, 1949; Bruner, 1960; Scheffler, 1965; Anderson, 1983; Alexander, Schallert, Hare, 1991; Li, 2002). Cognitive psychologists, such as Tolman (1948) and Miller (1967), have contributed to the understandings of how new information is processed in the brain and stored through memory. Cognitivist theory describes the process through which students are perceptively intrigued and mentally engaged in their environment. This engagement leads to the formation of schema, or mental representations, which help organize information in the brain (Bartlett, 1932). Constructivists recognize the importance of activating prior knowledge to construct new knowledge. Constructivist learning theorists, such as Bruner (1960) and Piaget (1971), have contributed to the process of using existing knowledge to make connections to new knowledge at developmentally appropriate levels. These connections build understanding of relationships between information, increasing conceptual (schematic and strategic) knowledge. Experiential learning theory examines the influences of the environment on student active participation in the learning process. Through experience, students gain understanding of how and when to use other knowledge types (declarative, procedural, schematic), increasing their strategic knowledge (Wells, 2016a) and overall conceptual understanding. T/E DBL provides students with experiences that promote learning opportunities.

Integrative STEM Education

The goal of education for the past century has been the preparation of students who are adequate decision makers and can face current and future issues in the real world (Bonser & Mossman, 1923; Dewey,1938; Wilber & Pendered, 1948/1967; Raizen, Sellwood, Todd, & Vickers, 1995). The focus of education today continues to be the preparation of students to utilize knowledge to solve problems in the real world (Wells, 2017). However, as the world has evolved, the issues that people face in their daily lives have also evolved, becoming more complex than could have been anticipated a century ago. Thus, as the societal and workplace demands of people have become increasingly complex, the education system must continue to help students become adults who can meet these demands by taking these complexities into pedagogical consideration.

Technology and engineering education serves as integrator of the academic and innovative skills necessary for life in the 21st century (Miaoulis, 2010; Burdick & Willis, 2011; Goldstein, Omar, Purzer, & Adams, 2018; Johnston, Akarsu, Morre, & Guzey, 2019). Design-based learning is the primary pedagogical strategy used in both technology and engineering education through which students learn specific disciplinary content through the design of a solution to a real-world problem (Fortus, Dershimer, Krajcik, Marx, & Mamlok-Naaman, 2004). Studies have shown that students can learn academic, communication, collaboration, and decision-making skills through design- based learning (Kolonder, Gray, & Fasse, 2003; Fortus et al., 2004; Doppelt, Mehalik, Schunn, & Krysinki, 2008).

Integrative STEM Education (I-STEM ED) is defined as "the application of technological/engineering-design-based approaches to intentionally teach content and practices of science and mathematics education concurrently with content and practices of technology/engineering education" (Wells & Ernst, 2012/2015). Technology/engineering design-based learning (T/E DBL) is a pedagogical approach which combines the content and practices of technology and engineering education to teach science and mathematics content and practices through the design of a solution to a real-world problem (Wells, 2019). Through T/E DBL, educators purposefully design instruction so that students experience a need for specific disciplinary content and skills to make decisions regarding their designed solution. The goal of I-STEM ED is for students to use higher order thinking skills (strategic knowledge) while designing to understand content (declarative, procedural, and schematic knowledge) intentionally taught through technology/engineering design-based learning (T/E DBL) (Wells, 2016b).

Development of Technology and Engineering Education

What was considered an adequate education a century, or even 50 years, ago is not sufficient for the preparation of students for college, careers, and citizenship today in the 21st century (National Education Association (NEA), 2012). In 1893, when Charles Elliott met with the "Committee of Ten" to prioritize educational disciplines, the world was largely based on agrarian and manufacturing economies, lifestyles, and careers (Miaoulis, 2010). The disciplines deemed necessary to be taught in schools then (e.g. biology, chemistry, physics) did not include technology or engineering because of the nature of technology of that time – technology largely included tools that were farm-based and learned about at home. In 1923, Bonser and Mossman highlighted the importance of student understanding of the "products of industry" through industrial arts education so students can sufficiently use them in everyday life (p.6). This real-world application aligned with Dewey's (1938) ideas about an experiential, student-centered education and the necessary reform of teacher-centered pedagogical practices.

By the 1960s, a shift began to emerge in the paradigm of industrial arts education. Warner, Gary, Gerbracht, Gilbert, Lisack, Kleintjes, & Phillips (1947/1965) operationally defined the industrial arts through the function, scope, content, method, physical setting, and history necessary to successfully teach it. Their work outlined curriculum goals and connections between the industrial areas of management, communication, construction, power, transportation, and manufacturing which were being promoted in all levels of education. Sanders

(1997) recognized the work by Warner et al. (1947/1965) as the groundwork behind the much-needed curriculum for technology education.

In *The Maryland Plan,* Smith (1970) addressed the need to prepare students to adapt to a "technically and socially changing" society (p. 9). Smith (1970) also advocated for a student-centered classroom, with the role of the teacher as facilitator, and the differentiation of instruction based on student need. Snyder and Hales (1981) moved even further toward what is now considered technology education by addressing "technological literacy" and recognizing products, services, or other resource outputs as part of technology in the *Jackson's Mill Industrial Arts Curriculum Theory* (p. 65). In 1985, The American Industrial Arts Association changed its name to The International Technology Education Association (ITEA) and published *Technology Education: A Perspective on Implementation* (1985) to explain the official shift in focus from industrial arts to technology education and how to implement such changes. The evolution of vocation-based industrial arts education into the general education discipline of technology education as "the study of technology and its effect on individuals, society, and civilization" can be seen in the *Conceptual Framework for Technology* Education (ITEA, 1990, p.20). ITEA (1990) sought to create awareness of what technology is, how it affects society, and how to effectively teach technology education as an educational discipline.

The evolution of industrial arts education into technology education in the 20th century paralleled the societal shift from the Industrial Age to the Knowledge Age. In 1991, United States spending on industrial goods, such as engines, machinery, and equipment ($107 billion), was surpassed by spending on information technology, such as computers and telecommunications necessities ($112 billion), marking the transition from the Industrial Age to the Knowledge Age (Trilling & Hood, 1999). In 1967, 54% of the American economy was based on material goods and services. By 1997, 63% of the economy was based on information goods and services (Partnership for 21st Century Skills, 2008). This change marked the shift from an industrial-based society (e.g., manufacturing, distribution, products) to a more knowledge-based society (e.g., data, information, expertise, services) (Trilling & Hood, 1999). Similarly, the skills and knowledge needed for students to be prepared for life and work shifted as well.

In 2010, ITEA changed its name to the International Technology and Engineering Education Association (ITEEA), officially recognizing the connections between technology and engineering education. ITEEA has since promoted the integration of technology and engineering education with science and mathematics education by developing curricula, such as Engineering by Design, and instructional models, such as 6E Learning by DeSIGN, to increase student knowledge through experiences in an Integrative STEM education context.

Technology/ Engineering Design Based Biotechnical Learning

Design based learning (DBL) is "an educational approach grounded in the processes of inquiry and reasoning towards generating innovative artifacts, systems, and solutions" (Gómez Puente, Van Eijck, & Jochems, 2012, p. 718). DBL allows students to take on the role of professionals to complete design challenges that require multidisciplinary knowledge and skills. Through design, students explore a problem, constraints of the problem, user perspectives, analyze prototype failure, and reflect on the design process (Gómez Puente, 2014). The difference between DBL and T/E DBL in Integrative STEM Education lies in the emphasis on technology and engineering design as the pedagogical focus of T/E DBL. Through T/E DBL, technology and engineering design content and practices are used to teach the content and practices of science and/or mathematics concurrently (Wells, 2019). Technology/engineering design based biotechnical learning (T/E DBBL) uses T/E DBL in the content area of biotechnology within the technology education discipline specifically. According to the following definition by the Office of Technology Assessment of the Congress of the United States (1991), biotechnology includes:

> "includes any technique that uses living organisms (or parts of organisms) to make or modify products, to improve plants or animals, or to develop micro-organisms for specific uses" (p.5).

A T/E DBBL design challenge requires specific biotechnical knowledge and skills to solve a real word problem through a biotechnical solution. A biotechnical solution, according to the definition of biotechnology, would require the use of a living organism to solve a technological problem. For example, students may design an organic energy source using electrons emitted from living organisms, such as benthal bacteria.

Design to Understand

The goal of T/E DBBL is the development of designerly ways of knowing that are necessary to design solutions to problems in the real world (Cross, 1982). These designerly ways of knowing relate to the cognitive demands inherent when utilizing knowledge types (declarative, procedural, schematic, and strategic) that promote deep-level processing (Wells, 2016a), described by Marton and Saljo (1976), which help students understand the content intended by the educator. Through T/E DBBL, students "design to understand" concepts intended by the teacher (Wells, 2017, p. 326). Students have "hands-on" experiences that engage them in learning science, technological, engineering, and mathematical concepts (Wells, 2019, p.2). These "hands-on" experiences lead to habits of hand (designerly abilities) that then lead to habits of mind (designerly ways of knowing) (Wells, 2019). As students engage in the design process, they are developing technology and engineering designerly skills that promote their cognitive development of academic concepts and 21st century skills.

Dewey (1938) described a habit as a way of responding to a condition that is met in life. Design requires distinct cognitive processes and abilities (Cross, 1982). As students experience the active design process, they develop habits-of-hand, or designerly abilities, that help them develop habits-of-mind, or designerly ways of knowing, that help them make decisions during the design process (Wells, 2016a).

Through T/E DBBL students are asked to complete a design challenge to solve an authentic real-world problem. Students seek academic scientific, technological, engineering, and mathematical (STEM) knowledge to design a solution to that problem. Depending on the design challenge, students must understand underlying concepts in multiple disciplines and how the content and practices in those disciplines are integrated in the design of a solution (Wells, 2019). Students design their solution in groups, utilizing the academic and skill-based strengths of each student in the group. In these groups, students learn to communicate their ideas for a design solution effectively and collaborate to decide on the most effective collective design. There are often physical, time, and other constraints that designers must consider in their design of a solution that are experienced by students through T/E DBBL. Students make decisions about their design, test the design, critique its effectiveness, and make further design decisions to create the best possible solution to the problem throughout an iterative design process (Wells, 2016b).

As students design solutions to a real-world problem, they naturally experience the iterative phases of the PIRPOSAL model, the design process aligned with T/E DBL (Wells, 2016c). The PIRPOSAL model describes eight phases of design that students naturally experience through T/E DBL. During the design process students define the problem, generate ideas, explore research, analyze potential solutions, construct and optimize their prototype, test and analyze their solution, alter or redesign the solution as necessary, and justify their learned outcomes (Wells, 2016c). Figure 3 depicts the phases of the PIRPOSAL model.

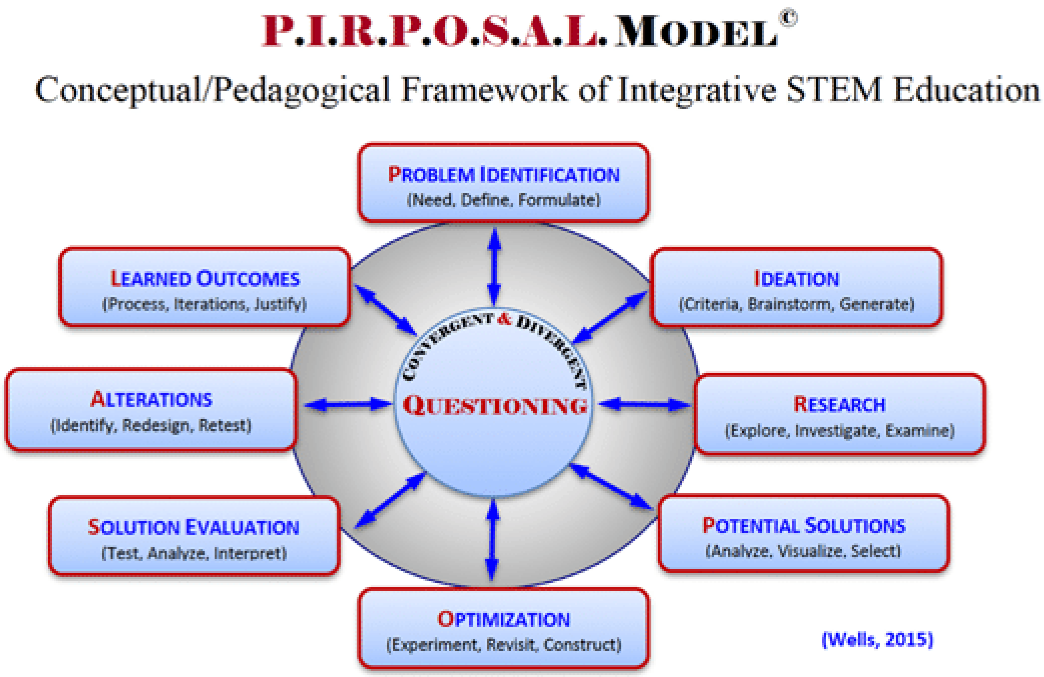


Figure 3. The PIRPOSAL Model of Integrative STEM Education. Reproduced from "PIRPOSAL Model of Integrative STEM Education: Conceptual and Pedagogical Framework for Classroom Implementation" by J.G Wells, 2016, *Technology and Engineering Teacher*, *75*(6), p. 15. Copyright 2016. Reprinted with permission.

An important feature of the PIRPOSAL model is the iterative nature of the design process demonstrated by the model. At any point in the design process, students revisit parts of the PIRPOSAL model as necessary. For example, if students are constructing their prototype and realize they need more information, they can revise their idea, conduct further research, and continue through the process repeatedly as needed until their desired solution is reached. Each phase of the model represents a design experience that leads to another experience as students solve problems through a need-to-know information to design their solution – an example of the continuity of experiences envisioned by Dewey (1938). The PIPOSAL model is not explicitly taught to students, rather it is an instructional tool used by educators to guide students as they learn through T/E DBL.

Using T/E DBBL to Teach Mathematics Content

Mathematical literacy, including statistical literacy, is necessary to analyze data to make informed decisions (English, 2015). NCTM (1989) states that a person who is mathematically literate has the ability "to explore, to conjecture, and to reason logically, as well as to use a variety of mathematical methods effectively to solve problems" (p.5). The Organization for Economic Co-operation and Development (OECD) (1999) provides the first explicit definition for mathematical literacy in the initial framework for the Programme for International Student Assessment (PISA) (Jablonka & Niss, 2014). The OECD (2010, p.4) version of the definition for mathematical literacy reads:

> "Mathematical literacy is an individual's capacity to formulate, employ, and interpret mathematics in a variety of contexts. It includes reasoning mathematically and using mathematical concepts, procedures, facts, and tools to describe, explain, and predict phenomena. It assists individuals to recognise the role that mathematics plays in the world and to make well-founded judgments and decisions needed by constructive, engaged and reflective citizens."

By this definition, cognitive, constructivist, and experiential learning theories support the use of technology/engineering design-based biotechnical learning (T/E DBBL) to foster mathematical literacy to create a mathematically literate individual who can "formulate, employ, and interpret" mathematics. Cognitive learning theory explains how individuals can come to “formulate” mathematics knowledge through the processing and storage of information. Constructivist learning theory discusses how to build on that formulated knowledge to learn to “employ and interpret” mathematics. When students demonstrate an understanding of the connections between existing and new knowledge through their own interpretation of that knowledge, they demonstrate conceptual understanding (Hiebert and Lefevre, 1986). Contextual application of mathematics can be practiced through experience (experiential learning theory). An increase in strategic knowledge, or the knowledge of using mathematical knowledge in application, is one learning outcome of T/E DBBL (Wells, 2016a). T/E DBBL is supported by learning theories which explain how students come to know and have a conceptual understanding of the information which qualifies them to be mathematically literate.

Integrative STEM Education focuses on the intentional teaching of other disciplines through the design of a technological/engineering solution (Wells, 2016b). T/E DBL requires conceptual understanding of any I- STEM ED discipline to make decisions about a design solution. Mehalik, Doppelt, and Schuun (2008) found that during the design process “students make choices that have an extensive basis in thinking that involves articulating clear decision criteria” (p.75). Without conceptual understanding of individual disciplines and the connections between them, students are unable to accurately justify their design decisions. The Standards for Technological Literacy discuss the need for scientific and mathematical principles to influence technological design (ITEA, 2001/2007). National Council of Supervisors of Mathematics (NCSM) and National Council of Teachers of Mathematics (NCTM) (2018), in their position statement on STEM education, emphasize the role of mathematics in making sense of “STEM-related topics” in education and real life (p.1). Mathematics conceptual understanding is vital for students to design solutions to problems and evaluate those designed solutions. When students engage in mathematical experiences, they recognize patterns, forming mathematical conceptions. As they experience the reliability of and abstractly reflect on the relationships between these patterns, they form conceptual understandings.

T/E DBBL provides contextual experiences that engage students in the learning process. To solve a real-world problem, students feel a need-to-know information to design a solution to this problem. Because mathematics is a language through which I-STEM ED disciplines communicate, mathematical conceptual understanding is vital (ITEA, 2001/2007). Students recognize this need to understand and seek to actively engage in the cognitive processes which develop mathematical conceptual understanding.

The Role of Bivariate Data Concept Knowledge in T/E DBBL

In *The Principals and Standards for School Mathematics*, NCTM (2000) emphasizes the importance of students' abilities to investigate and recognize trends and patterns in bivariate data in the middle grades because of the foundational importance of conceptual understandings of bivariate data analysis to high school data analysis. T/E DBBL provides an avenue through which students can collect and analyze their own data. When students design and construct a prototype, they must evaluate its success by collecting bivariate data and analyzing that data for patterns in order to critique the prototype's design. It is the role of the eighth-grade mathematics teacher to ensure the T/E DBL design challenge is instructed in a way that students are collecting bivariate data that will most likely result in a linear pattern those students can use to predict data because this is the mathematical standard requirement of students in the middle grades. It is through this intentional design of instruction that T/E DBBL can be used in the eighth-grade mathematics classroom to intentionally teach grade appropriate mathematics content. Students feel a need to collect data to determine the success of their prototype, make design decisions, and predict how well the prototype will work in the distant future by using the linear patterns they have detected.

Data analysis is an important skill for making health, technology, monetary, and other life decisions. By posing questions and collecting data to answer to their own questions, students are engaged in the learning process and see a relevance for learning. With a global pandemic as a most recent example, the need for data awareness and analysis is crucial for students to become informed decision makers who can analyze and evaluate information they have collected on their own or are provided by others. The goal of I-STEM ED is to create citizens who are scientifically, technologically, engineeringly, and mathematically literate. Through T/E DBBL students are engaged in an avenue to be literate and make decisions for themselves, their community, and their world in the 21st century.

Students often ask questions, not only about mathematical tasks but about why they should be learned (Williams, 2007). In other words, students want to know how mathematics content applies to them. The NCTM (2000) suggests making connections during problem solving tasks. Meaningful contextual experiences are essential for learning in mathematics. By engaging students in meaningful experiences, as originally suggested by Dewey (1938), students see a relevance in their education. Foundational to daily decisions is the ability to think critically and reason statistically (Batanero, Burrill, & Reading, 2011).

The West Virginia College and Career Readiness Standard requires eighth grade students to "use the equation of a linear model to solve problems in the context of bivariate measurement data, interpreting the slope and intercept" (West Virginia Department of Education, 2016, p.22). These standards are mindfully written by teams of professionals based on student developmental appropriateness and prior knowledge of previous standard requirements. A specific example given by the WVDE to teach and assess this specific standard (M.8.27) includes the use of a " linear model for a biology experiment," highlighting the importance of student knowledge and application of this standard in the context of science.

By working with real scientific data, students can investigate real world problems that are relevant to them. A current example of the importance of statistical understanding can be seen through the recent global pandemic. Several statistical models have been produced to describe the current case data and potential of the COVID-19 virus (Centers for Disease Control and Prevention (CDC), 2020). People with statistical understanding would be better able to read, interpret, and evaluate these models The Principals and Standards for School Mathematics emphasize that "students should learn how to collect data, organize their own or others' data, and display the data in graphs and charts that will be useful in answering their questions" (NCTM, 2000, p. 50). By posing their own research questions and collecting and analyzing prototype data to answer those questions through T/E DBBL, student experiences mirror those of professionals who must collect and analyze data to solve problems such as the recent global pandemic.

Middle School Students

Piaget and Inhelder (1969) describe the abilities of children at different stages in their cognitive development. It is in the formal operational stage (ages 11 to 15) that children are able to think abstractly. In mathematics, this level of cognitive development allows them to form hypotheses, deduce consequences, and construct their own mathematics (Ojose, 2008). The cognitive abilities of mathematics learners at this stage would be considered on the higher level of Bloom's taxonomy of cognitive processes. Students in the formal operational stage would also be able to clarify, infer, evaluate, and apply knowledge to design solutions (Ojose, 2008). Students who would fall in the formal operational stage according to their age would be in the middle grades 6-8. Eighth grade students (ages 12-14) could generally be categorized in this cognitive development stage. Piaget and Inhelder's (1969) work indicates that many students at this stage of development would be cognitively ready for the higher level thinking skills inherent in T/E DBL.

A study by Cai, Moyer, Wang, Hwang, Nie, & Garber (2013) demonstrated a connection between student mathematical experiences and understanding in middle school and their understanding in high school mathematics, particularly in algebra. Middle school mathematics conceptual understanding provides a foundation for higher level mathematics (Iuculano & Menon, 2018). Middle school mathematics teachers, specifically, need to consider pedagogical approaches that promote deeper conceptual understanding.

Connections Between Learning Theory and Mathematical Conceptual Understanding

Cognitive learning theory describes how students perceive stimuli, process new information, and store it in memory for later retrieval. Tolman (1948) specifically studied how the brain stores information for later use in problem solving. Constructivist learning theorists, such as Piaget (2001), have particularly analyzed how students reflect on the stored information in the brain to make connections to new information in a process of reflective abstraction. Conceptual understanding is a result of logic and rationalization between existing and new knowledge (Posner et al., 1982). In connection to T/E DBBL, student experiences influence their engagement in solving a problem. Their need-to-know information to design a solution for that problem motivates them to be active in the learning process (experiential learning theory). During their active engagement in the learning process, they seek new information to solve a problem. When that information connects to existing information, students form conceptual understandings. Mathematical conceptual knowledge emerges from a logical understanding of recognized mathematical patterns and relationships between mathematical objects and ideas (Simon, 2017; Simon, Saldanha, McClintock, Akar, Watanabe, & Zembat, 2010). Through experience, students learn to utilize their mathematical conceptual knowledge to logically use mathematics to design their solution to the problem, increasing their strategic knowledge and conceptual understanding.

For example, if students construct a prototype that generates electricity, they would likely need a way to measure and record how much electricity is flowing through the prototype. Conceptual knowledge of bivariate data would be a necessary result of this task. Depending on the existing knowledge students have about bivariate data collection and recording, students could make connections to where this information is applicable in other disciplines and real life. This provides them with an opportunity to gain knowledge, including what bivariate data is (declarative knowledge), how to collect and represent bivariate data (procedural knowledge), connections between bivariate data and science contexts (schematic knowledge), and how to use bivariate data collection to predict future prototype results (strategic knowledge). Learning is often internal but may be inferred through observation of student behaviors (Gagne & Driscoll, 1988). When students are able to make decisions by utilizing their knowledge, particularly conceptual knowledge, those decisions, including student reasoning for those decisions, demonstrate the student's level of conceptual understanding.

Summary of Integrative STEM Education

Over the past century, research has called for pedagogical approaches which better meet the needs of students in an ever-changing world (Bonser & Mossman, 1923; Dewey, 1938; Wilber & Pendered, 1948/1967; Savage & Sterry, 1981; ITEA, 1990; Partnership for 21st Century Skills, 2008; NEA, 2012). Traditional teacher-centered pedagogical approaches have progressed into those that are more student-centered to help students increase academic knowledge and competency in 21st century skills. The evolution of industrial arts education into technology education paved the way for integrative educational experiences, particularly those including science, technology, engineering, and mathematics. Technology/engineering design-based learning (T/E DBL) is the pedagogical approach used to teach Integrative STEM Education (I-STEM ED). Through T/E DBL, educators design instruction so that students experience a need for specific disciplinary content and skills to make decisions regarding their designed solution to a real-world problem.

T/E DBL utilizes the iterative design process represented by the PIRPOSAL model (Wells, 2016). Through T/E DBL, students are first given a problem to solve then inspired to acquire the knowledge and skills used to solve the problem. Through a need to know information to solve that problem, students are purposefully guided by the structure of the problem to develop the knowledge and skills intended by the instructor. The instructional goal for T/E DBL is student understanding (Wells, 2019). Understanding is a state in the learning process when existing knowledge and new information are appropriately connected (Hiebert and Lefevre, 1986). Understanding is an outcome as learners make cognitive connections between knowledge types. T/E DBBL utilizes T/E DBL in the specific field of biotechnology. During a T/E DBBL design challenge, students utilize living organisms, such as bacteria, to design a solution to a real-world problem.

Research Utilizing DBL to Teach Disciplinary Content

Technology/ engineering design-based biotechnical learning (T/E DBBL) requires students to work deeply with content, developing disciplinary expertise that is needed and utilized (Wells, 2019). However, the disciplinary content being explored is pre-determined and intentionally emphasized by the teacher based on the content standards being addressed through the design challenge. The teacher must plan a T/E DBBL design challenge with explicit goals and concepts intentionally chosen to be learned. T/E DBBL can be used to focus student learning on various biotechnical or mathematical concepts; it is the role of the teacher to choose a design challenge that best emphasizes the concepts to intentionally be taught/learned. Several studies have successfully utilized design-based learning to teach science and mathematics concepts. The concepts taught within each discipline were pre-determined by the teacher and the design challenges were carefully crafted to promote these conceptual understandings in students. Through T/E DBBL students design to understand, making student understanding the "principal learning outcome to be attained through T/E DBL" (Wells, 2019, p. 5).

Mixed Methods Research Design

A research design describes the "plan of action" linking philosophy and research methods during a study (Creswell, 2007, p. 4). Research methods refer to the techniques used to collect data and analyze it during the study (Creswell, 2007). Mixed methods research combines quantitative and qualitative research methods, providing a better understanding of phenomenon than either approach alone (Leavy, 2017). By using both the deductive design of quantitative research and inductive design of qualitative research, the researcher can gather data from multiple sources and use the data collectively to address research questions.

Collectively, the following studies demonstrate the efficacy of using variations of design-based learning to increase students' scientific and mathematical content knowledge. The research methods chosen by the researcher(s) play a large role in the outcomes of a study. Several studies have used a mixed methods research design to study science and mathematics content learning through design-based learning in the classroom. Others have chosen either quantitative or qualitative methods depending on the purpose of the research. The proceeding sections discuss studies utilizing variations of design-based learning in science and mathematics classrooms.

Research Utilizing DBL to Teach Science Content

In a quantitative study by Wells (2016a), graduate students enrolled in a 16-week Biotechnology by Design™ course completed a series of technology/engineering design-based biotechnical learning design challenges that were intentionally designed to teach technology and engineering content and practices concurrently with science and mathematics content. The purpose of the study was to determine the efficacy of Design Based Biotechnology Learning ™ to improve student capacity to respond to the higher order cognitive demands of the T/E DBBL challenges. All 16 of the students were licensed k-12 educators but prepared to only teach one of the four STEM disciplines. The design challenges required the students to design solutions to "Problem Scenario 4A: Alternative Fuel Bioreactor" and "Problem Scenario 4C: Microbial Fuel Cell" (Wells, 2016a, p. 10). These challenges were designed to emphasize content and practice knowledge of technology and engineering as well as science content assessed by the National Assessment for Educational Progress (NAEP) science twelfth grade assessment. Students were given a pre and posttest to assess their technology and engineering content and practice knowledge as well as science content knowledge that was intentionally targeted through the design of solutions to the two problem scenarios.

Findings from the pre and post assessments indicated that students demonstrated "significantly better understanding" of the intended technology, engineering, and science content after being immersed in technology/ engineering design-based learning design challenges (Wells, 2016a, p. 14). Wells's (2016a) study indicates that T/E DBBL experiences increase the development of higher order thinking skills and student capabilities of responding to problems requiring high levels of cognitive demand.

Although mathematics was not specifically included in the content assessment during this study by Wells (2016a), the design, construction, and performance of the design prototype through testing and evaluation provided natural avenues through which mathematics could have been emphasized and evaluated. For example, to construct a design solution for the Problem Scenario 4A: Alternative Fuel Bioreactor, students would need to calculate the volume and flow rate of the vessel (Wells & Van de Velde, 2020). These are two examples of mathematics concepts that could be intentionally incorporated in the planning, instruction, and assessment of this T/E DBBL design challenge. Wells (2016a) did not choose to assess the learning of these mathematical concepts because the students were enrolled in a Biotechnology by Design™ course focusing on the specific connections between science and technology through biotechnology. However, the knowledge students needed to complete the design challenge included mathematical reasoning and skills even if they were not the focus of the challenge. T/E DBBL provides avenues through which to teach disciplinary concepts intentionally emphasized by the instructor.

Mamlok, Dershimer, Fortus, Krajcik, and Marx (2001) conducted a mixed methods study to document developments in a Design-Based Science curriculum, Learning Science by Designing Artifacts (LSDA), over two semesters at a Midwest high school. The curriculum was design as part of a larger project, Primary Sources Network (PSN), a federally funded Technology Innovation Challenge Grant, by the C enter for Highly Interactive Computing in Education (hi-ce) at.the University of Michigan. Specifically, this study implemented the *Safer Cell Phones* curriculum which required students to design a physically and environmentally safer cell phone with specific design requirements. Students completed the challenge by experiencing the “design studio process” (p. 6). The study curriculum evolved as it was conducted over either a nine- or five-week period during two 18-week semesters. Two teachers, one mathematics and one science teacher, instructed the unit to 75 ninth-grade students. Quantitative data was collected through a two pre/posttests, one measuring science content knowledge and the other an attitude questionnaire. The science content knowledge pre/posttest included 15 multiple-choice and five open-ended questions addressing low, medium, and high levels of cognitive demand inherent of the DBS curriculum. The instrument measured knowledge of science content, such as electromagnetic waves, batteries, electron flow, and circuits, as well as the design process used to teach the DBS curriculum. Some questions for the pre/posttest were modeled after the TIMSS. Qualitative data were collected through classroom observations, video recordings of lessons, and targeted student interviews. Paired *t* tests run for each semester of the implementation revealed statistical significance between the pretest and posttest for both semesters.

Like Wells (2016a), Mamlock et al. (2001) did not intentionally incorporate the intentional teaching or measurement of mathematics concept knowledge into this study, but the implications for mathematics concept knowledge were there. DBS concepts such as electron flow, design size requirements, and circuits could have been avenues through which ninth grade mathematics concepts of solving equations, surface area, and volume could have been intentionally addressed and included in the content knowledge measures throughout the study.

Fortus, Dershimer, Krajcik, Marx, and Mamlok-Naaman (2004) built on the work of Mamlock et al. (2001) also using design-based science (DBS) as a “vehicle through which scientific knowledge and real-world problem-solving skills” were intentionally taught (p. 1081). In this study, one certified science teacher taught three ninth and tenth grade physical science classes (N=92) the same *Safer Cellular Phones* unit (8 weeks) but added two additional DBS units, *Environmentally Safe Batteries* (3 ½ weeks) and *Extreme Structures* (6 weeks). DBS instruction engaged students in the design process to teach scientific concepts. The DBS design processes is as follows: identify and define the context, background research, develop personal and group ideas, construct 2D and 3D artifacts, and feedback. DBS is similar to the PIRPOSAL model that guides instruction of T/E DBL. Missing from the DBS design process is initial ideation before research and a final presentation of learned outcomes. The opportunities for optimization and evaluation of iterations of designs during DBS are within the feedback portion of the process. During feedback, students are able to test their designs and receive feedback from other students and the teacher.

During the mixed methods study by Fortus et al. (2004), scientific knowledge gains were quantitatively assessed through pre/post Science Knowledge Tests, serving as a final exam for each unit. The test for each unit included 13-15 multiple-choice items and 2-5 open-ended items with 8 sub-parts each. The test was designed to measure science content with low, middle, and high levels of cognitive demand. Inter-rater reliability was used to score the test to achieve 95% agreement. Paired *t* tests and statistical analysis were used to analyze quantitative data. Results show that there was a statistical significance between pre/posttest scores for each of the three units. Further analyses showed that both high and low achievers demonstrated knowledge gains between the pre/posttests. Student understanding was qualitatively measured through artifacts constructed during each of the three units. Checklist rubrics were used to assess the artifacts created by students. Inter-rater reliability was again used to achieve at least 95% agreement. The rubrics were used to compare student concept knowledge difference through application between early and late iterations of artifacts. For each of the units, early artifact designs demonstrated the lack of scientific concept knowledge that was more clearly applied to final iterations which scored higher on artifact rubrics. The goal of the study was to determine the efficacy of DBS for the construction of scientific knowledge and designerly problem-solving skills. The design challenges presented students with ill-defined, real-world problems.

Fortus, Krajcik, Dershimer, Marx, and Mamlok-Naaman (2005) took the use of DBS to teach science content knowledge through design-based learning even further through the *Extreme Structures* unit, this time entitled “How Do I Design a Structure for Extreme Environments?” The focus of this work was not only to increase science concept knowledge through experiences in artifact design but also to demonstrate knowledge transfer through a transfer task after the unit. The science content taught through this unit included weather, loads, structural integrity, thermal insulation and technical drawings. For this study, two science teachers taught 149 ninth and tenth grade students in six integrated and physical science classes at a public high school. Students were arranged in self-selected groups of four. The unit lasted 11 weeks. To collect quantitative data about student concept knowledge gains, a pre/posttest was given before and after the intervention. The pre/posttest consisted of 15 multiple choice items measuring middle and low cognitive demand and 3 open-ended items with 8 subitems measuring middle and high cognitive demand. Results were analyzed through statistical measures of central tendency and significance (*t* test). The results demonstrated significant gains in scientific concept knowledge between the pre/posttests. A transfer task was then used to measure students’ abilities to apply their scientific concept knowledge and designerly skills in a different context. The transfer task was only given to four of the six classes with 66 students complete each of the three assessments (pretest, posttest, and transfer task) and 49 of those transfer tasks being used for analysis. Statistical analysis of scatter plots and Pearson correlation coefficients between the transfer tasks and pretest and posttest results demonstrate a stronger correlation between the transfer task and posttest results than between the transfer tasks and pretest results. This indicates significant knowledge gains relative to the DBS intervention.

The relationships between the studies demonstrating the development of the DBS curriculum (Mamlock et al, 2001; Fortus et al. 2004; Fortus et al. 2005) paint a picture of the efficacy of design-based learning to be used to teach disciplinary concept knowledge. The purpose of the DBS curriculum is to teach science content; therefore, a certified science teacher was used to teach the DBS units for each study. However, these studies missed an opportunity to include intentional teaching of mathematics concept knowledge that was inherent in the science content but not officially brought forth to the students. The research design and data collection methods chosen by the researchers for these studies should influence future researchers seeking information about the use of design-based learning in any discipline. The ability of these researchers to build on previous work and demonstrate concept knowledge gains in each of these studies demonstrates the efficiency of each research design. Each study used more than one method of data collection including both quantitative (pre/posttest instruments) and qualitative (artifacts, classroom observations, video recordings of lessons, targeted student interviews, transfer task) methods. In each of these studies, a pre/posttest instrument was used to measure scientific concept knowledge gains as a result of an intervention. This supports this use of a mixed method design to determine the way in which student engagement in T/E DBBL supports change in mathematical concept knowledge. The following studies discuss the use of variations of design-based learning to teach science content in a middle school setting, specifically.

Research Utilizing DBL to Teach Science Content in Middle School

Holbrook, Gray, Fasse, Camp, & Kolodner (2001) use LBD to teach specific science content to three cohorts of middle school students in grades 6-8 in comparison to matched students taught through an inquiry approach. The LBD, Vehicles in Motion, unit sought to improve understanding of sciences concepts of mass, motion, and force. This study utilized a 36-item pre/posttest to assess science content knowledge, performance tasks to assess application of content and practices, student self-assessment surveys, and structured interviews to provide additional insight into students learning. The content assessment results indicated that students in both LBD and matched groups gained science content knowledge, with higher content scores in the LBD classes. On the performance assessment, students learning using LBD "use[d] scientific reasoning and collaboration skills more successfully than comparison students" (Holbrook et al., 2001, p.15). The focus on this study was the teaching and learning of science content through LBD, however, the success of design-based learning to teach intentional science content provides a path for examining the study of design-based learning to intentionally teach mathematics content.

Kolodner, Camp, Crismond, Fasse, and Gray (2003) provided information about the combined theoretical contributions of problem-based learning and case-based reasoning, referring to past experiences (cases) for guidance, to implement Learning by Design™ (LBD), teaching science concepts and skills by designing a solution to a real-world problem, in a middle school science classroom. LBD is similar to T/E DBBL with the exception of the specific focus of LBD on science content and skill assessment, T/E DBBL relays both technology and engineering content and practices as well as inherent science and mathematics content. By designing solutions in both approaches, students are required to learn concepts and skills in disciplines that are needed to solve a problem. To develop habits of mind as part of the crucial middle school experience, LBD specifically fosters a collaborative classroom atmosphere that allows students to learn cognitive, social, and communication skills. T/E DBBL can often be collaborative but is not exclusively designed to be such. One of the challenges of LBD is ensuring that the teacher chooses the kinds of design challenges that "clearly benefit from scientific understanding" and help students make those explicit connections between disciplines (p. 510). Through T/E DBBL, the educator chooses a design challenge that benefits from specific science and/or mathematics knowledge and skills, depending on the educator's disciplinary intentions.

Kolonder, Gray and Fasse (2003) implemented LBD for two consecutive years, each including four classrooms of middle school students including: a typically performing LBD, typically performing comparison class, high-performing LBD class, and high-performing comparison class. The comparison groups were matched to the LBD groups for achievement level, socioeconomic status, and teacher understanding of the material. The primary goal of the two LBD studies was to infer transfer of knowledge through design-based transfer tasks. The qualitative data sources included performance assessment tasks, observations, videos, homework assignments, and interactions with teachers. The students engaged in an introductory unit, *Apollo 13,* and an 8-week unit entitled *Vehicles in Motion.* This *Vehicles* unit was designed to teach Newton's Laws through the design of a miniature vehicle and propulsion system. The first year of implementation, students completed performance assessment tasks at the end of the *Vehicles* unit and in the second-year students complete performance assessment tasks before and after the *Vehicles* unit. The performance assessment was run in all four classes for both years. The recorded interactions between students were used for analysis of: self-checks, science practice, distributed efforts, negotiation, prior knowledge adequate, prior knowledge, and science terms. A likert scale of 1-5 (5 being highest) was used to score each group. Although this study used predominantly qualitative methods, the findings demonstrated a higher score for LBD students that comparison students for using skills more collaboratively and effectively during the performance assessment tasks. Without the use of a quantitative measure (i.e., concept knowledge pre/posttest), it is difficult to measure the amount of knowledge each student had prior to and after the LBD units.

Doppelt, Mehalik, Schunn, and Krysinski (2008) used a mixed methods approach during their research on DBL to teach science content to 38 eighth grade students in two classes, one high and one low-achieving class, at a public school. The goal of the study was to examine the effects of DBL on student engagement and the achievement gaps between high and low-achievers and race/ethnicity, gender, and socio-economic status. Prior to the study, the researchers examined gaps between state and local standards and the learning environment of the existing classroom. The standards needing emphasized included technological design process and systems thinking, leading to the focus on these standards in the science curriculum of the study. During the study, students met for an hour five days a week to learn about alarm systems, technological systems, constructing an alarm system, the design process, and evaluating designs. This variation of design-based learning was based on the following design process framework: Purpose, Input, Solutions, Choice, Operations, and Evaluation (PISCOE).

Quantitative data were collected through a researcher-made seven-question pre and posttest. Two versions of the test were created and randomly assigned to each student. The post test was given immediately after the last day of the unit. Qualitative data were collected through teacher and peer-assessed oral presentations, including twelve presentation transparencies, and students' final designs. All 38 students submitted portfolios completed from the unit. Two students who reached average scores on the posttest were randomly selected for detailed analysis. Two researchers observed 64% of classroom activities, keeping independent observation and student logs. The findings from this study revealed that the students in the lower-achieving class scored lower on the knowledge test, but they scored significantly higher on the presentations. The presentations, observations, and portfolios demonstrated that the low-achieving students "reached similar levels of understanding of scientific concepts" even with lower scores on the knowledge test. This study largely supports the use of triangulation of quantitative and qualitative data to analyze student learning (Doppelt, et al., 2008, p. 34). It also also highlights a need for multiple avenues through which to assess student learning to ensure student learning is evaluated thoroughly.

Mehalik, Doppelt, and Schunn (2008) expanded the analysis of design-based learning with 26 eighth grade science classes (10 teachers and 587 students) in a public-school district. In this study, the design-based learning approach was compared to a scripted inquiry approach in 20 eighth grade science classes (five teachers and 466 students) in the same public-school district. A scripted inquiry approach is one that provides heavy scaffolding and step by step directions on a how an experiment is conducted, and data is collected (Nagle, Hariani, and Siegel, 2006). To teach the systems design-based learning unit, *Electrical Alarm System: Design, Construction, and Reflection,* the following "seven stages of systems design and analysis" were followed: describe current situation, identify needs, develop criteria, generate alternatives, choose an alternative, create prototype/test, and reflect and evaluate (Mehalik et al., 2008, p. 74). The goal of the study was to help students discover the principles of electricity, such as current, voltage, resistance, and types of circuits, and improve reasoning skills through the context of design thinking. Pre and post assessments were designed by the researchers and used to determine the changes in conceptual knowledge of electricity. The assessments included electrical concepts that ensured both the design based learning and scripted inquiry groups were evaluated on the same focused content. The results showed that the gains of the DBL group (16 percent) were twice as high as the gains of the scripted inquiry group (7 percent). These results indicate that design-based learning leads to conceptual knowledge gains in achievement in comparison to the more traditional approach of scripted inquiry.

Schnittka and Bell (2010) discuss the work of Schnittka's (2009) dissertation study of learning as a process of conceptual change. She assessed alternative conceptions about heat transfer and thermal energy in three classes of eighth grade students. She then investigated the impact of engineering design activities on the conceptual change of students as well as the attitudes and knowledge about engineering. One class received instruction through engineering design, one class served as a control group, and one class received instruction using engineering design plus additional demonstrations by the teacher to specifically target the alternative conceptions of students discovered through the initial interviews and pre assessment. This study not only examined the effects of utilizing engineering design, but also the effects of specifically targeted explicit instruction on student alternative conceptions.

Two researcher-made pre and post tests were used to collect quantitative data about scientific conceptual change and student attitudes toward engineering. Student entrance and exit interviews, classroom observations, discourse analysis, and artifact analysis were also used to collect qualitative data during the study. Both quantitative and qualitative data were important to support the conclusions of the study. Schnittka (2009) emphasizes the importance of researcher knowledge of both quantitative and qualitative methods for accurate data collection and analysis. Data were collected through interviews, audio and video recordings, pre and posttests on science content and engineering attitudes, and student artifacts. The alternative conceptions held by the students in the class receiving targeted demonstrations were reduced by half in comparison to the other students by the end of the instructional unit. In addition, students in the class which received explicit alternative conception instruction performed better on the design challenge than in the other two classes. However, the class learning through engineering design without demonstrations performed well on the design challenge, but not as well as the demonstration group on the content assessment. The study indicates that the use of engineering design activities positively affects student abilities to apply concepts to successfully design solutions to a problem especially when student alternative conceptions are targeted and intentional efforts to change those conceptions are made.

The studies above demonstrate the efficacy for utilizing several forms of design-based learning (DBL) in the science classroom. The success of DBL and T/E DBBL lie in the explicit connections made between student experiences and intentional learning outcomes planned by the teacher. The above studies have taken place primarily in the science classroom; therefore, student learning has been focused on increasing science concept knowledge through experiences in a form DBL. The reason for analyzing these studies is to emphasize that student learning is dependent on the intentional disciplinary focus of the design challenge that is presented by the teacher. T/E DBBL, DBS, LBD, DBL, and engineering design were used to teach scientific content because that is the discipline these researchers intentionally structured the units to teach. Fewer studies have utilized any variation of DBL in the mathematics classroom. However, those studies that have, demonstrate the efficacy for T/E DBBL to increase conceptual understanding and strategic knowledge (habits of mind) through design thinking.

Table 1

Research Using DBL Variations to Teach Science Content

Author(s)	Data Source(s)	Participants	Content Area	Pedagogical Approach
Wells (2016a)	Pre/posttest	16 students Graduate school	Science Technology Engineering	Biotechnology by Design™
Mamlock et al. (2001)	Pre/post Science Content Knowledge Test Pre/Post Attitude Questionnaire Classroom observations Video recordings of lessons Targeted student interviews	75 students Grade 9	Science	Design-Based Science (DBS) *Safer Cell Phones*
Fortus, et al. (2004)	Pre/post Science Knowledge Test Artifacts	92 students Grades 9-10	Science	Design-Based Science (DBS) *Safer Cellular Phones* *Environmentally Safe Batteries* *Extreme Structures*
Forus et al. (2005)	Pre/posttest Transfer task	149 students Grades 9-10	Science	Design-Based Science (DBS) "How Do I Design a Structure for Extreme Environments?"
Holbrook et al. (2001)	Pre/posttest Performance task Student self-assessment survey Structured interview	3 cohorts Grades 6-8	Science	Learning by Design™ *Vehicles in Motion*

Author(s)	Data Source(s)	Participants	Content Area	Pedagogical Approach
Kolonder, Gray and Fasse (2003)	Performance Assessment Tasks	Middle school students	Science	Learning by Design™ *Vehicles in Motion*
Doppelt et al. (2008)	Pre/posttest Oral presentation assessment Student portfolios	38 students 2 classes Grade 8	Science	Systems Design-Based Learning (DBL) *Electrical Alarm System: Design, Construction, and Reflection*
Mehalik et al., (2008)	Pre/posttest	1,053 students 46 classes 15 teachers Grade 8	Science	Systems Design-Based Learning (DBL) *Electrical Alarm System: Design, Construction, and Reflection*
Schnittka (2009); Schnittka a nd Bell (2010)	Pre/posttest Interviews Audio/Video Recordings Student Artifacts	71 students 3 classes Grade 8	Science	Design-Based Science *Save the Penguins* (Schnittka, Bell, & Richards, 2010)

Table 1 provides a summary of the studies utilizing variations of design-based learning to teach science content. The variety of design-based methods within these studies demonstrates the breadth of this pedagogical approach simultaneously indicating a significant relationship between design experiences in the classroom and gains in content knowledge at different grade levels. The similarity between the various pedagogical approaches of design used in these studies is the engagement of students in the higher order thinking skills inherent in design-based learning, including T/E DBBL. The experiences students had during their engagement in each study led them to gain content knowledge, predominantly scientific knowledge, pre-determined by the researcher.

Most of these studies are related to at least one other study by multiple researchers implementing the same or a similar curriculum to determine the results of that curricular intervention on student scientific concept knowledge. Most studies were able to demonstrate gains in concept knowledge through the use of a similar variation of DBL curriculum with different participants, year, and context. This consistency further demonstrates the efficacy of DBL, specifically, T/E DBBL to teach intentional disciplinary concept knowledge.

Research Utilizing DBL to Teach Mathematics Content

Pines, Nowak, Alnajjar, Gould, and Bernardete (2002) integrated mathematics into a college freshman engineering design course, Principles of Design, at the University of Hartford. The purpose of the study was to increase awareness of the connections between engineering design, Calculus II, and Physics I. Instructors for each of the three courses worked together to create two design challenges throughout the semester that intentionally integrated specific mathematics, physics, and engineering design content. The first design challenge was for students to create a three-person sling shot that could consistently launch a tennis ball into a box with specific size constraints. Students actively participated in the challenge during all three classes, learning material relevant to each discipline to complete the challenge in each class. The second challenge required students to build a solar-powered amphibious vehicle that could go to a selected point across a 42-foot stream. Again, specific calculus and physics content was addressed in the according class so students could use that knowledge to complete the design challenge. The primary data source for this study was a survey taken by 38 students at the end of the three courses. The survey sought to determine if students felt they achieved the learning outcomes of the three connected courses. When asked if they "felt comfortable using their skills in math, physics, and engineering to solve multidisciplinary problems," 35% of students strongly agreed and 55% of students indicated that they somewhat agreed (Pines et al., 2002, p. 6). The results of the survey were only a measure of student comfortability and recognition of the connections between the three disciplines. They were not an indication of the actual content that was learned by the student.

Research Utilizing DBL to Teach Mathematics Content in Middle School

Akins and Burghardt (2006) used engineering design to teach mathematical concepts of area, perimeter, percentage, and linear and non-linear equations as well as science concepts of humidity and evaporation to 63 students in grades 7 through 9. Through collaborations between The Center for Technological Literacy at Hofstra University, Dutchess Community College, and the New York State Professional Development Collaborative (NYSPDC) project, four middle and high school teachers used informed design to teach science and mathematics concepts to students. Informed design is a type of design-based learning where students make informed decisions about their design based on knowledge learned from specific knowledge and skill builders (KSB), lessons designed to prepare students for the design challenge. The KSBs are targeted lessons which teach students specific content and skills they will need to approach the design challenge. KSBs are used to avoid the trial-and-error problem solving approach often used by students.

A researcher-made pre/post assessment based on the New York state annual assessment for science and mathematics was used to collect quantitative data measuring student content knowledge before and after the implementation of an informed design unit. To collect qualitative data, a pre and post self-assessment was used to measure students' perceptions of their own conceptual understanding. Rubrics were used to determine student progress during KSB lessons and to analyze students' Design Folios. A combination of quantitative and qualitative methods helped Akins and Burghardt (2006) collect data to measure student learning throughout their study. Data were analyzed for student knowledge gains overall and further examined in achievement quartiles, determined by the pre-assessment, to determine the effects of the informed design unit on students at different levels of initial achievement. Students in the lowest and second lowest quartiles showed the most improvement of conceptual understanding by improving their scores by 125% and 85% respectively. The highest quartile improved their score by 21% and the second highest improved their score by 51%. The findings during this study indicate the efficacy of design-based learning to increase student conceptual understanding in mathematics and science.

Another study was also conducted by Hofstra University's Center for Technological Literacy as part of the Mathematics, Science, and Technology Project, a part of the National Science Foundation funded The Mathematics and Science Partnership Project built on the works of Akins and Burghardt (2006) in the specific incorporation of mathematics content in a design-based curriculum (Burghardt, Hecht, Russo, Lauckhardt, & Hacker, 2010). This study was designed to determine the effects of mathematics infusion into an engineering/technology education (ETE) curriculum. Students were required to plan, design, and model a bedroom with specific cost and building requirements in the 20-day study entitled *Bedroom Design*. The study compared the effects of mathematics infusion on mathematics content knowledge and attitudes toward mathematics between the ETE curriculum and a control curriculum with particular attention paid to students with below average levels of mathematics. Participants were eighth grade students in 13 middle schools. The mathematics infusion ETE lessons were taught by 15 technology-certified teachers to 598 students. The control curriculum was taught by 14 technology-certified teachers to 455 students. The ETE curriculum was taught in 20 days, including 7 lessons of tasks that infused grade-related mathematics content including geometric shapes, factoring, percentages, scaling, mathematical nets, aesthetics, and spreadsheets/ pricing.

Two pre and posttests, one assessing mathematical content knowledge and one assessing attitude toward mathematics, were given to both curriculum groups. The mathematical content assessment included seven multiple choice and ten open ended questions based on state mathematical assessment items and an expert mathematics consultant. The concepts addressed on the assessment were related to six of the seven KSBs. The infusion students scored higher on four out of seven multiple choice items and four of the ten open-ended items in the categories of percentages, geometric shapes, scales/ percentages for both types of questions. The scores of the infusion students increased with statistical significance between the pre and posttest. The control group increased their scores on three multiple choice items alone, but the difference between the pre and posttest scores were not statistically significant. Scores also indicated that the scores of the students in the two lower quartiles improved most. This study further supports the influence of technology/engineering curriculum on increased mathematics knowledge.

Kelley and Sung (2017) analyzed student thinking during an engineering design task as part of a National Science Foundation funded Math Science Targeted Partnership (MSP) called Science Learning through Engineering Design (SLED). Specific thinking aloud protocol helped them analyze how students in grades 3-6 were mathematically reasoning and learning science content during an engineering design-based challenge. The first year, Cohort 1, of implementation revealed that students spent almost half of their time generating ideas and less time on computing, testing, managing, and predicting results. It was also found that students did not interpret data at all during Cohort 1. Because these mathematical skills are important for engineering design, in the second year of implementation, Cohort 2, mathematical thinking in these areas was targeted through two math-specific design tasks. Two additional activities were constructed to address the mathematical reasoning and science content needed for successful completion of the original design challenge. The time spent on mathematical thinking on the math-specific design task increased by 34 percent in Cohort 2 in comparison to Cohort 1. These findings indicate that students do not naturally utilize mathematical skills and reasoning; however, by intentionally targeting mathematical content, students learn to utilize mathematical knowledge through reasoning.

Limitations of Research Utilizing DBL to Teach Mathematics in Middle School

The studies discussed above demonstrate both the efficacy of design-based learning to teach mathematics content in middle school and the need for further research in design-based middle school mathematics. Although there is much literature supporting design-based learning approaches to teach mathematics (Narode, 2011; Fowler, Cutting, Fiedler, & Leonard, 2022), there is limited research contributing to the literature and providing empirical support for specific design-based learning pedagogical approaches, such as T/E DBBL, in the mathematics classroom. Table 2 provides further details about three studies utilizing design-based learning to teach mathematics in middle school specifically.

Table 2

Studies Using DBL to Teach Middle School Mathematics Concepts

Study	Participants	Content Area	DBL Curriculum	Mathematics Concepts	Data Source(s)
Akins and Burghardt (2006)	63 students 4 teachers Grades 7-9 5 weeks	Mathematics Science	Informed Design *Drying by Design*	Area Perimeter Percentage Linear and non-linear functions	Pre/posttest Student Self-Assessment KSBs Design Folio
Burghardt, Hecht, Russo, Lauchhardt, & Hacker (2010)	13 schools 29 teachers 1.053 students Grade 8	Mathematics	Engineering/ Technology Education (ETE) *Bedroom Design*	Percentages Geometric shapes Factoring Scaling Mathematical nets Spreadsheets/ pricing	Pre/posttest
Kelley & Sung (2017)	5 years about 100 preservice teachers about 200 in-service teachers 5,000 students Grades 3–6, particularly grade 5	Science Mathematical Reasoning	Engineering Design	Computing Testing Managing and predicting results Interpreting data	Pre/posttest 6 Concurrent Think-Aloud Audio/Video Recorded Sessions Transfer Task

These studies were chosen to be compared because of their use of a variation of design-based learning to teach mathematics concepts specifically in the middle grades. Akins and Burghardt (2006) list several intentional mathematics concepts that were addressed in grades seven through nine during their study. Although this study implies the use of engineering design to teach mathematics concepts, the range of mathematics concepts provided would be difficult to measure in a single study. The developmental levels necessary to teach each of those concepts to students within three different grade levels together must also be considered. Although the study demonstrates gains in knowledge as a result of student engagement in the engineering design experience, the depth to which these concepts were taught/learned was not addressed.

Akins and Burghardt (2006) do state that the academic levels of the seventh and eighth grade students were not significantly different from the ninth-grade students, but there is no elaboration on the differences in prior knowledge or students' specific academic levels. There are at least two years of mathematics education difference between the seventh and ninth grade students. The assessment used for all students was based on an eighth-grade level state assessment, which may or may not affect the pre/posttest outcomes for the seventh and ninth grade students. Although the same test was given as a pre and post assessment, the grade level of the assessment did not match the grade level of all students. This study also uses informed design which is different from design-based learning because of the prior knowledge that the teacher presents students before the design challenge in the form of KSBs. This inhibits the seeking of knowledge by the student in a need-to-know that information to complete the task. The teacher prepares the student before the student presents their own ideas.

Burghardt et al. (2010) built on the preliminary work of Akins and Burghardt (2006) by using informed design to teach several math concepts through lessons requiring students to design a bedroom with specific cost and building requirements. Different from Akins and Burghardt (2006), Burghardt et al. (2010) used an assessment based on the eighth grade New York state mathematics assessment to assess learning for the study which only included eighth grade students. Therefore, the developmental appropriateness of the instruction and the assessment was within a single grade level for this study. However, the number of concepts addressed in this study increased to six making it increasingly difficult to teach and thoroughly assess each concept within a single study. Again, the types or depth of knowledge addressed by the study were not presented. The mathematics assessment data presented gains for the 2 to 4 questions addressing each of the six concepts. This limited number of questions per concept would also make the analysis of gains in any single concept difficult to infer.

Kelley and Sung (2017) combine the teaching of mathematics with the teaching of science in the context of engineering design. To measure student science knowledge, a pre/posttest was used. The study did not specifically determine an increase in mathematical knowledge but implied use of math knowledge through science-based transfer tasks and the use of mathematical reasoning in an engineering design context. Unlike the two previous studies, this study did not specifically assess the development of mathematical knowledge. Instead, this study focused on the time students spent during the design challenge on mathematical reasoning which increased simultaneously with an increase in pre-determined math-focused activities from none to two between cohorts one and two. Kelley and Sung (2017) realized that students in cohort one did not naturally use mathematical reasoning during their design challenge, so cohort two students were engaged in mathematical tasks specifically designed to increase the use of mathematical reasoning. In cohort two, mathematical reasoning was inherent through design and increased as the intentional instructional focus on it increased. This study was also different from the two previous because of the focus on elementary and lower middle school students (grade 3-6) instead of the older middle school students in grades seven through nine.

Summary of Research Utilizing DBL to Teach Disciplinary Content

Research utilizing various forms of design-based learning has continued to develop over the past few decades in science and mathematics education. Studies have demonstrated the efficacy of student engagement in experiences through which their knowledge gains are founded in context and usefulness to complete a design challenge. Most studies involving design-based learning are focused on the increase of science knowledge (Wells, 2016a; Mamlock et al., 2001; Fortus, et al., 2004; Fortus et al., 2005; Holbrook et al. 2001; Kolodner, Gray, & Fasse, 2003; Doppelt et al., 2008; Mehalik et al., 2008; Schnittka, 2009). There are some studies that highlighted the simultaneous knowledge gains in science and mathematics through DBL (Akins and Burghardt, 2006; Kelley and Sung, 2017), but even fewer are dedicated to the specific mathematical knowledge gains that are the result of engagement in DBL (Burghardt et al., 2010). The open-ended nature of DBL, specifically T/E DBBL, requires the educator to intentionally structure the design challenge so that students need the content knowledge intended to be taught through the challenge in order to complete the challenge. The disciplinary intentions of the instructor influence the outcomes of DBL. As was demonstrated by Kelley and Sung (2017), students do not naturally make connections between disciplinary content even when immersed in a multi-disciplinary experience. It is the role of the educator to instruct and design the T/E DBBL design challenge so that students learn intentional disciplinary content through intentional experiences.

The researcher's choice in research design plays a large role in the outcomes and findings of the research. Most research in DBL utilizes at least two methods of data collection to support the findings of the research. Eleven out of the twelve studies described above utilized pre/posttests as a quantitative data source. Eight of those eleven studies supported their quantitative findings with qualitative sources (classroom observations, video recordings of lessons, targeted student interviews, transfer tasks, performance assessment tasks, etc.). Triangulation, acquiring multiple data sources, strengthens study inferences by using the results of one data source to support the findings of another (Schoenfeld, 2000). Triangulation can be used to provide a better understanding of the ways T/E DBBL promotes change in mathematics concept knowledge.

Depending on a student's development, conceptual knowledge can be implicit or explicit (Rittle-Johnson, Schneider, & Star, 2015). In the absence of an appropriate instrument to provide quantitative data during research, several studies have utilized existing international, national, or state standardized assessments with prior evidence for their validity and reliability to design one that can be used for that particular study (Wells, 2016a; Holbrook et al., 2001; Schnittka, 2009; Schnittka and Bell, 2010; Kolodner, 2002; ; Burghardt & Hacker, 2008; Akins & Burghardt, 2006; Thornton & Sokoloff, 1998). However, the ability to demonstrate knowledge explicitly is a product of language skills. A student can have mathematical conceptual understanding without being able to verbalize or explain that understanding. Therefore, a student's level of conceptual understanding is often inferred through indicators such as the ability to use multiple representations of a single concept or solving a problem in more than one way (Kilpatrick, Swafford, Findell, 2001; Crooks and Alibali, 2014; Scheibling-Sève, Pasquinelli, and Sander, 2020). Therefore, it is imperative that more than one method of data collection is used to infer student learning during a study. Journals and interviews are two qualitative sources that have been used by mathematics and DBL researchers to collect qualitative data to gain insight into student conceptual understandings. A mixed methods research design, using both quantitative and qualitative methods to collect data, would best guide a study analyzing the ways in which engagement in T/E DBBL promotes change in mathematical concept knowledge.

Qualitative Data Sources for Insight into Conceptual Understanding

A student's level of conceptual understanding can be seen through the richness of their connections between procedures and concepts, ability to solve new and unfamiliar problems, provide arguments for decisions, apply one mathematical or scientific concept to another, or rationalize a procedure or response (Kilpatrick, Swafford, Findell, 2001). The connections between the methods of measure of conceptual understanding and the definitions of conceptual knowledge and understanding provided by the researcher are important for inferences made from the research. In mathematics research, concept knowledge has been measured by a variety of methods.

Research Utilizing Journals for Insight into Conceptual Understanding

Journals, particularly in mathematics, support the metacognition needed to develop deeper conceptual understanding (Benson-O'Connor et al., 2019). A journal can be defined as "an ongoing record that people use to record their thoughts, occurrences, experiences, and observations" (Kostos & Shin, 2010, p.225). The National Council of Teachers of Mathematics (NCTM) has supported the use of writing as an instructional technique for several decades (1991). Student journals provide insight into student understanding through student articulation of concepts, frustrations, insights, and positions on developing concepts during the learning process (Benson O'Connor, McDaniel, & Carr, 2019).

Journaling has been used in a variety of ways, purposefully determined by the classroom teacher, in mathematics education as an avenue of meta-cognition, concept development, and connecting mathematics to the real world for some time (Stewart & Chance, 1995; Albert &

Antos, 2000; Williams & Wynne, 2000). Journals can be used by the researcher to gain insight into student thinking and conceptual understanding. Benson-O'Connor et al. (2019) used journaling in a fourth-grade classroom of thirteen students as a qualitative data source to study students' abilities to relate mathematical concepts to the real-world. In this study, journals were used to document details about mathematical concepts, draw models for the concept, build vocabulary, and reflect on the learning of those concept. Students were also encouraged to include real-life applications of concepts in their journals. A checklist and format guide were provided by the teacher to help students include specific information in the journals. Each student's journal entries were coded as high, middle, or low-level entries based on rubric of concept understanding/mastery. The entries were also examined for the types of strategies that students used to solve problems. Students were also given a "Math Self-Efficacy Survey" after the study to enhance the researcher's understanding of the connections between writing and learning mathematics from the perspective of the student. Survey results of the study showed that the number of students that felt the journal helped them understand math increased from 38.5% to 41.7%. Overall, the journals provided insight into students' levels of understanding and the types of strategies students used to solve problems.

A study was conducted by Bicer, Capraro, & Capraro (2013) utilizing journals in a middle school after school STEM program to enhance student problem-solving skills. One teacher taught 96 students in a six-week program for 75 minutes two days per week. Students were assigned to one of two groups. One group focused on learning through the writing process including interpreting, generating, and writing story problems. The other group answered high stakes test questions that were generally missed by students, but this group did not focus on writing. A pre/posttest was given to both groups. Results on the pretest showed that students were at similar levels before intervention. Posttest results were compared for number of correct answers and cognitive complexity. Results on the posttest showed that the writing group outperformed the comparison group on the cognitive complexity items, but the comparison group demonstrated more growth in correct answers. This study demonstrates the ability of a writing-focused pedagogy to increase student problem-solving skills. Providing students with opportunities to generate their own ideas and document their thinking increases their higher order thinking skills associated with cognitive complexity. Later, Bicer, Perihan, and Lee (2018) conducted a meta-analysis of 12 studies to determine the impact of writing intervention on student mathematical attainment. Overall, the findings reported that writing in the classroom demonstrated a significant, positive effect on mathematical attainment with an effect size of 0.42.

Wells (2016b) discusses the importance of using journals when utilizing T/E DBBL. As students experience the design process, particularly the PIRPOSAL model of design in T/E DBBL, they need a way to document their questions, ideas, findings, research, data, etc. to help them reflect on what they know, have come to know, and still need to know to complete the design challenge. Therefore, writing in a journal, specifically an Interactive Engineering Journal (IEJ), is a necessary part of the daily experiences involved in the design process. Students come to rely on their IEJ as a resource for information, data, and note-taking, and so the IEJ becomes a rich source of insight into a students' conceptual knowledge through engagement in the design process.

Research Utilizing Interviews for Insight into Conceptual Understanding

Interviews are used in qualitative research to gather descriptions and interpretations of phenomenon by the interviewee (Anyan, 2013). Interviews allow interviewees to think about and discuss their experiences and understandings. Interviews can be conducted using structured, semi-structured, or unstructured formats (Merriam & Tisdell, 2016). Structured interviews involve predetermined wording and ordering of questions. Sem-structured interviews utilize predetermined questions flexibly as a guide for the interview. Unstructured interviews are more like a conversation and are usually used to guide questioning in a later interview. An important aspect of a quality interview is asking good, informative questions. Asking “why” and “yes-or-no” questions are discouraged (Merriam & Tisdell, 2016, p. 122). Good questions should be worded clearly and use language familiar to the participant.

Interviews have been used as a supportive qualitative source of data for mixed methods research in the fields of mathematics and DBL in science. Panasuk (2010) used student interviews to gain insight about the conceptual understanding of students in algebra. Students were asked to reflect on a survey previously taken and then were asked to solve problems as the research audio-taped the interviews and took notes on the students’ abilities to think abstractly. Groth, Jones, and Knaub (2018) used individual pre/post interviews to measure student concept knowledge of informal lines of best fit on a scatter plot. For one question, students were shown a picture of a table and asked to use predictive analysis to provide futuristic data for the table. Another question on the interview provided students with a scatter plot and asked the students to provide the meaning and relationship between the points. The next item on the interview asked students to describe the relationship between the variables on a scatter plot with a negative correlation. The same problems were used on the pre and post interviews, and all interviews were video recorded and transcribed for analysis.

Interviews have also been used in DBL research as a way of collecting information about students’ experiences, thinking, and concept knowledge (Davis, Hawley, McMullan, & Spilka, 1997; Sadler, Coyle, & Swartz, 2000). Although further details were not provided, Mamlock

(2001) discussed the use of interviews to support quantitative findings about learning before and after a DBS intervention. Holbrook et al. (2001) also used structured, individual interviews to capture a student's description of their problem-solving strategies. During one set of interviews, students were asked to simulate a design to answer questions. At first, the student did not demonstrate the knowledge of scientific processes required to test variables. However, after probing by the interviewer to explain their results, the student began to follow the scientific process learned during their design challenge experiences. Holbrook et al. (2001) suggest that interviews be interactive where the interviewer provides scaffolding and asks probing questions about student choices and results. As demonstrated by this example, students may not initially demonstrate the knowledge that they have until probed by the researcher.

Schnittka (2009) provided details about the intentionally structuring of open-ended questions for use in scaffolding during pre/post intervention interviews. Interviews for this study were used to support quantitative and findings from other qualitative sources. The interviews were conducted before the intervention to gather preliminary information about student scientific conceptions. Post-intervention interviews were conducted to gather information about change in conceptions after the intervention. Information from the pre/post content test used in the study was used to ask students about some of their responses during the interview. The sample of students represented those with low, middle, and high scores on the content pretest. Student artifacts were used as prompts for the post-intervention interview as well. All interviews were audio-recorded. Each interview took about 20 minutes each and were transcribed for analysis. The transcriptions were analyzed for frequency of codes which emerged as conceptions. The frequency of conception codes for scientific and alternative conceptions were compared between pre/post intervention interviews. Schnittka (2009) did provide several student utterance examples used to create conception codes for both sets of interviews.

Interviews provide opportunities for students to explain their thinking and conceptual understandings. Open-ended interviews have been used in several studies in mathematics and DBL research settings to allow students to use their own language to provide the researcher with insight into a student's level of concept knowledge (Groth et al., 2018; Schnittka, 2009). Researchers must specifically design the interview to provide them with information that will answer the research question which guides the study.

Analyzing Qualitative Data Sources

Coding is a primary process for analyzing qualitative data (Creswell, 2014). A code is a word or phrase that is assigned to a portion of qualitative data (Rogers, 2018). Coding is an iterative process that involves several cycles depending on the researcher. The researcher must identify any of their own bias and subjectivity to address ethical concerns and increase the validity and reliability of the findings (Rogers, 2018).

Journals and interviews are both qualitative data sources that can require the use of coding to interpret data collected from them. Often, coding is used as an inductive process to make sense of text by narrowing it into themes through identification of patterns and commonalities among text segments (Creswell, 2014). When beginning the coding process, the researcher first reads the original text and identifies small segments which are coded with a small phrase or word to identify the meaning of the segment. Specifically, a code is a "label that assign[s] symbolic meaning to descriptive or inferential information compiled during a study" (Miles, Huberman, & Saldana, 2020, p.71). In vivo codes are those that use the participant's own language as a code to signify the meaning of the text segments (Creswell, 2014). In the study by

Groth et al. (2018), transcriptions of interviews were analyzed through coding. Codes were developed and assigned to segments to capture student thinking. For example, the researcher associated knowledge about trends in linear relationships through a student's verbal recognition that the points on a scatter plot "'looked straight'" (Goth et al., 2018, p. 264).

Once the text is analyzed for segments that are assigned a code, the codes are then analyzed for commonalities and categorized into key points, also called themes or categories (Creswell, 2014). These key points can then be used to answer the research question(s) for a study.

Summary of Qualitative Data Sources for Insight into Conceptual Understanding

Several studies support the use of journaling in the mathematics classroom to capture student thinking and learning as a source of qualitative data (Benson-O'Connor et al., 2019; Bicer et al., 2013; Wells, 2016b). Journals provide the researcher with data, such as drawings and explanations, which help capture student understanding in a student's own language. During T/E DBBL specifically, journals (IEJs) are helpful to students for remembering what they have learned over a period of time and continuing to grow that knowledge throughout their learning experience. For the researcher, IEJs provide insight into student thinking and understanding through demonstrations of using new knowledge to make design decisions relative to the T/E DBBL task at hand (Wells, 2016b).

Interviews have also been used during mathematics and DBL studies as a supporting data source for gaining insight into student thinking (Panasuk, 2010; Groth et al., 2018). Schnittka, 2009) specifically used interviews to support quantitative and other qualitative findings regarding change in science conceptions during her study of DBL. Coding is the primary method for analyzing qualitative data (Creswell, 2014). Journals already provide written sources of data, but interviews are often transcribed prior to analysis. In vivo codes are often used to summarize sections of data by capturing the language of the participant for further analysis (Creswell, 2014). These in vivo codes are then examined for patterns and categorized by those patterns to answer the research question. Both journals and interview transcriptions can be analyzed through coding methods depending on the purpose of the research and the questions being answered by these qualitative data sources.

Summary of Literature Review

"Teaching does not *cause* learning. Rather, teaching involves promoting the likelihood of students learning…" (Simon, Saldanha, McClintock, Akar, Watanabe, & Zembat, 2010, p. 75). Student learning is the increase of knowledge represented through different knowledge types, including declarative, procedural, schematic, and strategic knowledge (Li, 2002). The primary goal of Integrative STEM Education (I-STEM ED) is teaching for understanding (conceptual knowledge) through technology/engineering design-based learning (T/E DBL) (Wells, 2019). T/E DBL teaches the content and practices of technology and engineering concurrently with the content and practices of other disciplines, such as science and mathematics, as intentionally determined by the teacher.

A theoretical framework is the foundation building the processes and understandings a researcher uses during a study. That framework is used to guide the methodology chosen to answer the research question(s). The theoretical framework is a lens through which the researcher sees the world they are exploring through their chosen research design. To study learning outcomes, one must first understand the learning process. There is almost a century of literature dedicated to the understanding of the learning process. Learning is defined as the process of increasing knowledge (Greeno et al., 1996). There are four types of knowledge:

declarative (knowing that), procedural (knowing how), schematic (knowing why), and strategic (knowing when, where, why, how) (Ryle, 1949; Bruner, 1960; Scheffler, 1965; Anderson, 1983; Alexander et al., 1991; Li, 2002). These acquisition of each knowledge type leads to conceptual understanding. Declarative and procedural knowledge are the lowest levels of concept knowledge. Schematic and strategic knowledge are types of conceptual knowledge, a higher level of concept knowledge, that requires contextual understanding of a concept.

Cognitivist, constructivist, and experiential learning theories explain how knowledge is increased through internal and external influences. Cognitivist learning theory describes the internal sensory stimulation that leads to the processes of internal memory construction and storage elaborated on by constructivist learning theorists (Jordan, Carlile, & Stack, 2008). Constructivists contribute to the understandings of developmental readiness and reflection that are important to the cognitive learning process (Piaget & Inhelder, 1969; Bruner, 1960). Experiential learning theory describes the external environmental factors that influence learning. According to experiential learning theory students benefit from engagement in stimulating learning environments that peak their interest and are interactive (Dewey, 1938; Kolb, 1984).

Technology/engineering design-based learning (T/E DBL) is the pedagogical approach of Integrative STEM Education (I-STEM ED) utilizing experiential learning to teach technology, engineering, and other disciplinary content (Wells, 2008). T/E DBL provides contextual experiences that engage students in the learning process. In order to solve a real-world problem, students feel a need-to-know information to design a solution to this problem. Because mathematics is a language through which I-STEM ED disciplines communicate, mathematical conceptual understanding is vital (ITEA, 2001/2007). Students recognize this need to understand and seek to actively engage in the cognitive processes which develop mathematical conceptual understanding. When students engage in mathematics experiences, they begin to recognize patterns, forming mathematical conceptions. As they experience the reliability of and abstractly reflect on the relationships between these patterns, they form conceptual understandings. Experiences in T/E DBBL also help students to develop habits of hand (designerly ways of knowing) which lead to the habits of mind needed to face challenges in every-day life (Wells, 2019). These habits of mind develop when students respond to situations requiring high levels of cognitive demand.

There are several previous studies dedicated to variations of design-based learning (DBL) in the science classroom (Wells, 2016a; Holbrook et al., 2001; Kolonder, Gray, & Fasse, 2003; Fortus et al., 2004; Fortus et al., 2005; Doppelt et al., 2008; Mehalik et al., 2008; Schnittka, 2009). Foundational research, such as that by Holbrook et al. (2001) and Mamlock et al. (2001), paved the way for other studies using similar curriculum to demonstrate the efficacy of DBL in the science classroom. Although most of these studies did not specifically address the mathematics knowledge being used and gained through the design challenges used in the study, there are many inherent mathematics skills and concepts highlighted by the DBL curriculum used in the study. Of the studies previously discussed, there was only one study specifically dedicated to the teaching and learning of exclusively mathematics content through DBL. Burghardt (2010) specifically dedicated their *Bedroom Design* unit to the study of teaching and learning of mathematics concepts. Nevertheless, this study focuses on the breadth of mathematics concept learning rather than the depth of it. Therefore, there is much to be contributed to the field of mathematics education research from a study with on the focus of DBL to promote change in targeted mathematics concept knowledge.

Many of the studies contributing to the DBL literature utilize a mixed methods research design. A pre/posttest instrument was used to collect quantitative data in 92% of the studies reviewed for this research, and 75% of the studies used a qualitative measure. One study utilized a purely qualitative design while one study utilized a quantitative research design. A mixed methods design, including both quantitative and qualitative research methods, was used in 66% of DBL research. The use of a mixed methods design in the majority of research supports the mixed methods approach chosen for this research.

Multiple sources, including measures of both implicit and explicit knowledge, are important to gain insight into student understanding (NCTM, 2000). Niemi (1996) emphasizes the importance of allowing students to demonstrate their conceptual understanding through a variety of representations in order to gain insight about the depth of understanding that students have. The purpose of qualitative research is to "describe and clarify experience" through the collection of qualitative data which provide evidence for this experience (Polkinghorne, 2005,p. 139). In the mixed methods research provided in this literature review, qualitative methods were used to support the findings of a pre/posttest instrument.

Doppelt et al. (2008) found that students of lower achievement on the pre and posttest demonstrated the same amount of understanding on the other forms of assessment as the students who achieved higher on the pre and posttest. When students are asked to justify, explain, and represent their knowledge in a variety of ways, their level of conceptual understanding becomes clearer. As students develop deeper conceptual understanding about mathematics, their ability to reason abstractly increases. Specifically in algebra, students' abilities to "recognize functional relationships between known and unknown, independent and dependent variables, and to distinguish between and interpret different representations of algebraic concepts" increase with conceptual understanding (Panasuk, 2010, p. 237). Panasuk (2010) also supports the use of multiple representations to analyze student conceptual understanding through student ability to communicate their mathematical thinking. Through the use of multiple sources, patterns may emerge that provide support for research inference about student understanding.

Journals and interviews are sources of qualitative data which have been used both independently and as supporting evidence for gathering insight into student conceptual understanding in mathematics and during studies in DBL (Schnittka, 2009; Panasuk, 2010; Groth et al., 2018). Through journals, student drawings and explanations provide information about their thinking and learning. During interviews, the researcher can ask questions intentionally designed to draw information from the participant which helps them capture information about student thinking and understanding. Both journals and interview transcriptions can be analyzed using coding methods (Miles, Huberman, & Saldana, 2020). In vivo codes are used to summarize sections of data by capturing the language of the participant (Creswell, 2014). In vivo codes are then examined and categorized into key points which can be used to help the researcher answer corresponding research questions.

Numerous studies have contributed to the literature on understanding learning of mathematics through a variety of methods and domains within the discipline (Crooks and Alibali, 2014; Bisson et al., 2016; Groth and Bergner, 2006; Epstein, 2007; Scheibling-Sève, Pasquinelli, and Sander, 2020; Groth et al. 2018). Many studies have also contributed to the knowledge of design-based learning in the science and mathematics classrooms, including the use of quantitative and qualitative methods to collect and analyze data. However, few have examined the connections between design-based learning and mathematics concept knowledge of pattern recognition and lines of best fit, particularly in middle school mathematics. This study will use a mixed methods research design to investigate the evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) which documents a change in student mathematical concept knowledge.

CHAPTER THREE: RESEARCH METHOD

Overview

This chapter describes the research design and method followed in conducting this study. Specifically, it provides the research questions, research design, participant selection and research setting, instrumentation, and data collection and data analysis procedures.

Research Questions

Based on a thorough review of the literature, a mixed methods approach (Teddlie & Tashakkori, 2006) was identified as most appropriate given the explanatory nature of this study, the instructional environment in which the research was conducted, and the multiple data types collected. The following research question guided this study and was answered in the context of eighth-grade mathematics students:

RQ1 – What evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) documents a change in concept knowledge of:

a) patterns of association between bivariate measurement data on a scatter plot, and
b) lines of best fit used to model predictive relationships among two quantitative variables on a scatter plot

The independent variable in this study is the T/E DBBL intervention, and the dependent variable is student concept knowledge, specifically of patterns of association between bivariate measurement data on a scatter plot and predictive relationships between quantitative variables. Table 3 presents the alignment between the research questions, data sources, and data analyses used in answering the Research Question (RQ).

Table 3

Alignment Between Research Questions, Data Sources, and Data Analyses

Research Question	Data Sources	Data Analysis
What evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) documents a change in concept knowledge of:		
(a) patterns of association between bivariate measurement data on a scatter plot, and	Quantitative • Bivariate Data Pretest • Bivariate Data Posttest	• Descriptive statistics • Two-tailed, paired *t*-test • Cronbach's Alpha
(b) lines of best fit used to model predictive relationships among two quantitative variables on a scatter plot?	Qualitative • Interactive Engineering Journals (IEJs) • Individual Student Interviews	• Content Analysis

Research Design

A mixed method, sequential explanatory multiple embedded case study research design (Creswell, 2014) was followed in conducting this research. This study investigated the implementation of a T/E DBBL instructional intervention intended to enhance middle school mathematics students' conceptual understanding of patterns of association and the use of lines of

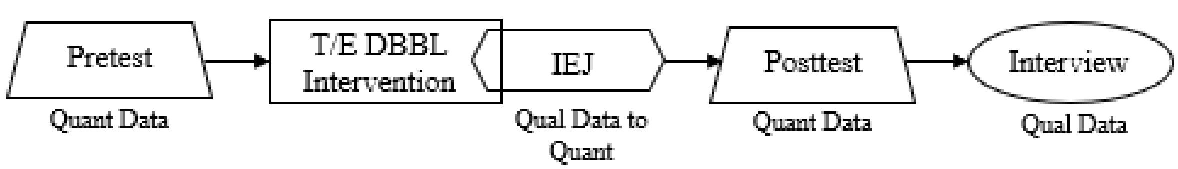


Figure 4. Four-stage sequential mixed method research design

best fit (trendlines) to model predictive relationships. In this mixed-method study, data were collected across four sequential stages: preassessment, intervention (IEJ entries), post assessment, and individual interviews (Figure 4). Each of the four stages collects data (quantitative and/or qualitative) that, when correctly analyzed, can be used to indicate a student's change in level of mathematics concept knowledge of patterns of association. As depicted in Figure 4, prior to the intervention students were administered the Bivariate Data Pretest (BDPre) as a quantitative preassessment of their initial level of mathematics conceptual understanding. Throughout the T/E DBBL intervention, all students were required to make daily entries in their Interactive Engineering Journals (IEJ). These entries were analyzed qualitatively as both a formative and summative assessment of a student's conceptual understanding throughout the instructional intervention. The Bivariate Data Posttest (BDPost) was used as a post assessment of knowledge gains following implementation of the intervention. Low, middle, and high distances between pretest and posttest scores were used to purposefully select a sample of six students whose IEJ entries were further analyzed to corroborate findings derived from the pre/posttest data. Individual, semi-structured interviews were then conducted for those same six students as a means of further corroborating qualitative and quantitative findings.

Participants

This study took place at a small, rural high school, located in a mid-Atlantic state. The school included grades 7-12 and had an enrollment of 281 students, including 144 males and 137 females. The school was comprised of 95 percent white students and 5 percent multi-racial students. Sixty-seven percent of students qualified as Low Socioeconomic Status (SES) and 21 percent of students qualified for special education services.

Student participants included 30 of the 42 eighth-grade students (71%) enrolled at the high school, all of whom were preassigned to a class by school administration based on scheduling needs. The student participants comprised 11 percent of the total student body with 13 females and 17 males in the sample. Ten percent of these eighth-grade students qualified for special education services. Eighth-grade students were used in this study because eighth-grade mathematics and High School Algebra I for 8th Grade standards focus specifically on linear bivariate data vital for success in high school mathematics (WVDE, 2022b). This convenience sample of eighth-grade students were enrolled in three eighth-grade mathematics courses and one eighth-grade Algebra I course.

Quantitative Data Source

State and national assessment of concept knowledge of patterns of association and lines of best fit (trendlines) between bivariate measurement data on scatter plots is required of all eighth-grade mathematics students (WVDE, 2016, p. 22; NCTM, 2000, p. 50). The eighth-grade mathematics and eighth-grade Algebra 1 students in this study were required to take the same eighth-grade mathematics state summative assessment. State assessment of eighth-grade mathematics uses the test blueprint (Figure 5) to construct exams and to generate practice tests for use by classroom mathematics teachers. Similarly, practice tests are also generated at the

WVGSA Blueprint - Grade 8			
	Domain	**Number of Items**	
	Cluster	**Min**	**Max**
	Calculator Total		
EE & NS	**Expressions and Equations & Number System**	**10**	**13**
	Know that there are numbers that are not rational, and approximate them by rational numbers	0	2
	Work with radicals and integer exponents	0	4
	Understand connections between proportional relationships, lines, and linear equations	0	4
	Analyze and solve linear equations and pairs of simultaneous linear equations	0	4
F	**Functions**	**8**	**10**
	Define, evaluate, and compare functions	2	6
	Use functions to model relationships between quantities	2	6
G & SP	**Geometry & Statistics and Probability**	**13**	**16**
	Understand congruence and similarity using physical models, transparencies, or geometry software	1	6
	Understand and apply the Pythagorean Theorem	0	4
	Solve real-world problems involving volume cylinders, cones, and spheres.	0	2
	Investigate patterns of association in bivariate data	1	6

DOK Ranges	Min	Max
DOK 1	5	9
DOK 2	17	22
DOK 3	5	9

Mathematical Habits of Mind Sub-Score	Min	Max
MHM: Modeling and Problem Solving	9	12
MHM: Use Mathematical Reasoning	8	11

Figure 5: WVGSA Grade 8 Mathematics Blueprint (WVDE, 2019)

national level. Capitalizing on the availability of these practice tests, relevant state and national assessment items were used as the framework for developing the pre and post Bivariate Data Test instrument (BDPre and BDPost, Appendix A and B respectively).

Bivariate Data Test **(**BDPre and BDPost) items were closely modeled after practice items drawn from the West Virginia General Summative Assessment (WVGSA) (Cambium Assessment, Inc., 2022) and the 2007 NAEP (National Center for Education Statistics, 2022) that have already been validated for measuring specific eighth-grade mathematics concept knowledge.

Test Item Selection

Items identified in the national and state practice tests were selected for inclusion in the BDPre and BDPost instrument based on their targeting of content and constructs relative to the research question guiding this study. Table 4 and Table 5 provide information about the state and national sources and the concept knowledge associated with each item on the BDPre and BDPost instruments.

Table 4

Items Selected to Measure Concept Knowledge of Patterns of Association

Test Item		Source
Pre	Post	
1	7	WVGSA - Interim Module Assessment Math G8 Statistics and Probability A Question 2
2	9	NAEP Question ID: 2007-8M7 #13 M144801
3	1	WVGSA - IMA Math G8 Statistics and Probability B Question 1
5a	4a	WVGSA- Diagnostic Grade 8 Math InvestigatePatternsBivariateData Question 3
5b	4b	WVGSA- DIA Grade 8 Math InvestigatePatternsBivariateData Question 3
6	2	NAEP Question ID - 2007-8M7 #13 M144801
9	5	WVGSA- IMA Math G8 Statistics and Probability B Question 2
12a	11a	WVGSA- DIA Grade 8 Math InvestigatePatternsBivariateData Question 3
12b	11b	WVGSA- DIA Grade 8 Math InvestigatePatternsBivariateData Question 3
13	12	WVGSA - IMA Math G8 Statistics and Probability B Question 1
14	13	NAEP Question ID - 2007-8M7 #13 M144801

Table 5

Items Selected to Measure Concept Knowledge of Lines of Best Fit

Test Item		Source
Pre	Post	
4	10	WVGSA- IMA Math G8 Statistics and Probability A Question 5
5c	4c	WVGSA- IMA Math G8 Statistics and Probability B Question 5
5d	4d	WVGSA - IMA Math G8 Statistics and Probability A Question 3
7	8	WVGSA - IMA Math G8 Statistics and Probability A Question 3
8	3	WVGSA- IMA Math G8 Statistics and Probability B Question 5
10	14	WVGSA- IMA Math G8 Statistics and Probability A Question 5
11	6	WVGSA - IMA Math G8 Statistics and Probability A Question 3
12c	11c	WVGSA- IMA Math G8 Statistics and Probability B Question 5
12d	11d	WVGSA - IMA Math G8 Statistics and Probability A Question 3

Both the pre and post BDP instruments contained 20 individual items, 11 of which addressed RQa (patterns of association) and 9 of which addressed RQb (lines of best fit on scatter plots). Of the 20 items, 12 were multiple choice, 8 were completion, 13 were contextual, and 7 were non-contextual.

Test Item Modification

Both the pretest and posttest BDP items were modeled from the same original West Virginia General Summative Assessment and 2007 NAEP practice items. The BDPre instrument was created first, then modified minimally to create the BDPost instrument. BDPre items were slightly altered both linguistically and contextually without changing the math content or construct measured by each item when creating the BDPost items. Those items containing numbers or graphs were also modified by simply using different numbers or rearranging the graphs to avoid student memorization and threat to the validity of results. BDPre items were also reordered on the BDPost so that students would not recognize the previous order of items. Table

6 provides examples of how original items were modified linguistically and contextually to create the BDPre.

Table 6

Comparison of Item Excerpts from Original and Modified Instruments

Item Source	Modification	Original Item Excerpt	Modified Item Excerpt
WVGSA-IMA	Linguistic	**Which** scatter plot show**s** a linear relationship with a positive correlation?	**Circle the letter of the** scatter plot show**ing** a linear relationship with a positive correlation
2007 NAEP	Contextual	According to the scatterplot, what is the relationship between **test scores** and **the average number of fish meals per month**?	According to the scatterplot, what is the relationship between **the age of a person** and **how many minutes they spend talking on the phone**?
WVGSA-DIA	Linguistic/ Contextual	**There is** a linear association between **average body weight and average brain weight for animals. True/False**	**Is there** a linear **or non-linear** association between **the time (days) and electricity produced (mV)?**

Note. Bold font signifies modified language.

The minimal linguistic or contextual changes made to the original items did not affect the content or concept measured by each item. The complete pre and post instruments are included in Appendix A and B respectively.

The state and national tests also included items that provided data within a context. Modeled after such items, two novel design scenarios were included in the BDPre and BDPost instruments to assess the contextual connection of mathematics concept knowledge within the technology/engineering design-based learning intervention. The inclusion of these design scenarios was also intended to directly correspond with IEJ entries of original data students collected during the instructional intervention. Each novel design scenario, one regarding a hydroponics system and one regarding a microbial fuel cell prototype, included in both the BDPre and BDPost, required students to use original data provided in a table to create a scatter plot and answer four questions (parts a, b, c, and d) based on the scatter plot they created. The novel situations in the BDPre were modified in the BDPpost only numerically by changing the output numbers in each table.

Instrument Validity

The validity of an assessment refers to whether the assessment measures what it is supposed to measure (John, 2015). The items used for the BDPre and BDPost instruments were those already validated to measure progress on eighth-grade mathematics content by the West Virginia General Summative Assessment (WVGSA) and the 2007/2009 National Assessment of Educational Progress (NAEP). Given these items were not substantively altered, either in the math content or constructs targeted, the assumption of validity was maintained. However, to support this assumption, additional confirmation of validity was conducted.

Face Validity, Content/Construct Validity

To measure face validity and content/construct validity, a 3-member panel of experts was used to co-rate each item on the test. Individuals considered for inclusion on the expert panel met two or more of the following three criteria: 5 or more years teaching eighth-grade mathematics, a terminal degree in mathematics or closely related discipline, 5 or more years of mixed-methods research experience. Panelists were asked to examine the BDPre and BDPost instruments for use in measuring concept knowledge of patterns of association on scatter plots and lines of best fit between bivariate measurement data on a scatter plot. Specifically, panelists were asked to review each item and complete a table of specifications (Table 7, Appendix C), indicating the concept knowledge they believed was being measured, any suggestion for items they felt required modification, and a decision on each item regarding whether to be included or not.

Table 7

Excerpt from Panelist Rubric for Determining Face and Content/Construct Validity

Item #		Concept Knowledge Measured (Check One)		Decision (Check one)		
Pre	Post	Patterns of Association	Lines of Best Fit	Accept	Modify	Remove
1	7	☐	☐	☐	☐________________________	☐
2	9	☐	☐	☐	☐________________________	☐
3	1	☐	☐	☐	☐________________________	☐

Several rounds of review and arbitration among panelists were conducted, with revisions made to the BDPre and BDPost accordingly until a minimum of 66 percent agreement was reached among panelists for inclusion of a given item on the instruments.

Instrument Reliability

The reliability of an instrument is a measure of how reliable the responses of a test are or how consistently the items measuring the same construct on a test provide similar results (Bujang, Omar, & Baharum, 2018). The internal reliability of a test given on one occasion to a sample is commonly measured by Cronbach's alpha (John, 2015; Taber, 2018). The formula for Cronbach's alpha is $\alpha = (\frac{k}{k-1})(1 - \frac{\sum_{i=1}^{k} \sigma_{y_i}^2}{\sigma_x^2})$ and was used to measure reliability of the BDPre and BDPost (Goforth, 2015). The marginal reliability, the measure of overall reliability based on the average conditional standard errors of measurement, of the instrument (WVGSA) containing the original items used for creation of the BDP was calculated to be 0.89 for the eighth-grade mathematics assessment (WVDE, 2020). An alpha reliability formula is used to measure the consistency of item scores on the NAEP (NCES, 2020). The weighted alpha reliability calculated for six item blocks for the 2012 NAEP Mathematics assessment for 13-year-old students was $0.82 \leq \alpha \leq 0.88$ (NCES, 2014). The reliability of the NAEP is additionally studied by panels of experts established by the National Center for Education Statistics (NCES) or external organizations, such as the Buros Center for Testing, the University of Massachusetts/Center for Educational Assessment, the University of Georgia, or the National Academy of Sciences (NCES, 2020). These panels are used to conduct external evaluations of the NAEP.

Instrument Readability

To ensure the BDP was at an appropriate eighth grade reading level, the readability was calculated using the Flesch Reading Ease (FRE) test (Flesch, 1948). This test calculates the readability of a text using the number of words in a sentence and average number of syllables per word. The average sentence length (ASL) is multiplied by 1.015. The average number of syllables per word (ASW) is multiplied by 84.6. Those two numbers are added. That sum is subtracted from 206.835. The remaining number is a readability score, a number between 0 and 100 that tells the average readability of a text. Using this formula, the Readability of the BDP (pre/post) was calculated as follows: FRE = 206.835 – (1.015 x ASL) – (84.6 x ASW) with resulting scores of 69.6 (TextCompare, 2022a) and 75.6 (ReadabilityFormulas.com, 2022) on the Flesch Index. According to Flesch (1948), a score of 0 means the text is at a college graduate level, and a score of 100 is an elementary grade level close to 5th grade. An appropriate Readability score associated with 8th grade is between 60 and 70. Given readability calculations for the BDP pre and post were 69.6 and 76.2 respectively, both were found to be at an appropriate readability level for the target population.

As an additional measure of readability, the Flesch-Kincaid Grade Level (FKGL) test measured the grade level readability score of the text (Flesch, 1948; Kincaid, Rogers, Chissom, Fishburne, Rogers, & Chissom, 1975). The FKGL test was created based on the Flesch Reading Ease test with scores that were easier to interpret because of reduced need for a score index (TextCompare, 2022b). Scores from both tests were used in conjunction to firmly establish the readability of the BDP was at or below an average eighth-grade reading level. The Flesch Kincaid Reading Age (FKRA) corresponds to a FKGL. For example, a FKRA of 5.4 would correspond to a fifth grade FKGL. The FKRA is calculated by multiplying the average sentence length by 0.39. Then, the average number of syllables per word is multiplied by 11.8. The sum of those two numbers is subtracted by 15.59. The remaining number is the grade level associated with the readability level of the text. FKRA = (0.39 x ASL) + (11.8 x ASW) – 15.59. Based on these calculations, the FKGL of the BDPpre and BDPost is between sixth grade levels 6.3 (ReadabilityFormulas.com, 2022) and 6.4 (WordCalc.com, 2022), another indicator that the text was at a readable grade level for an average eighth-grade mathematics student.

Qualitative Data Sources

The Interactive Engineering Journal (IEJ) and semi-structured, individual interviews were used as sources of qualitative data that upon analysis would help in answering parts a and b of the research question. In the following sections, each qualitative data source is discussed.

Interactive Engineering Journal

Throughout the intervention (details provided in the Procedures section) and their engagement in the various phases of design as discussed previously through the PIRPOSAL Model (Wells, 2016c), students recorded daily journal entries in the Interactive Engineering Journal (IEJ) reflecting their design experience. During the data collection and analysis phases of design, students documented their experiences and recorded the data they collected over a period of five days. As a result, entries in the IEJ provided documentation of students utilizing their concept knowledge of patterns of association and lines of best fit during their engagement in T/E DBBL.

To ensure students included discussion of the targeted concepts in their IEJ, at the end of each day they were asked to respond to teacher-developed 3-2-1 prompts. The 3-2-1 prompts refer to three questions the teacher asked students to answer, two questions they asked about the design challenge, and one new thing they learned that day. Table 8 provides the three teacher-created prompts used to guide daily instruction throughout the design challenge.

Table 8

Interactive Engineering Journal Daily Prompts

PIRPOSAL Phases of Design	Day	Teacher-Developed Daily Prompts
Problem Identification	1	• Define the problem. • What is the human need? • How would an engineering design solution potentially solve the problem?
Ideation	2	• What are the criteria for your engineering design solution? • Sketch your initial ideas. Label the parts of your design and tell me what they do. • List at least 3 questions that you still need to answer before you begin.
Research	3-4	• What information did you collect to answer your main research question? • Write a short summary of each person in your group's independent research. Create one main research question for your group. • After answering your group's question, prepare one page in your journal, including a diagram, to present to the class to summarize your group's research.
	5	Based on the group research discussions… • What engineering solution are you designing? • Describe the parts of this system and how it will meet each criterion for the design challenge. • What do you want this system to do?

PIRPOSAL Phases of Design	Day	Teacher-Developed Daily Prompts
Potential Solutions	6	• Based on your research, list at least three of your group's potential engineering design solutions. • Sketch your initial ideas. Label the parts of your design. Describe what they do. • Generate a complete list of materials that you will need to build your group's system.
Optimization	7	• How will your design meet the design challenge criteria? • How will you record the amount of electricity your system produces? • Describe the steps you took to put your system together today.
	8	• What problems do you expect to have with your system? • How do you plan to solve those problems? • Describe the steps you took to put your system together today.
Solution Evaluation and Alterations	9	• Collect the following data from your system: -electricity measurement using multimeter -observations about the prototype -inferences about observations -re-design decisions -justification for those decisions • Record your data the way a scientist would. • What variables did you measure today?
	10	• Record your daily measurement data for each variable. • Is there a difference between day 0 and day 1 data? • If there is no difference, what does that mean? If there is a difference, what does that mean?
	11	• Record your daily measurement data for each variable. • Is there a difference between day 1 and day 2 data? Day 0 and day 2? • If there is no difference, what does that mean? If there is a difference, what does that mean?

PIRPOSAL Phases of Design	Day	Teacher-Developed Daily Prompts
	12	• Record your daily measurement data for each variable. Create a visual model to show someone how well your system is working. • What does the visual model show about the change in your daily amounts of electricity? • On your model how would you show that change?
	13	• Record your daily measurement data for each variable. • How can you summarize the overall pattern you see on your visual model? • If your pattern continues, what do you predict your electricity measurement will be on day 6? day 10?
	14	• What overall patterns do you see in your data? What has been most helpful in helping you to see those patterns? • How does your visual model compare to the computer generated one? Include: intervals, slope, y intercept, prediction for electricity tomorrow • Prepare one page in your journal to summarize the data you collected over the past five days for your system.
Learned Outcomes	15	• Has your system been successful in meeting the design challenge criteria? Does it have the potential to do so? How do you know? • How long would your system need to run to light a 2V LED bulb? How do you know? What changes would you make to your design to increase the amount of electricity it produces? • How could your design potentially be used in a waste-water treatment plant?

All of the 3-2-1 prompts were tailored to specifically address the type of engagement students would be experiencing in each of the Phases of Design. Specifically, the prompts for Days 1 and 2 (Problem Identification and Ideation Phases) were designed to address the authentic need for the design challenge, setting the context for a design solution to a real-world problem. The prompts on these days required students to consider the criteria of the solution before documenting their initial design ideas. Day 2 prompts served to record students' original ideas before research is conducted to document the evolution in their ideas as their science and math knowledge increases throughout the design phases. Days 1 and 2 prompts connected the design challenge to the real world and allowed the researcher to answer the research question in relation to students' experiences with T/E DBBL design practices and artifact criteria considerations.

The IEJ prompts for Days 3-5 (Research Phase) were used to help students use their science and mathematics content knowledge in order to justify their design solutions. The Potential Solutions Phase (Day 6) IEJ prompts were used to document student artifact ideas and use of science and mathematics content knowledge through discussion of the working parts and purpose of those parts for their artifact. On Days 7 and 8 (Optimization Phase), the IEJ prompts were used to document student experiences with design practices, such as ensuring that their artifact met the design challenge criteria and documenting their construction procedures for future reference. The prompts used for Days 3-8 were intended to help students build a T/E DBBL context for increasing mathematical concept knowledge and making informed design decisions based on that mathematics knowledge. These prompts allowed the researcher to gather data regarding mathematics-based design decisions about the prototype solution referenced throughout these prompts.

The Solution Evaluation and Alterations Phases (prototype testing) were the points in the design process where students collected and analyzed data in order to make design decisions. Therefore, the daily prompts were designed to have students address targeted math concept knowledge. Specifically, on Day 9 students began engaging in mathematics to evaluate and alter their design, and prompts were used to gather qualitative data about students' abilities to record data for the variables they were measuring. Day 9 prompts also provided information about students' ability to make inferences about their designed solution based on the data they collected. On days 10 and 11, prompts asked students to enter data into a table and analyze changes in the amount of electricity that their system generated over time. Students' responses were used to document their recognition of changing patterns between variables over time. On Day 12, the IEJ prompts shifted to ask students to provide a visual model of their data. The purpose of these prompts was to have students demonstrate their use of data in a scatter plot to document how well their system was performing. On Day 13, the IEJ prompts were designed to have students communicate information provided by their linear or non-linear patterns using lines of best fit on their scatter plot. Prompts were also used to have students use predictive analysis of linear or non-linear patterns to plot future data points on the scatter plot.

At the conclusion of the Solution Evaluation and Alterations Phases (Day 14), students were prompted to assess the performance of their designed system based on the analysis of data they collected over time. These data served as indicators of students' understandings regarding patterns of association and lines of best fit in the context of the design challenge. Prompts provided during the Learned Outcomes Phase (Day 15) were used to indicate students' abilities to use the data collected for their prototype. Students were first asked to evaluate whether or not they met the design challenge criteria (i.e., could their system light an LED or run a small motor) and then predict future outcomes of the system based on design ideas to improve electricity production. These questions specifically required students to calculate how long their system would take to produce two volts (2,000 millivolts) of electricity using the data they collected from their existing system. Then, the prompts asked them to discuss ways to improve their system to increase electricity production based on these calculations. The final IEJ prompt question connected the classroom MFC back to the real-world use of MFCs in a waste-water treatment plant.

As students responded to the IEJ prompts, they each demonstrated their level of conceptual understanding through the use of mathematics in connection to experiences with T/E DBBL. Student responses demonstrating variable recognition, design decisions, and data collection, organization, or analysis were coded to represent mathematics-related design experiences. To gather information about the connection between these experiences and change in mathematics concept knowledge, IEJ entries demonstrating conceptual understanding of patterns of association or lines of best fit were coded accordingly and later analyzed to answer RQa and RQb.

Individual, Semi-structured Interviews

Interviews are the "conversational process of knowing" as two people share views on a subject (Brinkmann, 2013). Qualitative interviews are specialized conversations where the researcher seeks information about informants' experiences or interpretations (Hatch, 2002). Semi-structured interviews are defined as interviews "where topics and open-ended questions are written but the exact sequence and wording does not have to be followed with each respondent" (Cohen, Manion, and Morrison, p. 278, 2003). Semi-structured interviews follow a pre-determined protocol including the following seven stages: thematizing, designing, interviewing, transcribing, analyzing, verifying, and reporting (Knox and Burkard, 2009; Cohen et al., 2003).

When designing interview questions, question and response types vary. The advantages to open-ended items, which minimalize restraints on participant answers, are flexibility, encouragement of cooperation, rapport establishment, and the possibility of unanticipated answers (Cohen et al., 2003). The interviewer asks the same questions of all participants; however, the interviewer can guide the interview to clarify or investigate in more depth the situation of an interviewee.

Based on the seven stages protocol, this study utilized open-ended, semi-structured interview questions (Appendix D) designed to gather information about the relationships between student experiences during the MFC design challenge and change in mathematical concept knowledge. IEJ prompts guided the development of interview questions that directly connected to the sequence of experiences students had during the T/E DBBL design challenge. The open-ended interview questions were designed to have students use their own language to express their level of understanding. Individual interview questions were therefore crafted to elicit student clarifications or further explanations regarding the concept knowledge targeted by the research question. This approach led to the development of six main interview questions, each addressing specific topics that connected back to the 3-2-1 IEJ prompts, and all of which aligned with the concepts assessed by the BDP. Sub-question prompts were also created prior to the interview in anticipation of possibly needing to further prompt students for additional information or clarification of their concept knowledge.

According to Morse (1994), a sample size of six is sufficient for protocols involving in-depth conversational interviews. Based on this suggested sample size and given the low number of student participants in this study, only a small subset of six interviewees was needed to serve as a representative sample. Details regarding the procedures used to select the six interviewees are presented in the IEJ data analysis section.

Procedures

IRB approval (Appendix E) from Virginia Tech was obtained prior to engaging in any part of the research. Once approved, this study utilized the following data collection procedures:

a) emails were sent to the public-school system to obtain permission to conduct the study (Appendix F),
b) parental permission (Appendix G) and student assent (Appendix H) forms were sent to all parents, participants
c) BDP pretest administered (Appendix I)
d) Implementation of the three-week intervention
e) All IEJs collected
f) BDP posttest administered (Appendix I)
g) BDP pre/posttest results analyzed
h) IEJ analysis/Interview participant selection (6) based on pre/posttest results
i) IEJ data content analysis conducted
j) Individual Interviews conducted with the six IEJ analysis participants (Appendix J)
k) Interviews transcribed
l) Interview data content analysis conducted
m) Triangulation of data

The following paragraphs provide descriptions of the data collection procedures adhered to during the four sequenced stages of the research: pre-assessment, intervention (IEJ entries), post assessment, and individual semi-structured interviews.

Data Collection

Pre-Assessment: Bivariate Data Pretest

Stage one pre-assessment was the administration of the Bivariate Data Pretest (BDPre) (Appendix A), a paper/pencil instrument. Prior to introducing the T/E DBBL instructional intervention, the BDPre was administered to pre-assess students' concept knowledge of patterns of association and the use of lines of best fit (trendlines) for predictive analysis of scatter plots. The pre-assessment was an integral part of classroom instruction and therefore did not impact instructional time. To be consistent in administration of the BDPre across all eighth-grade classes participating in the study and to adhere to IRB requirements, a script (Appendix I) was read to students in each class to explain the research purpose of the test and provide instructions for its completion. The BDPre was completed within one 60-minute class period, after which all student responses were collected and secured by the researcher in a locked cabinet in the researcher's classroom.

Intervention

The research intervention was a three-week Technology/Engineering Design-Based Biotechnical Learning (T/E DBBL) instructional approach. Three eighth-grade teachers (mathematics, science, and special education) collaborated on the facilitation and implementation of the T/E DBBL intervention, with the researcher participating as the mathematics teacher. Throughout the three weeks, students engaged in the T/E DBBL intervention during both of their regularly scheduled 60-minute mathematics and science classes (a total of 120 minutes each day). The timeline for implementing the intervention (Table 9) occurred over 15 instructional days as pre-planned by the researcher.

Table 9

Timeline of T/E DBBL Instructional Intervention

Timeline	Sequence of Instruction
Day 1	• Design challenge initial presentation • Read and discussed design challenge document
Day 2	• Documented societal problem, human need, solution, individual initial sketch of ideas, and research questions in IEJ
Days 3-4	• Students placed into groups • Students answered research questions
Day 5	• Students combined individual research into one group summary for their group research discussion with the class • All groups discussed their findings • Class notes were taken during group discussions
Day 6	• Individual informed sketch and list of materials were documented in IEJ • Group prototype design was created, sketched, and materials list was submitted
Days 7-9	• Materials were gathered • Prototypes were constructed • Iterations of prototypes were built as needed
Day 10	• Began daily bivariate measurement data collection in IEJs • Iterations of prototype designs built as needed
Day 11	• Daily bivariate measurement data collection continued in IEJs • Continued iterations of prototype designs built as needed
Day 12	• Daily bivariate measurement data collection continued in IEJs • Create visual model of data (scatter plots) in IEJs • Analysis of bivariate measurement data patterns of association on scatter plot

Timeline	Sequence of Instruction
Day 13	• Line of best fit construction on scatter plot. • Use of trendline for predictive analysis for tomorrow and day 10 • Creation of online scatter plot and trendline
Day 14	• Comparison of individual scatter plot and trendline to online scatter plot and trendline (rate of change, pattern analysis, etc.) • Creation of one page data summary for MFC prototype
Day 15	• Predictive analysis for MFC potential to light a light bulb • Discussion of modification and suggestions for future MFC prototypes and design challenges in IEJ • Discussion of potential for use of prototype in waste-water treatment plants

The T/E DBBL instructional approach utilized a design challenge addressing the real-world need for a sustainable alternative energy solution which immersed students in the design of a microbial fuel cell (MFC). The goal of immersing students in this design challenge was to have them experience the authentic need for mathematical concept knowledge in making design decisions leading to a successful working MFC prototype.

The intervention used in this study, specifically the microbial fuel cell (MFC) biotechnical design challenge (Wells, 2015; Appendix K), required student participants to design a microbial fuel cell prototype that could power a small light emitting diode (LED). The prototype served as a demonstration of the potential for wastewater treatment plants to use the microbial fuel cell concept in the large-scale generation of electricity (alternative energy source). Throughout the intervention students engaged in all phases of design (PIRPOSAL Model) as they worked toward an appropriate solution by designing, building, and testing iterations of their MFC prototype (Wells, 2016c).

Interactive Engineering Journal Entries

An Interactive Engineering Journal (IEJ) is a composition book in which students record their daily progress (ideas, questions, sketches, research, etc.) toward the design of an acceptable design solution (Wells, 2016b). As such, in this research all daily IEJ entries served as a qualitative data source documenting student demonstrations of mathematical concept knowledge in response to the imposed need for design decision-making. Throughout all phases of design, students continually recorded their progress toward the design of an acceptable MFC solution. To ensure that students documented their use of mathematical concept knowledge, the researcher also presented students with daily 3-2-1 journal prompts. Final journal entries were made on Day 15, after which the researcher collected and secured all student journals in a locked cabinet in the classroom.

Post Assessment: Bivariate Data Posttest

Following IRB protocol, at the conclusion of the intervention within the prescribed timeline (Table 9), the Bivariate Data Posttest (BDPost, Appendix B) was administered (paper/pencil) and completed within one 60-minute class period (Appendix I). Student response documents were collected and stored in a secure cabinet in the classroom by the researcher.

Semi-Structured Interviews

The researcher conducted semi-structured, open-ended interviews with a select number of individual students to gather information about the relationship between experiences in T/E DBBL and gains in mathematics concept knowledge. Purposeful sampling was used to select six interview participants, two students representing each high, middle, or low distances between BDPre and BDPost scores, determined by quantitative statistical analyses. These students were chosen to represent a sample of students who demonstrated high, moderate, and low gains in concept knowledge on the BDP to gather additional insight about these students' levels of conceptual understanding which may or may not have been accurately demonstrated through their BDP scores. Twenty-minute semi-structured, open-ended interviews were conducted within a week of having given the BDPost to individual students. The researcher followed the same prepared interview protocol (Appendix J) with all students interviewed, including a script (Appendix J) read prior to each interview. Interviews were audio recorded using a video recording program (with the camera turned off) that automatically stores recordings in a password- protected web repository provided by the public-school system for instruction.

Data Analyses

Analyses of quantitative and qualitative data sources were conducted in the following order: pre/posttest, IEJ entries, individual semi-structured interviews, triangulation of data. The procedures for data analysis are provided in the following sections.

Bivariate Data Pretest and Posttest Analyses

Analysis of BDP pre/post scores was conducted to discern changes in student concept knowledge of patterns of association and lines of best fit. Descriptive statistics (e.g., measures of central tendency, standard deviation) were used to summarize analyses of data comparisons. A two-tailed, paired *t*-test was used to determine the significance between pretest and posttest scores with a confidence interval of 95% and a significance level of $\alpha = .05$ (Stelman, 2018).

IEJ Analyses

Analysis of student entries in their Interactive Engineering Journals (IEJs) was conducted to provide evidence of engagement in T/E DBBL which helped document change in mathematical concept knowledge. Student IEJ entries provided additional qualitative data to corroborate and/or support the BDP pre/posttest results with analyses of only a representative subsample being necessary to establish this corroboration.

The six interviewees in the subset were purposefully selected based on criteria related to changes between pre/posttest BDP scores.

The subsample consisted of IEJs from six students based on criteria related to the degree of change (high, middle, low) among students' BDP pre/posttest scores. Specifically, the degree of change for each participant was calculated using the difference between their posttest and pretest score (degree of change = posttest score – pretest score**).** The six IEJs selected represented two students whose scores were closest to the mean change from each Change Sub-Group determined as follows:

- High Change Sub-Group: students with the highest degrees of change between pre/posttest scores were selected
- Middle Change Sub-Group: all degrees of change were averaged (mean), and students with degrees of change closest to the mean were selected
- Low Change Sub-Group: students with the lowest degrees of change in pre/posttest scores were selected

Student IEJ entries recorded throughout the T/E DBBL intervention were analyzed qualitatively to gain insight into the ways T/E DBBL learning promotes change in mathematical concept knowledge. The following protocol was used to guide the researcher in qualitatively analyzing IEJ entries for the six students selected from the high, middle, or low Change Sub-Groups:

- All IEJ entries recorded during the 15-day intervention were scanned as pdf documents for each of the six students.

- Using “pre-codes” reflective of the two independent variables, content analysis was conducted on all IEJ entries to identify instances reflective of students using their mathematical concept knowledge (patterns of association and lines of best fit) and instances where design experiences imposed a need for students to use the targeted mathematical concepts. Instances of patterns of association (RQa) and lines of best fit (RQb) were pre-coded as follows:
    - Pre-codes for patterns of association concepts:
        - Increase Pattern Recognition – IPR
        - Decrease Pattern Recognition – DPR
        - Constant Pattern Recognition - CPR
        - No Pattern Recognition - NPR
        - Linear Pattern Recognition - LPR
        - Nonlinear Pattern - NLPR
    - Pre-codes for lines of best fit concepts:
        - Scatter Plot Construction - LBSPC
        - Drawing Lines of Best Fit - DLB
        - Predictive Analysis - LBPA
- Instances of design experiences imposing a need for the use of targeted mathematics concepts were pre-coded as follows:
    - Pre-codes for design practices:
        - Variable Identification – VI
        - Data Collection - DC
        - Data Organization - DO

    - Data Analysis - DA
    - Design Decisions - DD
- Pre-codes reflective of instances within a given category (patterns of association, lines of best fit, design experiences) were then quantified through frequency counts.

The research question addressed promotion of change in mathematical concept knowledge in relation to student experiences in T/E DBBL. IEJ entries provide a qualitative record of mathematical and design experiences that reflects a student's thinking, reasoning, and data analysis abilities. Similarly, the BDP data quantitatively reflects the same changes in student mathematical concept knowledge after the intervention.

Frequencies of pre-codes were quantified for use in calculating the frequency of student use of the mathematical concept knowledge measured by the BDP and design experiences imposing a need for the targeted mathematics concept knowledge. All pre-codes were organized into a table (Appendix L) for further analysis of patterns that emerged in the frequency data. Descriptive statistics were used to summarize data for the table.

The frequencies of these pre-codes were used to indicate how often students referenced each mathematical concept relative to RQa, RQb, and design experiences. The pre-codes were then used to show which phases of design were most closely connected to student use of mathematical concepts and thereby guiding the researcher toward analysis of the IEJ entries during these phases.

A content analysis of these IEJ entries was conducted to determine the mathematics concepts to which students were speaking. Their language was then used to generate in vivo codes (Appendix M) following protocols as outlined by Miles, Huberman, & Saldana (2020).

Once in vivo codes were created for each of the six students, codes were grouped based on commonalities and then categorized into key points (Appendix M). The purpose for this stage of coding was to support (corroborate) their BDP data through what they demonstrated in their IEJ regarding what they understood about the targeted math concepts. For example, the in vivo codes “points are mostly going up” and “energy still going up” were grouped under the key point “increasing pattern recognition” to demonstrate student gains in understanding of the math concept addressed by RQa. This same approach was used in demonstrating gains in student understanding of math concepts addressed by RQb.

After in vivo codes were compared for commonalities and categorized into key points per individual students, comparisons were made across key points generated for all six students. For example, if one student’s key points included “increasing pattern recognition” and another student’s key points included “decreasing pattern recognition”, these key points were collaboratively used to describe changes in concept knowledge relative to RQa. All key points, specific to the math concepts targeted by RQa and RQb, were used to corroborate the change seen in the BDP findings. A co-coder was used to achieve reliability in coding. The key points gathered from the IEJ entries were then organized by RQa and RQb and placed in table to look for patterns that emerged in the data (Appendix M).

Using similar procedures, frequency counts of pre-codes were used to identify those phases of design in the IEJ where design experiences required further investigation (Appendix L). In vivo codes were identified from the IEJ entries during these phases which represented design experiences involving variable recognition, data collection, organization, analysis, or design decisions. These in vivo codes were categorized into key points which were used to document experience with T/E DBBL to answer the research question (Appendix M). For example, the in vivo codes “our electricity was not high enough to power a light bulb” or “our MFC is still bad” were categorized into the key point “data analysis” which helped the researcher document experiences derived from T/E DBBL in connection to a change in mathematical concept knowledge. These key points were identified per individual and then placed in a table (Appendix M) to look for patterns that emerged in the data across all six students’ IEJs.

Evidence of change in concept knowledge supporting the BDP in relation to the intervention was also documented through a change in demonstrations of understanding in IEJ entries from the beginning to final entries. Therefore, the qualitative IEJ entries were used to support the findings of the quantitative measure (BDP) by documenting evidence that the change in mathematical concept knowledge was in connection to the mathematical experiences during the DBBL intervention as documented by the IEJs.

Individual Semi-Structured Interview Analyses

Following administration of the Bivariate Data Posttest and analyses of purposefully selected IEJ, individual semi-structured interviews were conducted with six students (Appendix J). Students selected for interviews were those whose IEJs were selected for qualitative analysis. Table 10 provides a list of all interview questions and corresponding IEJ pre-codes used to initially analyze interview data per RQa and RQb.

Table 10

Alignment of Interview Questions with IEJ Codes

Interview Questions	IEJ Pre-codes	Targeted RQ
1. Tell me about the purpose of the design challenge. a. Why did you choose your particular design? b. Describe the parts of the MFC and how they worked.	Design Decision (DD)	RQa & RQb
2. What criteria did your design have to meet? a. Do you think your MFC met the criteria? Why or why not? b. How did you know if your MFC was performing well or not? c. What variables did you have to measure to know how well your MFC was performing? d. How did collecting data from your variables tell you if the MFC was performing well or not?	Variable recognition (VR) Pattern recognition (PR) Data Collection (DC) Data Analysis (DA)	RQa
3. What did you do with your data when you collected it? a. What did the data tell you? b. What patterns did you see in your data? c. How did you organize your data to help you see those patterns? d. Describe to me how you constructed your scatter plot. e. What patterns emerged in the data when you put it on a scatter plot? f. What direction was the data going in your scatter plot? g. What was the difference between what patterns you saw you're the table and what patterns you saw on the scatter plot? h. How did the patterns you saw in your data affect your design decisions throughout the design challenge? i. What design decisions did you have to make? Why did you make them?	Data Organization (DO) Scatter Plot Construction (LBSPC) DC PR DD	RQa & RQb

Interview Questions IEJ Pre-codes Targeted RQ

4. How did you predict how much electricity your MFC would produce on day 10? a. What was the most helpful thing you did to see how well your MFC was working? b. Do you think your MFC prototype could eventually light a small light? How do you know? c. How could you use your data to figure out if it would light a small light? d. How could you use your scatter plot to figure out if it would light a small light? e. Describe to me how you constructed your trendline for your data. f. How could you use your trendline to figure out if your MFC prototype could light a small light in the future? g. When do you think it would take for your prototype to light a small light? h. How can you use your trendline to figure out how long it would take to light a small light?	Predictive Analysis (LBPA) Drawing Lines of Best Fit (DLB) DA DC VI LBSPC	RQb
5. Now that you have built your first MFC, if you did this design challenge again what data would you collect to see if it was successful? a. How did your data help you to make design decisions during this design challenge? b. How could your data help you to make future design decisions? c. What patterns would you look for to make design decisions? d. Based on your data, what would you do differently to your design next time to increase the amount of electricity it produces? e. What did you do that was the most helpful for you to complete the design challenge?	DC DO VI PR DD LBPA	RQa & RQb
6. Is there anything else you would like to tell me about your experiences during the design challenge?		

Interview questions were created to align with the mathematical concepts targeted by the BDP as well as the 3-2-1 IEJ prompts students responded to throughout the intervention. The purpose of the interview was to have students provide additional information about their design experiences and mathematical concept knowledge that would more clearly explain their IEJ entries. These explanations would be used to further to corroborate the findings of the BDP as well as document design experiences utilizing targeted mathematical concept knowledge.

All individual interviews were audio-recorded by the researcher. Following the same procedures used in analyzing the IEJ entries, interview data analysis procedures occurred as follows:

- All individual interview correspondence was transcribed by the researcher and saved on a password protected device.
- Content analysis was conducted on all interview transcriptions using pre-codes for patterns of recognition (RQa) and lines of best fit (RQb).
- Pre-codes were used to identify instances of design experiences imposing a need for the use of targeted mathematics concepts.
- Pre-codes were quantified through frequency counts (Appendix N) of instances within each category (patterns of association, lines of best fit, design experiences).
- Student language was used to generate in vivo codes (Appendix O).
- In vivo codes were categorized into key points based on commonalities (Appendix O).

Transcriptions of student verbal responses to individual interview questions were analyzed using the same coding procedures as the written IEJ entries. Frequencies of pre-codes relative to RQa, RQb, and design experiences were quantified (Appendix N) for use in documenting evidence of demonstrations of student mathematical concept knowledge in connection to design experiences imposing a need for the targeted mathematics concept knowledge. These code frequencies were also used to indicate to the researcher which segments of the interview to further analyze for language indicating each student's mathematical concept knowledge.

Following the use of frequency counts for identifying sections of the interview needing further analysis, similar procedures to those used in IEJ entry analysis were used to identify in vivo codes and categorize those codes into key points used to answer the research question. Student language guided the creation of in vivo codes representing the understanding students had about the mathematic concepts used during the intervention (Miles et al., 2020). Commonalities among in vivo codes for individuals were identified and those codes were organized into key points by RQa and RQb. Those key points were used to corroborate the BDP findings for that individual student. The key points derived from the in vivo codes for individual students were then used collaboratively to answer the research question by corroborating findings of the BDP for all students.

Once the interview transcriptions were coded to identify key points used to answer RQa and RQb, they were re-examined to create in vivo codes representing design experiences. These in vivo codes were then categorized into key points which were used to help answer the research question regarding the documentation of experiences in T/E DBBL in relation to utilization of mathematical concept knowledge. The key points were organized by RQa, RQb, and design experience in a table to be further examined for patterns which existed in the data (Appendix O).

The evidence documented by the interviews was used in collaboration with the evidence documented by the IEJ entries to support the findings of the BDP, indicating a change in concept knowledge in connection with the design experiences of the intervention. The individual interview data, in conjunction with the IEJ data, helped to clarify each student's level of concept knowledge, indicated by the BDP, in connection to the intervention design experiences documented by both qualitative data sources. Both the IEJ entries and individual interviews provided qualitative data used to corroborate quantitative findings and answer the research question.

Triangulation

In this explanatory, sequential mixed-methods design, qualitative data were used to corroborate quantitative findings (Teddlie and Tashakkori, 2006). Triangulation of data sources enriches research by attempting to corroborate various assessments of the phenomenon being studied (Noble and Heale, 2019). For this study, qualitative data analysis was performed to gain a better understanding of the outcomes of the quantitative BDPre/BDPost data analysis. Both quantitative and qualitative data were used to infer the ways in which the T/E DBBL intervention promoted a change in mathematical concept knowledge. Quantitative data provided information about whether the change in student concept knowledge outcomes before and after the intervention was significant at the 0.05 level. Qualitative data provided an alternative assessment of change in mathematical concept knowledge outcomes to corroborate the quantitative findings. Specifically, IEJ journal entries from six purposefully selected students (two from each high, middle, low Change Sub-Group) provided detailed text and graphical information reflective of student concept knowledge of bivariate data in the context of the design challenge. Individual interviews with the same six purposefully selected students were designed to elicit further explanations of IEJ entries and design justifications as additional indicators of their level of concept knowledge of bivariate data in the context of the design challenge. Quantitative and qualitative research methods were sequentially used to answer the research question, allowing findings from the qualitative methods to support the findings of the quantitative method.

Summary of Research Method

This chapter presented the research questions, research design, participant selection, research setting, instrumentation, data collection, and data analysis procedures used during this study. The mixed-methods, sequential explanatory design chosen for this research provided opportunities for quantitative and qualitative data collection, analysis, and corroboration of findings through data triangulation (Denzin, 1989). All quantitative and qualitative methods were used to capture demonstrations of mathematical concept knowledge reflective of understanding as indicators of change. Data collected before, during, and after the instructional intervention supported findings of relationships between technology/engineering design-based biotechnical learning and change in concept knowledge of patterns of association between bivariate measurement data and lines of best fit used to model predictive relationships between two quantitative variables on a scatter plot.

A mixed-methods approach was the most appropriate choice for answering the research question because of the multiple opportunities for data collection methods supported by this research approach. The need for multiple sources documenting students' levels of mathematical concept knowledge necessitated the use of both quantitative and qualitative methods to answer the research question. The purpose of this research was to explain the connection between T/E DBBL design experiences and change in mathematical concept knowledge as measured by quantitative, summative high stakes assessments. The nature of T/E DBBL yielded the IEJ as a natural source of qualitative data. In addition, the individual, semi-structured interviews offered students a non-written way to provide information about their mathematical concept knowledge in relation to their T/E DBBL experiences during the intervention. Choosing the mixed-methods approach provided a breadth of qualitative data to corroborate quantitative data findings necessary for answering the research question. Findings from analyses of the data collected are presented in Chapter Four.

CHAPTER FOUR: FINDINGS

This chapter presents participant demographics, establishments of reliability and validity of the quantitative instrument, and findings from quantitative and qualitative data analysis. Quantitative data analysis addresses the results of the Bivariate Data Pretest and Posttest (BDP) for all participants. Qualitative data analysis is used to corroborate quantitative findings through discussion of the Interactive Engineering Journals and semi-structured, individual interviews of the six purposefully selected participants.

Participants

Eligible participants for this study were all eighth-grade mathematics students enrolled in a rural high school (grades 7-12) in West Virginia. These students were enrolled in either an eighth-grade mathematics course or eighth-grade Algebra 1 course. All 42 students enrolled in either course engaged in this design challenge, but only the 30 students who returned both parental permission and student assent forms were included as participants for this study. Demographics for the entire body of students attending the selected West Virginia high school research site are presented in Table 11 (ZOOMWV, 2023).

Table 11

Demographics: Selected West Virginia High School Research Site

Category	Sub-Category	Frequency (n)	Percent (%)
Enrollment	School	281	100
	Grade 7	53	19
	Grade 8	42	15
	Grade 9	60	21
	Grade 10	47	17
	Grade 11	42	15
	Grade 12	37	13

Category	Sub-Category	Frequency (n)	Percent (%)
	Special Education	59	21
	English Language Learner	281	100
	Low Socioeconomic Status	188	67
Gender	Male	144	51
	Female	137	49
Ethnicity	White	267	95
	Multi-Racial	13	5

Table 12 presents select demographic data collected on the self-selected participant sample (n = 30) from the eighth-grade population.

Table 12

Select Demographics: Grade 8 Participants

Category	Sub-Category	Frequency (n)	Percent (%)
Enrollment	8th Grade Participants	30	100
	Special Education	3	10
	English Language Learner	30	100
Gender	Male	17	57
	Female	13	43
Ethnicity	White	27	90
	Multi-Racial	3	10

Participants in this study represented approximately 11% (30/281) of the total school population and approximately 71% (30/42) of the total eighth grade population enrolled at the selected school site. The participant population was split nearly even between males and females, the majority of whom were white and English learners. Given these demographics, the research participants could be considered a representative sample of the general student population of the selected school site.

Instrumentation

The Bivariate Data Pre/Posttest (BDP) was used to assess the mathematical concept knowledge of participants before and after the intervention. The relevant reliability and validity information for the BDP instrument is presented in the following sections.

Reliability

Cronbach's alpha was used to calculate the reliability of the Bivariate Data Pretest (BDPre) and Bivariate Data Posttest (BDPost) each in its entirety, as well as for the subset of items used to answer RQa and RQb for each instrument. Interpretation of reliability results were determined based on the scale (Table 13) developed by Gliem and Gliem (2003) which assigns a level of consistency for various ranges of Cronbach alpha.

Table 13

Interpretation of Cronbach's Alpha for Internal Consistency

Cronbach's Alpha Calculation	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Note. (Gliem & Gliem, 2003)

Table 14 presents the reliability values and internal consistency interpretations for all BDPre/BDPost instrument items and subset items (RQa and RQb).

Table 14

Internal Consistency of Bivariate Data Pre/Posttest Items

Instrument	Items	Cronbach's Alpha	Internal Consistency
BDPre	All	0.886	Good
BDPost	All	0.855	Good
BDPre	RQa	0.815	Good

Instrument	Items	Cronbach's Alpha	Internal Consistency
BDPost	RQa	0.803	Good
BDPre	RQb	0.764	Acceptable
BDPost	RQb	0.75	Acceptable

Cronbach reliability values calculated for the BDP (whole) and subset RQa fell within the "Good" range, while the subset RQb was in the acceptable range (Table 14). Therefore, as calculated, the BDP used in measuring changes in concept knowledge would be considered reliable.

Validity

A panel of three co-raters was used to determine face validity and content/construct validity of the BDP. Panelists were asked to review each item and complete a rubric (Appendix C) indicating the concept knowledge they believed was being measured, any suggestion for items they felt required modification, and a decision on each item regarding whether to be included or not. Revisions were made to the BDP following each round of arbitration until an agreement equal to or greater than 66% was reached among the panelists. Table 15 provides the final inclusion results of the rubrics submitted by the panelists.

Table 15

Panelist Final Agreement Results for BDP Items

BDP Item Number		**Panelist Decision Per Arbitration Round**			**Final Agreement (%)**
Pre	Post	Round 1	Round 2	Round 3	
1	7	A	A	A	100
2	9	A	A	A	100
3	1	A	A	A	100
4	10	A	M	A	100
5a	4a	M	A	A	100
5b	4b	A	A	A	100
5c	4c	A	A	A	100
5d	4d	A	A	A	100
6	2	A	A	A	100
7	8	A	A	A	100

BDP Item Number		Panelist Decision Per Arbitration Round			Final Agreement (%)
Pre	Post	Round 1	Round 2	Round 3	
8	3	A	A	A	100
9	5	A	A	A	100
10	14	A	M	A	100
11	6	A	A	A	100
12a	11a	M	A	A	100
12b	11b	A	A	A	100
12c	11c	A	A	A	100
12d	11d	A	A	A	100
13	12	A	M	A	100
14	13	A	A	A	100

Note. Accept = A, Accept with Modifications = M

Items marked “M” (Accept with Modifications) were modified as necessary until agreement was reached among at least 66% of panelists. Following the final round of arbitration, each item was accepted by all panel members.

Quantitative Data Analysis

Bivariate Data Test: Overall Pre/Post Score Analyses

The BDPre and BDPost test scores were analyzed to demonstrate participant gains and/or losses in concept knowledge overall and in relation to patterns of association (RQa) and lines of best fit (RQb). Results of the Pre/Post analyses comparing BDPre and BDPost scores overall and for RQa and RQb subset items can be found in Table 16. Gains/Losses were calculated as the percent increase or decrease from pretest to posttest (gain/loss = (posttest score - pretest score)/ original score). For example, comparing a pretest score of 4 with a posttest score of 10 would be calculated as (10 – 4)/4 to equal 1.5, which equates to a 150% gain.

Table 16

BDP Pretest/Posttest Score Analyses

Participant		***BDP Overall Scores (N=20)***		***RQa Items Scores (N=11)***		***RQb Items Scores (N=9)***	
		# Correct	% Gain/Loss	# Correct	% Gain/Loss	# Correct	% Gain/Loss
P-1							
	Pre	4		3		1	
	Post	10	1.50	7	1.33	3	2.00
P-2							
	Pre	5		4		1	
	Post	18	2.60	10	1.50	8	7.00
P-3							
	Pre	3		2		1	
	Post	10	2.30	9	3.50	1	0.00
P-4							
	Pre	9		6		3	
	Post	18	1.00	11	0.83	7	1.33
P-5							
	Pre	6		4		2	
	Post	11	0.83	8	1.00	3	0.50
P-6							
	Pre	6		3		3	
	Post	2	-0.67	1	-0.66	1	-0.66
P-7							
	Pre	9		6		3	
	Post	11	0.22	5	-0.17	6	1.00
P-8							
	Pre	4		2		2	
	Post	15	2.75	9	3.50	6	2.00
P-9							
	Pre	7		5		2	
	Post	16	1.29	10	1.00	6	2.00
P-10							
	Pre	1		1		0	
	Post	10	9.00	6	5.00	4	U
P-11							
	Pre	4		3		1	
	Post	5	0.25	1	-0.66	4	3.00
P-12							
	Pre	6		5		1	
	Post	13	1.17	9	0.80	4	3.00
P-13							
	Pre	4		4		0	
	Post	8	1.00	4	0.00	4	U
P-14							
	Pre	1		0		1	
	Post	13	12.00	8	8.00	5	4.00

Participant		***BDP Overall Scores (N=20)***		***RQa Items Scores (N=11)***		***RQb Items Scores (N=9)***	
		# Correct	% Gain/Loss	# Correct	% Gain/Loss	# Correct	% Gain/Loss
P-15							
	Pre	7		6		1	
	Post	18	1.57	10	0.67	8	7.00
P-16							
	Pre	4		2		2	
	Post	8	1.00	6	2.00	2	0.00
P-17							
	Pre	5		3		2	
	Post	13	1.60	7	1.33	6	2.00
P-18							
	Pre	1		1		0	
	Post	11	10.00	8	7.00	3	U
P-19							
	Pre	10		8		2	
	Post	9	-0.10	4	-0.50	5	1.50
P-20							
	Pre	5		3		2	
	Post	13	1.60	9	2.00	4	1.00
P-21							
	Pre	6		4		2	
	Post	18	2.00	10	1.50	8	3.00
P-22							
	Pre	14		9		5	
	Post	19	0.36	11	0.22	8	0.60
P-23							
	Pre	19		11		8	
	Post	20	0.05	11	0.00	9	0.13
P-24							
	Pre	2		2		0	
	Post	10	4.00	4	1.00	6	U
P-25							
	Pre	13		9		4	
	Post	16	0.23	8	-0.11	8	1.00
P-26							
	Pre	12		7		5	
	Post	19	0.58	11	0.57	8	0.60
P-27							
	Pre	4		4		0	
	Post	10	1.50	6	0.50	4	U
P-28							
	Pre	16		11		5	
	Post	19	0.19	10	-0.09	9	0.80

Participant		***BDP Overall Scores (N=20)***		***RQa Items Scores (N=11)***		***RQb Items Scores (N=9)***	
		# Correct	% Gain/Loss	# Correct	% Gain/Loss	# Correct	% Gain/Loss
P-29							
	Pre	15		10		5	
	Post	15	0.00	8	-0.20	7	0.40
P-30							
	Pre	14		9		5	
	Post	18	0.29	10	0.11	8	0.60
Total P							
	Pre	216		147		69	
	Post	396	0.83	231	0.57	165	1.39

Note. P=Participant, U=Undefined

Based on the gain/loss calculations between the BDPre and BDPost overall scores, 90% (27/30) of students demonstrated higher post scores in overall concept knowledge of bivariate measurement data. The number of students who earned a passing score (12 or more correct items) on the BDP increased from 23% to 57% (7/30 and 17/30 respectively), more than doubling the number of students who answered 60% of the questions correctly. Table 17 provides *t*-test analyses results for the BDP overall scores.

Table 17

Pretest/Posttest BDP Overall Score t-test Analyses

BDP	*M*	*SD*	*SEM*	*df*	*t*	*p*	†ES
Pre	7.2	4.85	4.43	29	7.82	0.0001*	1.27
Post	13.2	4.60	4.26	29			

Note. n = 30; *p < .05, two-tailed, paired; †Effect Size

Most students (90%) demonstrated gains on the BDP. The probability value was set a p < .05 and when analyzed the actual calculated probability was 0.0001. This *p* value indicates that the gains made in overall BDP scores were extremely statistically significant. There was an overall increase of 6 points between the means of the BDPre and BDPost scores and an average increase in score of 83% (Table 16) from pretest to posttest. Because of the small number of participants, Cohen's *d* was then used to calculate the Effect Size (ES) (d = 1.27) between the standard deviations of the BDPre and BDPost (McMillan, 2008). This value indicates a large effect size ($d > 0.8$) between the standard deviations of the pre/posttest, increasing confidence that the data are statistically significant.

RQa Items: Pre/Post Score Analyses

Eleven BDPre and BDPost items (Table 4) were used to measure levels of concept knowledge regarding patterns of association used to answer RQa. As revealed in Table 16, data indicate that 70% of students (21/30) demonstrated gains in concept knowledge for RQa items. Table 18 presents the *t*-test analyses results for only the RQa item scores.

Table 18

RQa Item Scores: t-test Analyses

RQa	*M*	*SD*	*SEM*	*df*	*t*	*p*	†ES
Pre	4.9	3.10	0.57	29	4.65	0.0001*	0.95
Post	7.7	2.82	0.51	29			

Note. n = 30; *p < .05, two-tailed, paired; †Effect Size

The probability value (p <.01) supports the statistical significance of gains for the 77% (23/30) of students that demonstrated increase in score between the pretest and posttest. Because of the small number of participants, Cohen's *d* was used to calculate the large effect size (d = 0.95) indicated by these scores, as an additional indication of accuracy that these gains were statistically significant. For RQa items, the mean difference was 2.8 points between the BDPre and BDPost. This indicates that on average student scores increased by 57% on these RQa items and demonstrates an increase in concept knowledge of patterns of association following the intervention.

RQb Items: Pre/Post Score Analyses

Nine BDP items (Table 5) were used to measure concept knowledge of lines of best fit (RQb). Similarly, according to the data in Table 16, the majority of participants (n=27, 90%) demonstrated gains in concept knowledge relative to RQb. Table 19 provides *t*-test analyses results for the RQb scores.

Table 19

RQb Item Scores: t-test Analyses

RQb	*M*	*SD*	*SEM*	*df*	*t*	*p*	†ES
Pre	2.3	1.97	0.36	29	8.89	0.0001*	1.48
Post	5.5	2.34	0.43	29			

Note. n = 30; *p < .05, two-tailed, paired; †Effect Size

The difference in mean scores was 3.2 points for items used to measure concept knowledge of lines of best fit (RQb). Students averaged a 139% (Table 16) increase in RQb item scores between the administration of the BDPre and BDPost. The calculated probability value (0.0001) of these score differences indicates a statistical significance between pretest and posttest scores. To further strengthen the confidence of this statistical significance, the Cohen's *d* value (*d* = 1.48) indicates a large effect size for these data as well.

Summary of Quantitative Data Analysis

The purpose for collecting quantitative data in this study was to determine if there were gains in student BDP scores following the intervention. Analyses did indicate large changes occurred in overall scores and for RQa and RQb items, and that this change was statistically significant at the 0.0001 level.

Comparison of pretest/posttest BDP results indicate students demonstrated higher gains in concept knowledge of lines of best fit (139% increase) than patterns of association (57% increase). It is important to note however, that the 8th grade participants as a whole demonstrated an overall increase (83%) in gains of mathematical concept knowledge after their engagement during the T/E DBL intervention. These findings provide support for the positive effects of the T/E DBL intervention on overall mathematical concept knowledge of bivariate measurement data as well as patterns of association (RQa) and lines of best fit (RQb). However, triangulation with the qualitative analyses of student IEJ entries during the intervention will be necessary to further substantiate that the T/E DBL intervention was instrumental in promoting changes in mathematical concept knowledge.

Qualitative Data Analyses

Quantitative BDP pre/posttest data analyses provided support for the positive effects of the T/E DBL intervention on overall mathematical concept knowledge of bivariate measurement data as well as patterns of association (RQa) and lines of best fit (RQb). However, to further support the connections between quantitative gains on the BDP and the T/E DBL intervention, qualitative analyses of student Interactive Engineering Journals are necessary.

Interactive Engineering Journals (IEJs) were used daily by students to record their research, thoughts, inferences, questions, etc. throughout the intervention. These journals were collected after Day 15 of the intervention to be used as qualitative data sources for corroborating the findings of quantitative data. Qualitative analysis of IEJ entries provides the means for making connections (triangulating findings from the QUAL data to confirm or disconfirm findings from the QUANT data) between student experiences with mathematics concept knowledge during the design challenge and their significant gains in knowledge demonstrated quantitatively.

Analyses of only a select number of participants' qualitative sources were necessary to provide the triangulation needed to confirm or disconfirm the BDP pre/post gains were due to student engagement in the T/E DBL intervention. Given the low number of self-selected participants in this study, a small Change Sub-Group of six individuals was purposefully selected to be a representative sample of the participant population (Morse, 1994).

Change Sub-Groups

Purposeful Selection

A participant Change Sub-Group representative of the Whole-Group was necessary for a thorough analysis of qualitative data (individual IEJs and subsequent semi-structured individual interviews). Morse (1994) suggests a sample size of six as sufficient for in-depth conversational interviews. As described in Chapter 3, Change Sub-Group participant selection was based on criteria related to the degree of change (high, middle, low) among BDP pretest/posttest scores. The degree of score change for all participants was calculated using the difference between individual posttest and pretest scores (degree of score change = posttest score – pretest score**).** Based on analyses of overall BDP pre/post scores (Table 16) the mean (*M*) of these differences was established as 5.96.

Student scores were then categorized into three groups that represent a degree of change below, near, and above (low, middle, high) this mean. The Low Change Sub-Group included students with low changes in score between the pre/posttest. The Middle Change Sub-Group included students with score differences closest to the mean difference (5.96). The High Change Sub-Group included students with the greatest difference between overall pre/posttest scores. Inclusion of students in each Change Sub-Group was determined by student scores. Students within 25% above or below the mean were determined to be in the Middle Change Sub-Group. Students below or above this percent spread were determined to be in the Low and High Change

Sub-Groups respectively. Table 20 presents Whole-Group student BDP score differences organized by change categories.

Table 20

Criteria Used for Qualitative Participant Selection

Change Categories	Participant	Pre/Posttest Score Change	Prompt Completion	Pattern Type	Attendance
Low	6	-4	N	I	A
	19	-1	N	I	A
	29	0	N	D	A
	11	1	N	N	B
	23*	1	Y	D	A
	7	2	Y	I	B
	28	3	Y	D	B
	25	3	Y	I	B
	30*	4	Y	D	A
	16	4	N	N	A
	13	4	N	I	A
Middle	5	5	Y	D	B
	22*	5	Y	D	A
	27	6	N	I	A
		5.96 = Mean			
	1	6	N	I	A
	26	7	N	D	B
	12*	7	Y	I	A
	3	7	N	N	A
High	24	8	N	I	A
	20*	8	Y	N	A
	10	8	N	D	A
	17	8	Y	I	B
	9	9	Y	N	B
	4*	9	Y	I	A
	18	10	Y	I	B
	8	11	N	D	A
	15	11	Y	D	A
	14	12	N	I	A
	21	12	N	I	A
	2	13	N	I	A

Note. *Change Sub-Group, Y=Complete, N=Not Complete, I=Increasing, D=Decreasing, N=No Pattern, A= At or above 80%, B = Below 80%

Two participants from within each Change Category (Table 20) were selected for further qualitative data collection and analyses. The selection of two participants from within each Change Category was based on (1) their completion of all IEJ prompts for each day of the intervention, (2) IEJ recorded data demonstrating increasing, decreasing, and no patterns, and (3) attendance throughout at least 80% of the intervention and interview participation days. Of the students in each Change Category that met all these requirements, those two students whose journals included the most thorough explanations were selected as participants within a given Change Sub-Group (Table 21).

Table 21

Selected Change Sub-Group Participants

Change Sub-Group	Participant #	Pre/Posttest Score Change	Prompt Completion	Pattern Type	Attendance
Low	23	1	Y	D	A
	30	4	Y	D	A
Middle	22	5	Y	D	A
	12	7	Y	I	A
High	20	8	Y	N	A
	4	9	Y	I	A

Note. Y=Complete, I=Increasing, D=Decreasing, N=No Pattern, A= At or above 80%

Change Sub-Group Data Analyses

Change Sub-Group BDP pretest/posttest scores were analyzed (Table 22) to measure gains in concept knowledge overall and in relation to patterns of association (RQa) and lines of best fit (RQb).

Table 22

Change Sub-Group BDP Pretest/Posttest Scores

Sub-Group	***Participant***		***BDP Overall Scores (N=11)***		***RQa Item Scores (N=11)***		***RQb Item Scores (N=9)***	
			# Correct	Change	# Correct	Change	# Correct	Change
Low	P-23							
		Pre	19		11		8	
		Post	20	1	11	0	9	1
	P-30							
		Pre	14		9		5	
		Post	18	4	10	1	8	3
Middle	P-22							
		Pre	14		9		5	
		Post	19	5	11	2	8	3
	P-12							
		Pre	6		5		1	
		Post	13	7	9	4	4	3
High	P-20							
		Pre	5		3		2	
		Post	13	8	9	6	4	2
	P-4							
		Pre	9		6		3	
		Post	18	9	11	5	7	4

Quantitative data from Table 22 were used to describe BDP pre/post gains for selected Change Sub-Group participants.

Low Change Sub-Group.

Participant 23. P-23 demonstrated low gains (1 point) in overall concept knowledge between their BDP Pre and Post scores. No gain was possible in the concept knowledge of patterns of association (RQa items) given a perfect score was earned for these subset items on both pre/posttests. Furthermore, the item measuring concept knowledge of lines of best fit (RQb) that P-23 answered incorrectly on the pretest was corrected on the posttest. It is of note that because the student answered the majority of questions correctly (19/20) on the BDPre, any degree of score change in score would be minimal, placing this student in the Low Change Sub-

Group. Although the perfect score earned by P-23 on the BDPost demonstrates a high level of mathematical concept knowledge, analysis of IEJ and interview data was necessary to corroborate the consistency in demonstrating high levels of mathematical concept knowledge relative to patterns of association (RQa) and lines of best fit (RQb) in their written work and responses to interview prompts.

Participant 30. P-30 also demonstrated low gains (4 points) between the overall BDPre and BDPost scores. This student answered one more RQa item correctly and three more RQb items correctly on the BDPost than on the BDPre. These score changes indicate a larger increase in concept knowledge of lines of best fit than in patterns of association. To substantiate these BDP quantitative findings, the IEJ entries and interview responses for P-30 were examined for instances demonstrating concept knowledge for both concepts, with particular attention paid to demonstrations of concept knowledge related to lines of best fit. Given the possibility that the quantitative assessment did not accurately measure knowledge gains, analyses of the additional qualitative data sources were necessary to provide corroboration with the outcomes of the quantitative assessment.

Middle Change Sub-Group.

Participant 22. P-22 demonstrated gains close to the mean difference (5.96) for all student scores and was therefore placed in the Middle Change Sub-Group. Their overall BDPre and BDPost scores increased by 5 points demonstrating a moderate increase in concept knowledge for both patterns of association (RQa) and lines of best fit (RQb). One reason for the demonstration of moderate growth for this student is that they scored 9/11 on RQa items on the BDPre, leaving little room to demonstrate growth. This student did score a perfect score 11/11 on BDPost RQa items, demonstrating high levels of concept knowledge of patterns of association. The IEJ and interview data for P-22 were used to corroborate this demonstration of high levels of concept knowledge of patterns of association concepts and investigate the higher gains (3 points) in concept knowledge of lines of best fit demonstrated quantitatively. Specifically, their IEJ was used to demonstrate their understanding of concepts through analyses of their written descriptions/explanations and drawings demonstrating their level of understanding of patterns of association and lines of best fit. In the same way and for the same purpose, their interview responses were analyzed to provide additional support of their true level of understanding through their ability to discuss both RQa and RQb concepts**.**

Participant 12. Participant 12 also demonstrated gains close to the mean difference (5.96) with a gain of 7 points between the BDP overall Pre and Post scores. This student more than doubled the number of correctly answered questions between the BDPre and BDPost overall scores. Given the small discrepancy between score gains between RQa (4 points) and RQb (3 points) subset items, the IEJ and interview data for P-12 were used to further substantiate the implications of their overall gains reflective of the quantitative assessment of bivariate concept knowledge. Their IEJ was specifically analyzed for written language that demonstrated concept knowledge of both patterns of association and lines of best fit, and their interview data were used to further corroborate the IEJ findings.

High Change Group.

Participant 20. The quantitative data analysis for P-20 indicates high gains between the BDP overall scores (8 points), as well as for the RQa items measuring patterns of association concept knowledge (6 points). Although much smaller gains (2 points) were seen in BDPre/Post scores for the RQb items measuring lines of best fit concept knowledge, it was still double their BDPre score for this subset. Furthermore, it is important to note that this student at least doubled their pretest scores on the posttest for all three sets of data. These significant gains placed P-20 in the High Change Sub-Group, which required analysis of IEJ and interview data to establish a connection between their engagement in the DBBL intervention and BDPre/post scores. Specifically, IEJ and interview data were analyzed for instances of changes in concept knowledge overall and for changes in both concepts of patterns of association and lines of best fit and to establish the rationale for observed higher gains on RQa items than RQb items.

Participant 4. As determined by their BDP scores, P-4 was also placed into the High Change Sub-Group. The BDPost overall scores showed P-4 doubled the number of questions they answered correctly. And for the BDP subsets, P-4 increased their score on the RQa subset items by 5 points and increased their RQb subset items score by 4 points. To substantiate the role of the DBBL intervention in fostering these gains bivariate concept knowledge, IEJ and interview data from P-4 were analyzed for instances of changes in concept knowledge overall and for changes in both concepts of patterns of association and lines of best fit. The IEJ was used to corroborate their gains in bivariate measurement data concept knowledge overall and for patterns of association and lines of best fit individually. Collectively, these data were used to evidence (confirm or disconfirm) the role of the intervention in promoting a better understanding of the targeted bivariate measurement concepts as demonstrated by the BDP pre/post quantitative findings.

Summary of Change Sub-Groups

Quantitative data for these six students were used to determine their Change Sub-Group and provide baseline data about their gains between the BDP pre/post. Qualitative data were then collected for these students to confirm or disconfirm (corroborate) the increase in concept knowledge as demonstrated through analysis of their BDP pre/post scores following participation in the T/E DBBL intervention. Each student's IEJ was analyzed through the multiple-step coding process (initial coding, in vivo coding, key points) described below. The IEJ data were then used to guide the questions asked during semi-structured, individual interviews described in a later section. Student interviews were then transcribed and coded using the same multiple-step coding process as the IEJs.

IEJ Data Analyses

The IEJs from each of these six students were analyzed prior to conducting individual interviews to corroborate student levels of concept knowledge demonstrated by their BDP score gains. The IEJ analysis for each student was used to direct questions in their interview to clarify their level of concept knowledge not present or not clearly presented in the IEJ.

The entire IEJ for each purposefully selected participant was initially coded using previously generated pre-codes reflective of the two independent variables, as well as those instances where the design experiences imposed a need for students to use the targeted mathematical concepts Specifically, the pre-codes aligned with student demonstrations of concept knowledge of patterns of association (RQa), lines of best fit (RQb), and imposed, data-driven design decisions made by students necessitating the use of targeted mathematical concepts during their engagement in the design challenge. As previously presented in the Method chapter, Table 23 presents the list of pre-codes applied during initial IEJ analyses for identifying instances of participant concept knowledge usage.

Table 23

Pre-Codes: Initial IEJ Analyses

CK Categories per RQ	Target Concept	Pre-code
Patterns of Association (RQa)		
	Increasing Pattern Recognition	IPR
	Decreasing Pattern Recognition	DPR
	No Pattern Recognition	NPR
	Linear Pattern Recognition	LPR
	Non-Linear Pattern Recognition	NLPR
Lines of Best Fit (RQb)		
	Lines of Best Fit Scatter Plot Construction	LBSPC
	Drawing Line of Best Fit	DLB
	Line of Best Fit Predictive Analysis	LBPA
Design Decisions (RQb)		
	Variable Identification	VI
	Data Collection	DC
	Data Organization	DO
	Data Analysis	DA
	Design Decision	DD

Note. CK=Concept Knowledge, RQ=Research Question

The initial coding process consisted of the researcher and a qualified co-coder independently analyzing each of the six student IEJs for instances of concept knowledge phrases reflective of the pre-determined codes (Table 23). All such instances were highlighted and appropriately coded resulting in frequency counts (Appendix L) for each pre-code according to the phases of design (PIRPOSAL Model) within which the phrase was identified. These frequency counts allowed the researcher to determine specific sections of the IEJ and phases of design that were to be coded during second round coding (in vivo codes). The identified IEJ sections and phases of design were then re-analyzed to generate in vivo codes (Creswell, 2014) reflective of the mathematical concepts to which students were speaking and the design decisions they were making (Appendix H). Specifically, the in vivo codes, as derived from student language, reflected the distinct phrasing used by students when describing situations demonstrating concept knowledge regarding patterns of association, lines of best fit, and technology/engineering design decision making. These in vivo codes were grouped based on conceptual commonalities, and then categorized into key points (Appendix M), which would be used in answering RQa and RQb as discussed in upcoming sections. Results of the pre-code frequency counts for RQa and RQb, and those for design decisions generated during the initial coding round (Appendix L) are presented in Tables 24 and 25 respectively.

Table 24

IEJ: Pre-Code Frequency Counts for RQa and RQb

Participant	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
23	2	15	2	4	0	3	4	14
30	10	19	4	4	0	5	8	16
22	0	17	0	3	0	8	2	10
12	8	9	1	4	0	4	5	7
20	3	6	5	2	3	4	3	7
4	11	8	1	5	0	4	4	8

Note. IPR=Increasing Pattern Recognition, DPR=Decreasing Pattern Recognition, NPR=No Pattern Recognition, LPR=Linear Pattern Recognition, NLPR=Non-Linear Pattern Recognition, LBSPC=Line of Best Fit Scatter Plot Construction, DLB=Drawing Line of Best Fit, LBPA=Line of Best Fit Predictive Analysis

Table 25

IEJ: Pre-Code Frequency Counts for Design Decisions

Participant	Design Codes				
	VI	DC	DO	DA	DD
23	33	6	7	4	2
30	44	17	13	16	22
22	21	7	3	12	4
12	40	8	7	8	6
20	25	5	4	10	7
4	27	5	6	8	9

Note. VI=Variable Identification, DC/DO=Data Collection/Data Organization, DA=Data Analysis, DD=Design Decisions

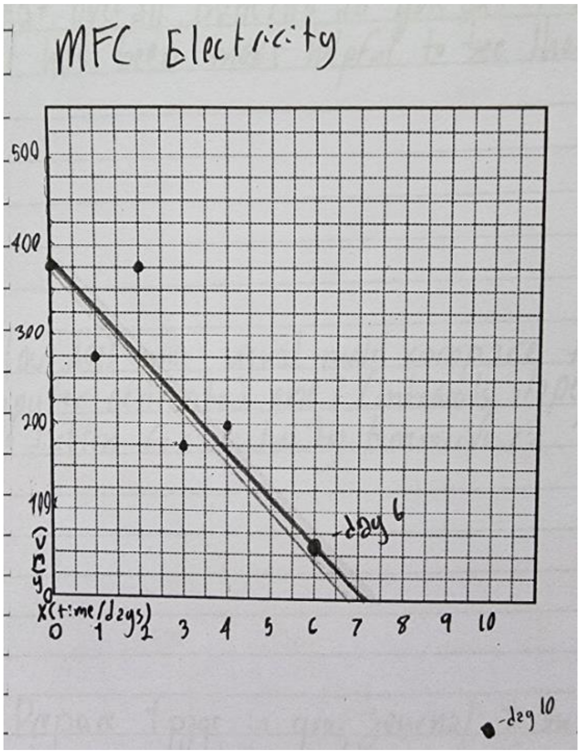
Low Change Sub-Group

Participant 23. Written descriptions, explanations, and drawings were considered as demonstrations of concept knowledge during the initial coding process. Initial coding revealed that P-23 demonstrated concept knowledge of patterns of association 23 times during the Solutions and Alterations Phase (days 9-14) and Learning Outcomes Phase (day 15) of the design challenge (Appendix L). The majority of their demonstrated pattern recognitions were of decreasing patterns (DPR) with zero demonstrations of non-linear pattern recognition (NLPR). In a further analysis of the student’s language using in vivo coding (Appendix M), phrases such as, “my points are mostly decreasing,” and, “our data went down,” were identified to relay the overall negative pattern they recognized in their data. In the few instances that their data increased, they were able to use language such as, “today they went up,” to demonstrate their recognition of an increasing data pattern.

Regarding concept knowledge of lines of best fit (RQb), P-23 demonstrated their ability to construct a scatter plot, draw a line of best fit, or use that line of best fit for predictive analysis 21 times within the Solutions and Alterations Phases and Learning Outcomes Phase of the design challenge (Appendix L). They demonstrated predictive analysis using lines of best fit 14 times during these phases of their journal (Appendix L). In their IEJ, this student described the construction of their line of best fit (LBSPC) as “making sure the same number of points were above and below my line” (Appendix M). The student was then able to use that trendline (Figure Z) to predict (LBPA) that their electricity measurement “should have reached 65mV” by day 6.

Figure 6

Participant 23 IEJ Line of Best Fit



This student demonstrated their understanding of the effects of their negative pattern on their system through their design decisions throughout 88% of their IEJ (all PIRPOSAL phases except one). They used variables (described in their IEJ as “electricity” and “millivolts”) to collect and organize data into a table or scatter plot throughout the Solutions and Alterations phases of their IEJ. Analysis of IEJ entries coded DA (Data Analysis) indicated that when P-23 used this data, they inferred that their system “may not have been set up properly and that might have caused it to go down.” They also documented that one of the design decisions their group made was to “drill another hole in our lid” to try to increase their electricity production. The negative data patterns this student documented helped them conclude that, because their data had a negative pattern, their design would not be able to meet one of the criteria for the design challenge – to be able to light a small light.

These IEJ data support that P-23 did gain concept knowledge of lines of best fit during the intervention. In Figure 6, they demonstrate their use of the line of best fit in predictive analysis. Their ability to draw the line correctly and then use it to predict future data points (days 6 and 10) is indicative of high levels of concept knowledge. Even though the student did not quantitatively demonstrate gains in patterns of association concept knowledge because of their perfect score on both pre/posttests, these qualitative data indicate they most certainly possess high levels of understanding for this concept. P-23 clearly discusses the negative patterns found in their data and how their system's inability to light a light bulb is reflective of that negative pattern.

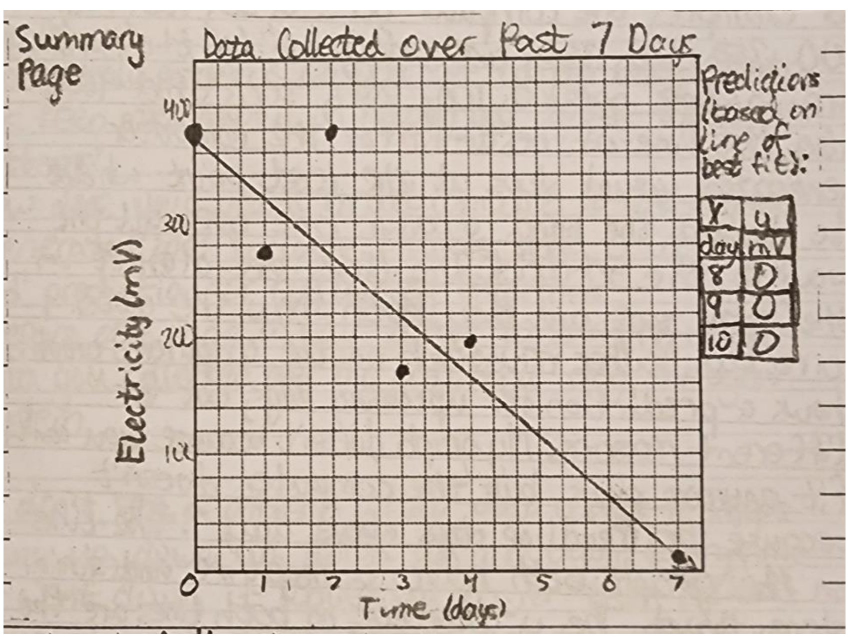
The interview of P-23 was used to further corroborate that this student was able to discuss these same negative patterns and how those patterns affected the future production of their system. If the student is able to relay these same high levels of understanding during the interview, they will further substantiate that the gains in mathematical concept knowledge resulted from their participation in the intervention.

Participant 30. Initial coding of the IEJ of P-30 revealed that this student most often demonstrated (f = 37) RQa (patterns of association) and RQb (lines of best fit) concept knowledge during the Solution and Alterations Phases and Learning Outcomes Phase through their descriptions, explanations, or drawings. In vivo coding provided a clearer picture of the experiences this student had through their descriptions of all pattern types (increasing, decreasing, no, linear) except for non-linear patterns. P-30 stated that their "system was very unsteady" and they could not see a pattern in their data. After collecting data for several days, P-30 came to a final conclusion that their data was "negative and linear." This student increased in this area by one point but scored an almost perfect score (10/11) on the RQa BDPost items. The documentation of their experiences with several data pattern types before reaching their negative, linear pattern conclusion confirms that although they did not demonstrate much quantitative growth in this area due to an already high score, they did have high levels of understanding of these patterns of association in the context of the design challenge.

P-30 demonstrated fewer instances of lines of best fit concept knowledge (f = 29), but their descriptions indicate their high levels of understanding of the drawing of lines of best fit (DBL) as well as the use of those lines for predictive analysis (LBPA). P-30 stated that to draw a line of best fit, they had “to get the dots on both sides to even amounts” clearly indicating their understanding of the location of a line through the center of their data pattern. They were also able to use their negative line to predict that they were going to reach zero millivolts because “the trendline stop[ped] above day 7” (Figure 7).

Figure 7

Participant 30 IEJ Line of Best Fit



Also contributing to support for this student's understanding of their negative line of best fit are the design decisions this student made to try to increase the amount of electricity produced. This student stated that their group "added more open space in the lid for the water container" and in the future would add more mud to the system to attempt to increase electricity production. These changes made to the system demonstrate the student's understanding that, because of their declining levels of electricity, their system did not meet the requirement of lighting a light bulb and that they needed more electricity to do so. These design decisions were their attempt to increase electricity production.

The interview of P-30 was used to clarify the level of concept knowledge this student has for patterns of association due to their low gains demonstrated on both the posttest and IEJ. Specifically, the interview will be used to identify instances of understanding demonstrated through the student's ability to discuss the patterns they saw in their data. The interview will also be used to corroborate the high levels of concepts knowledge indicated in the IEJ but not clearly present through quantitative data analysis.

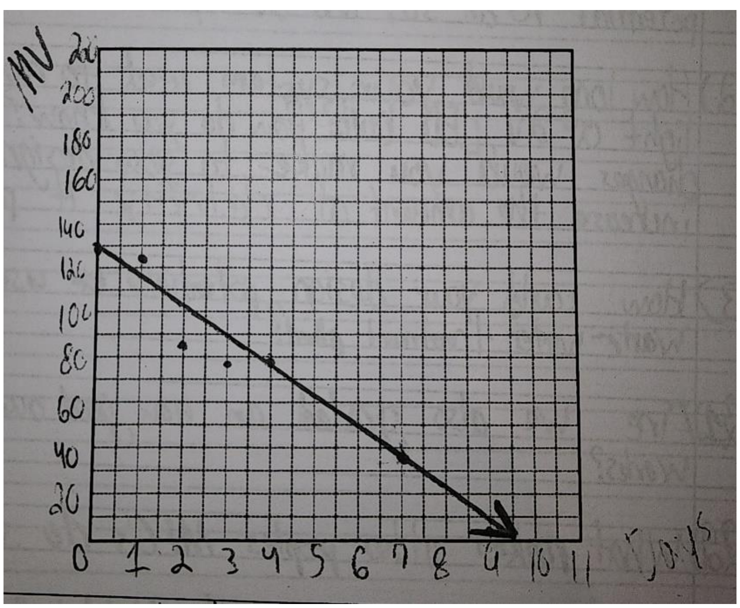
Middle Change Sub-Group

Participant 22. Initial coding of IEJ data for P-22 revealed that this student only documented experiences with decreasing (17 instances) and linear patterns (3 instances) in the Solutions and Alterations Phases and Learning Outcomes Phase. This lack of experiences with a variety of types of patterns of association could have contributed to this student's lower gains (2 points) with RQa subset items on the posttest. In vivo coding supported this student's understanding of negative patterns when they described their data as going "down just a little every day." They also clearly demonstrated their understanding of linear patterns stating, "our data is linear because we were able to draw a line." The experiences this student had through collecting and organizing data for their system helped their understanding of these two types of patterns, but did not increase their understanding of other types of patterns of association.

P-22 had a variety of experiences with lines of best fit concept knowledge as they documented experiences in constructing scatter plots, drawing lines of best fit, and using those lines for predictive analysis. Figure 8 shows this student's accurate construction of a scatter plot and drawing of a line of best fit to support their high level of knowledge of these concepts. They also clearly demonstrate their understanding of how to use the line of best fit that they drew when they stated "based on the line of best fit, I think it is going to hit 0 on day 9" also seen in Figure 8.

Figure 8

Participant 22 IEJ Line of Best Fit



To further support that this student did demonstrate high levels of concept knowledge relative to bivariate measurement data overall, they are clearly able to judge the success of their design by concluding that is it "bad" due to the fact that their "MFC cannot power the light bulb." They also provided design decisions such as stirring the mud more often and changing the size of their containers to try to increase electricity production. Although this student was in the Middle Change Sub-Group, they provided several demonstrations of high levels of concept knowledge of negative and linear patterns of association and lines of best fit through their data analysis and design decisions.

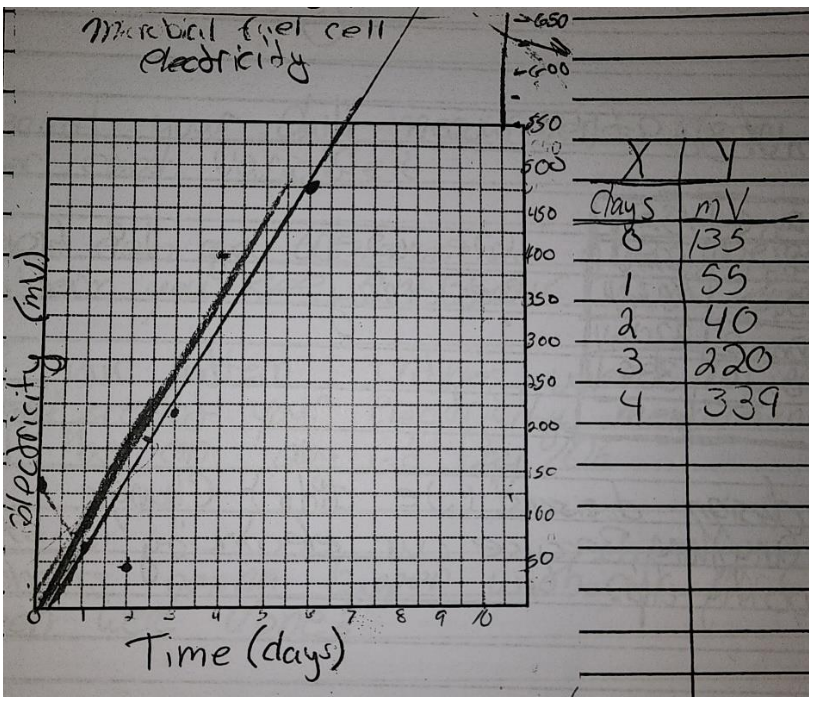
The interview of P-22 focused on the accumulation of additional qualitative data to support these IEJ findings. Specifically, the interview will be used to identify if P-22 acquired any concept knowledge of patterns of association other than negative and linear patterns. The interview will also be used to confirm the high levels of concept knowledge of linear and negative patterns and lines of best fit demonstrated by their IEJ.

Participant 12. The initial coding of the IEJ of P-12 revealed their experiences (f = 22) with all types of patterns of association (increasing, decreasing, linear, no pattern) except for nonlinear patterns during the Solutions and Alterations Phases. They most frequently documented instances regarding increasing and decreasing patterns of association until their final conclusion that their data had an overall increasing pattern because they "drew a positive line." This student's experiences with different types of patterns helped their understanding of different types of patterns. In vivo coding clarified this inference because the student specifically described each type of pattern in their IEJ. They stated that their data "has been going up and down" as they collected data until a clearer data pattern emerged as a "positive association." This student's descriptions of data patterns in their IEJ supports that the gains seen on the BDPost were related to the experiences this student had during the intervention.

Furthermore, during the Solutions and Alterations Phases, this student demonstrated understanding of constructing scatter plots, drawing a line of best fit, and using that line for predictive analysis 16 times. Specifically, this student was able to describe that they had "a total of 2 dots on each side of my line" as they carefully drew their line of best fit through their data points. They also used this line to predict that "day 6 is going to be 475 mV" as demonstrated by their scatter plot in Figure 9. This clear demonstration of drawing a line of best fit and using that line to accurately predict future data points is reflective of high levels of concept knowledge not demonstrated by this student's quantitative score gains.

Figure 9

Participant 12 IEJ Line of Best Fit



Further indication that this student acquired high levels of understanding of bivariate measurement data concepts lies within their statement that "we didn't change anything because our electricity is still going up." This shows that the student was able to identify an increasing pattern of association and understand the meaning of that pattern through their clear interpretation that their data was continuously increasing and therefore a design change was not necessary to increase their levels of electricity at that point in time. This also implies that the student understanding that a decreasing pattern would necessitate a change of some kind to their system. To be able to identify patterns of association and understand their meaning through design decisions is an indication of high levels of understanding.

The interview of P-12 will be used to support these high levels of understanding demonstrated by the IEJ but not by the BDP. Specifically, their interview was used to determine if this student could discuss the patterns of association they saw in their data and demonstrate understanding of these patterns through their design decisions as found in their IEJ.

High Change Sub-Group

Participant 20. P-20 documented several experiences with data in each pattern recognition category with the most frequently documented experiences as those with a decreasing or no pattern (Appendix L). The student documented their understanding that "the graph sometimes does not have a pattern" based on their experiences with data inconsistently going "up up down down up down" (Appendix M). This helped the student to increase their understanding of patterns of association because their data fluctuated frequently, exposing them to increasing, decreasing, and eventually the understanding of no pattern of association involving inconsistent data measurements.

The most frequent pre-codes relating to RQb were found during the Solutions and Alterations Phases and Learning Outcomes Phases of the IEJ. On the second scatter plot that they created in their IEJ (Figure 10), they drew a line of best fit stating that "there was 2 points below the line and three above the line". However, on their third scatter plot (Figure 11), the student did not draw a line of best fit as their nonlinear pattern emerged clearer with an additional data point. This difference in drawings in this IEJ demonstrates that this student increased their understanding of no pattern association during their experiences with their collected data.

Figure 10

Participant 20 IEJ Scatter Plot 2

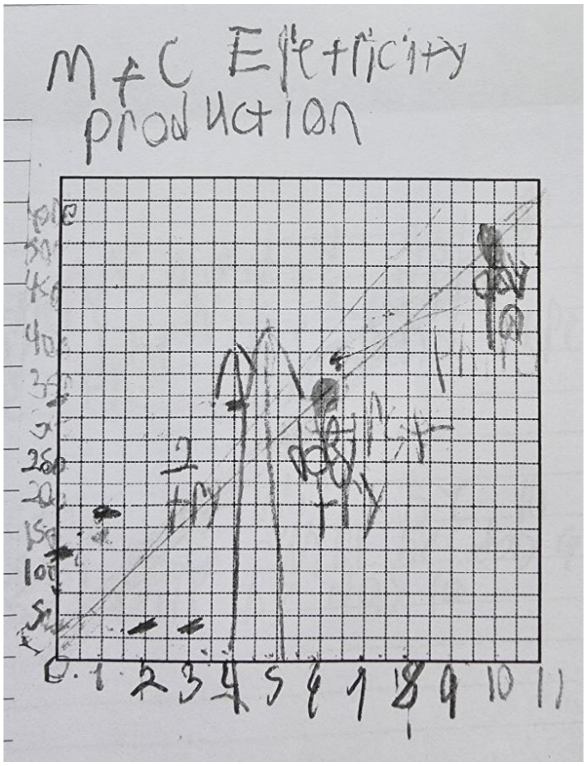
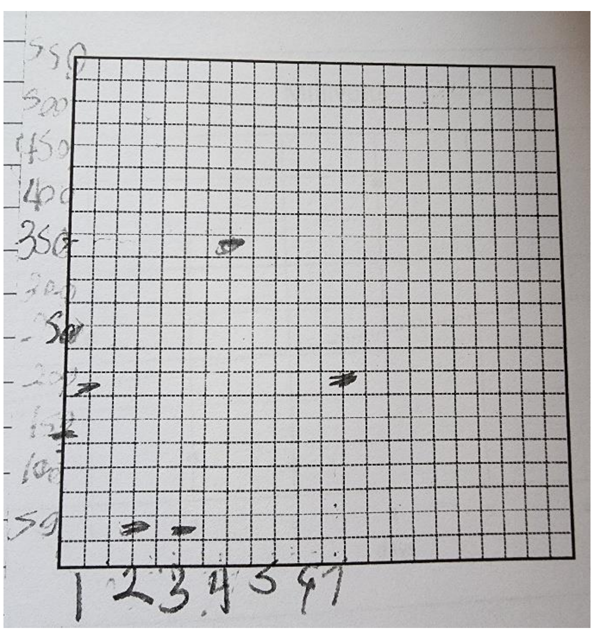


Figure 11

Participant 20 IEJ Scatter Plot 3



In Figure 10, this student also demonstrated their ability to use their line of best fit to predict future data points. They included two large points on their line of best fit to indicate their prediction for data points on day 6 and day 10.

Throughout their IEJ, this student clearly interpreted the fluctuating increasing and decreasing patterns of their variable data (DA) to tell them if their system was working or not. The student provided different interpretations for why their system was decreasing in energy based on their data through statements such as, “I think it dropped because the electrons stopped producing as much,” and, “I think it might be going down because the mu[d] iis drying up.” This student also asked questions in their journal such as, “How can we get a pattern?” as they realized their data was not generating a consistent pattern.

Support for quantitative findings for P-20 lies in their IEJ. This student had experiences with different types of data patterns, leading to the understanding of a “no pattern” of association. These experiences helped the student to recognize a variety of patterns and demonstrate larger gains on RQa posttest items than on RQb posttest items. Further support for these findings lies with the final scatter plot (Figure 11) drawn by P-20 in their IEJ. Due to the “no pattern” of association of their data, P-20 could not draw a line of best fit and therefore did not receive as much practice with this skill. The lack of a drawn line of best fit also lead P-20 to less practice with using that line for predictive analysis. Therefore, this student did not have as many experiences relative to RQb concepts as RQa concepts and demonstrated lower gains on those RQb posttest items.

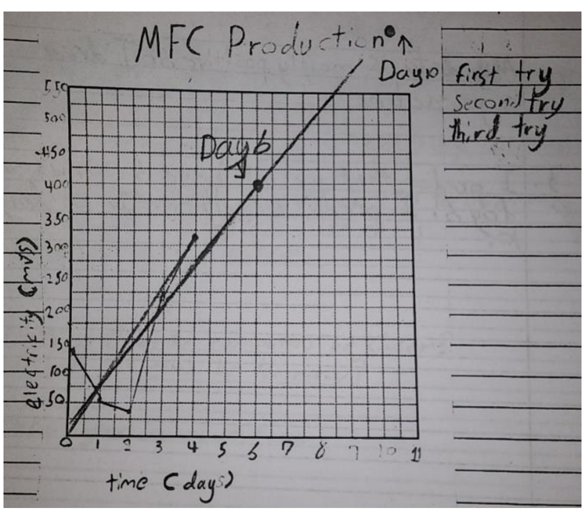
The interview with P-20 will be used to support moderate amounts of concept knowledge of bivariate measurement data. The interview will also be used to support the higher levels of concept knowledge of patterns of association than lines of best fit as demonstrated by the quantitative measure and IEJ findings.

Participant 4. The IEJ of P-4 revealed that during the Solutions and Alterations Phases, this student had experiences with all pattern types except for nonlinear patterns. However, their highest number of documented instances (f = 11) of demonstrating concept knowledge were with increasing patterns as they first described a fluctuating pattern as "the electricity that was decreased and increased" and final conclusion that "my data is mostly positive." In vivo coding confirmed that this student was able to accurately describe all pattern types except for nonlinear patterns, supporting this student's high levels of concept knowledge for RQa demonstrated by the BDP.

This IEJ also supported that P-4 had high levels of concept knowledge for lines of best fit because of their high number of documented instances regarding scatter plot construction, drawing lines of best fit, and using those lines for predictive analysis. As seen in Figure 12, three attempts were used by P-4 to accurately draw a line of best fit.

Figure 12

Participant 4 IEJ Line of Best Fit



In the first attempt, this student did not understand the concept of the line of best fit because they tried to connect the data points. On the second attempt, the student ended the line on the last data point and did not continue it to be used for predictive analysis. By the third attempt, the student accurately drew the line and used it to predict future data points for days 6 and 10 by placing them on the line. These experiences during the intervention support the high gains for this concept demonstrated quantitatively on the BDP.

This student also demonstrated understanding of the implications of an increasing data pattern through their statement that "we didn't have to redesign because my system worked." This statement supports that this student was able to relate their increasing data pattern with the success of their system. They also relate this pattern to the fact that as long as the electricity production was increasing, they did not need to make changes to their design, an indicator of high levels of understanding of bivariate measurement data.

The interview of P-4 was used to corroborate the high levels of concept knowledge of both patterns of association and lines of best fit as demonstrated by both their quantitative gains and IEJ documentations.

Interview Data Analyses

Following the completion of IEJ coding, individual semi-structured interviews were conducted with the six students. Interviews were audio recorded, transcribed by the researcher, and then analyzed following the same initial coding, in vivo coding, and key point identification process used in analyzing student IEJs. These data clarified student levels of concept knowledge and allowed for the qualitative IEJ findings to corroborate (confirm or disconfirm) the quantitative BDP findings. Based on content analysis of the interview transcripts (Appendix N), participant pre-code frequencies for RQa and RQb and those for their design decisions are presented in Table 26 and Table 27 respectively.

Table 26

Interview: Pre-Code Frequency Counts for RQa and RQb

Participant	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
23	2	11	0	1	0	6	1	5
30	9	15	7	0	0	18	16	6
22	1	6	0	0	0	2	5	5
12	7	2	1	0	0	1	1	5
20	0	1	2	0	1	1	0	2
4	8	5	1	0	0	2	1	4

Table 27

Interview: Pre-Code Frequency Counts for Design Decisions

Participant	Design Codes				
	VI	DC	DO	DA	DD
23	18	0	2	8	7
30	15	6	15	21	39
Participant	Design Codes				
	VI	DC	DO	DA	DD
22	6	1	2	8	7
12	4	0	4	14	12
20	3	1	4	2	3
4	4	1	2	5	10

Low Change Sub-Group

Participant 23. The patterns that emerged from the coding of interview data highlighted the high frequency (*f* = 11) with which this student discussed the decreasing patterns (DPR) in their data, far exceeding the mention of other data patterns they saw (Appendix N). During their interview, this student described these decreasing patterns by stating, “Most of the data our data would go down”, and, “our pattern seemed to have a negative slope” (Appendix O). These phrases confirm their recognition of this pattern type. During their interview this student also described an increasing pattern (IPR) as, “our data went up” during their data collection. They demonstrated their understanding of a linear pattern (LPR) by saying that “if it was linear we could tell for sure if it was going up or down.” These descriptions support that this student had experiences with different types of patterns during the design challenge with the most frequent being with negative patterns of association (NPR).

In their responses to interview question 4, this student was able to consistently describe both their construction of a scatter plot (LBSPC) using the *x* and *y* axis as well as the construction and use of a line of best fit (DLB) for predictive analysis (LBPA coding, Appendix I). They clearly described scatter plot construction through statements such as, “the x axis was each day we had,” and, “the y axis was every 100 millivolts.” Not only does this statement provide an example of understanding scatter plot construction but also variable recognition (VI) and the use of those variables (days and millivolts) for data organization (DO).

In their description of drawing a line of best fit, this student stated that they tried to “find the middle point of all of our plo, all the plots on our scatter plot.” They also iterated their understanding of the use of the line of best fit to determine their overall negative pattern of the line of best fit by stating, “our data specifically told us that our millivolts were going down into the negatives.” This led them to predict that their system “would not have been able to light a light bulb,” which was one of the criteria for their design.

To summarize, the content analysis of the interview with P-23 clearly documents their understanding of data driven design decisions through their use of data analysis (DA), the most frequently counted design pre-code, and their understanding of negative patterns used to drive future design decisions such as using “bigger containers.”

Participant 30. Initial coding of the interview of P-30 revealed that this student most frequently discussed both patterns of association and lines of best fit concepts during interview questions two through six (Appendix N). Specifically, this student discussed decreasing patterns of association (DPR) most frequently due to the negative pattern that emerged in their data. This was clear during the interview when they stated, "our system it just kept going down" and "it would drop down a lot". P-30 was also able to discuss having no pattern (NPR) prior to their negative pattern emerging as they stated, "and it would go up but then the next it would just go down" and "went up twice and down like three times." As more data was collected during the intervention, the student saw the overall decreasing pattern of association.

P-30 also frequently discussed the construction of their scatter plot (LBSPC, f =18), drawing their line of best fit (DLB, f = 15), and using that line for predictive analysis (LBPA, f = 13) while answering interview questions three and four. They demonstrated clear understanding of how to create a scatter plot when they stated, "Day one I think it had 270 so I lined up the x value of one." This statement clarifies that this student knew that the variable x represented the *day* and the y variable represented the number of *millivolts* measured. This student also knew that to plot this information on a scatter plot, they had to align the x and y values on the graph. They also clearly demonstrated their understanding of how to draw the line of best fit when they stated that they would use a ruler to draw a straight line and they would "create it a negative trendline" on their scatter plot to summarize the direction of their data. Further, this student clearly described how to use this line of best fit to predict when their system would reach 2,000 millivolts when they stated, "whenever it reaches 2000 I would take my finger and just go down to the day." This student described that they would follow their line of best fit until they were at a *y* value of 2,000. Then they would take their finger straight down the graph to see what *x* value corresponded to that *y* value.

P-30 further demonstrated understanding of the decreasing patterns of association that they saw in their data through their design decisions. This student discussed concepts related to decision making (f = 94) during their answers to interview questions two through five (Appendix N). Specifically, this student was able to relate that their negative data pattern warranted drastic changes to improve its electricity production. Specifically, the student stated that they would have to make a lot of changes or “just build a whole new system” in order to attempt to build a system which would light a small light.

Middle Change Sub-Group

Participant 22. P-22 was able to discuss patterns of association concepts (RQa) during questions three and four of their individual interview (f = 7). This student mostly discussed decreasing patterns (DPR, f = 6) and mentioned an increasing pattern recognition (IPR) one time. In vivo coding provided that this student fluently described decreasing patterns when they stated that their data pattern was negative and that their data would “go down just by a couple numbers.” Although they only referenced increasing patterns as “positive” and did not describe any other patterns at all, P-22 scored higher (perfect score) on RQa (patterns of association) items on the BDPost than on RQb (lines of best fit) items. The IEJ data demonstrated that this student mostly learned about decreasing patterns during their intervention experiences with data and their interview confirms this as well.

P-22 was able to describe lines of best fit (RQb) concepts (f = 12) in their responses to interview questions three and four. This student described how to draw a line of best fit through their statement that “it would tell us how many points were above and below the line.” Here, the student iterated creating their line of best fit by putting the same number of points above and below the line. They also demonstrated understanding of how to use this line for predictive analysis through their descriptions that they would “take a ruler and we would just continue the line past the most recent point” and “because eventually according the graph that we done eventually it is going to hit zero.” Through these statements, this student described how they would determine where future data points would lie on their line of best fit and, according to their line, that they interpreted their data to eventually be at zero.

Overall, P-22 interview data indicated that this student demonstrated high gains in concept knowledge of decreasing patterns of association due to their discussion of these patterns and through their suggestion that in the future they wouldn’t build their system the same way. This suggestion indicates they understand the meaning of a negative data pattern in terms of the success of their system. They knew that because their system would have reached zero eventually, many changes would need to be made to allow it to successfully light a light bulb as required by the design challenge.

Participant 12. Initial coding of the interview of P-12 revealed that this student most frequently discussed patterns of association while answering questions two through five during their interview. Specifically, this student discussed increasing data patterns (IPR) significantly more frequently (f = 7) than decreasing patterns (DPR, f = 2) and no pattern (NPR, f = 1). This student did not discuss linear or non-linear patterns at all. In vivo coding revealed that this student could accurately describe decreasing, no, and increasing patterns of association as the data collected from their system “went completely down almost”, then “went up and down”, and finally “kept going up” to reveal an overall increasing pattern. Language relaying these types of patterns helps confirm that this student increased their concept knowledge of patterns of association (RQa) through their intervention experiences. However, these findings cannot confirm that this student increased concept knowledge of linear or non-linear patterns based on their experiences because they did not provide documentation for such during their interview. The lack of documentation for all patterns of association could be the reason they only moderately increased their concept knowledge from BDPre to BDPost and were therefore placed in the Middle Change Sub-Group.

P-12 provided very few instances of concept knowledge for lines of best fit concepts of constructing a scatter plot (*f* = 1, question 4) and drawing a line of best fit (*f* = 1, question 3), but they did provide more instances (*f* = 5) that could be used to document their understanding of using a line of best fit for predictive analysis. The one in vivo code produced for drawing a line of best fit (DLB) indicates that this student did understand how to draw this line. They described their experiences as "you had to have points above and below the line." Although they did not include that they needed the same number of points, this comment implies they have a moderate understanding of DLB which would support the quantitative findings of moderate concept knowledge change. This student also indicates their understanding of how to use this line when they comment that based on their increasing pattern, they believe their system would have "went up to 2000."

In the part of the data collection that they saw a decreasing data pattern, this student demonstrated further understanding of what this meant by their design decision to stir the mud portion of their system. This indicates that not only did the student recognize the decreasing pattern but they understood that it meant that they should make some kind of change to their system to attempt to increase their amount of electricity produced.

High Change Sub-Group

Participant 20. In their interview, this student most frequently (*f* = 2) described their data as having “no pattern” (NPR). This student specifically stated, “There wasn't a pattern in the data”, and described the fluctuation of having no pattern as “it went up and then it went down and then it went up again and then it went back down.” They were also able to discuss a decreasing pattern (DPR) and non-linear pattern (NLPR) relative to their data one time each. In their interview, this student did not reveal how they drew a trendline (DLB) because their data did not follow a linear pattern.

The responses in the interview for this student also supported their understanding of the purpose of collecting data (DC) from their variables (VI) when they stated that “we would test it and see how much electricity it went up or went down.” Even though they did not have a pattern, when asked if their system could eventually light a light bulb, this student predicted (LBPA) that “I don’t think it could because it was going down.” They said that in the future, they would like to “do more to it” to make their system better in order for it to light a light bulb.

Although the frequency with which this student discussed bivariate measurement data concepts was low, the content provided by the student during their discussions provided evidence of their understanding. The student was clear in their statements of having no data pattern and did not mention a line of best fit because their data did not necessitate one.

Participant 4. Initial coding of the interview with P-4 revealed that this student was able to discuss increasing (IPR), decreasing (DPR), and no patterns (NPR) of recognition during their responses to questions two through five of the interview. In vivo coding provided descriptions of these patterns. Increasing patterns were described by P-20 as “rise” and “gain”, decreasing patterns were described as “drop” and “wasn’t rising”, and a “no” pattern was described as “we dropped and gained." These accurate descriptions provided evidence of this student's concept knowledge of these types of patterns of association.

In their answers to interview questions three and four, P-4 provided seven demonstrations of concept knowledge of lines of best fit (RQb). P-4 was able to discuss creating a scatter plot as a "graph" and described how they drew their line of best fit as "we drew like a line through like between dots" to demonstrate their understanding. They also described how they used the line of best fit for predictive analysis as they were "following the line until it reached day 10" as day 10 data were not yet collected for their system.

Although P-4 provided accurate descriptions of RQa and RQb concepts during their interview, further investigation into their design decisions provided further evidence of their understanding of these concepts. For example, P-4 stated that they used their data so "you could see how good it did" when referring to how much electricity their system produced. Although they had an increasing pattern, they provided examples of how they changed their system design to try to increase electricity production so their system could light a small light bulb.

Overall, this student provided evidence of their high levels of concept knowledge through their interview descriptions of patterns of association (RQa) and lines of best fit (RQb) concepts.

Triangulation

Qualitative analysis of IEJ entries and individual semi-structured interviews provided the means for triangulating findings from the QUAL data (phase two of the mixed method) to confirm or disconfirm findings from the QUANT data (phase one of the mixed method) resulting from student experiences during the design challenge and their documented gains in mathematics concept knowledge as demonstrated through analyses of BDP pre/post. The following section presents the results of triangulating these data for participants in each of the three change groups.

Low Change Sub-Group

Participant 23

P-23 demonstrated low gains on the BDPost due to their original high score (19/20) on the BDPre. The one question missed on the BDPre was regarding the concept of lines of best fit. These quantitative data indicate that this student had high levels of bivariate measurement data concept knowledge regarding both patterns of association (RQa) and lines of best fit (RQb) prior to the intervention. Therefore, analyses of both this student's IEJ and interview responses were used to corroborate whether or not the student was consistent in their level of demonstrated mathematical concept knowledge within the context of engagement in the intervention design challenge. Specifically, qualitative data were used to confirm if this student demonstrated instances of high levels of concept knowledge throughout the design challenge and in making design decisions for their system.

Frequency counts (Appendices L and N) were used to identify which PIRPOSAL phases (Wells, 2016c) to further analyze from each participant's IEJ and to subsequently craft the specific interview questions for follow up. In vivo codes (Appendices M and O) of IEJ entries and semi-structured, individual interview transcriptions were used to identify specific phrases (student language) representing bivariate measurement data concept knowledge. Table 28 and Table 29 summarize the frequencies of the pre-codes (Table 23) for patterns of association, lines of best fit, and design decisions used in qualitative analysis of data collected from P-23.

Table 28

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P-23

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	2	15	2	4	0	3	4	14
Interview	2	11	0	1	0	6	1	5

Table 29

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-23

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	33	6	7	4	2
Interview	18	0	2	8	7

P-23 discussed a decreasing data pattern (DPR) more than other patterns in both their IEJ and individual interview. This consistency revealed that this student had the most experience with this pattern due to the negative pattern that their system's data presented. This student was also able to discuss a linear pattern in both the IEJ and interview because their decreasing pattern was linear, indicated by the line of best fit drawn in their IEJ. Even though their data presented a decreasing pattern, they were still able to discuss an increasing pattern (f = 2) in each qualitative source.

P-23 also used their line of best fit to predict that their system would eventually reach zero millivolts of electricity in both their IEJ and individual interview (question 4). In their interview, the student stated that their system would not light a small light because "by day seven and eight our prototype had already reached zero". Because the student provided the same information in both qualitative sources, it is clear that they were able to demonstrate the concept knowledge of recognizing decreasing patterns of association and using their line of best fit for predictive analysis.

Design decisions documented in both the IEJ and interview provided additional evidence that this student understood the effect of the negative patterns of their data. In their IEJ, they documented that one of the design decisions their group made was to place a second hole in the lid of their system to add an aerator. P-23 also stated that they would use bigger containers in a future system to increase electricity production in both their IEJ and interview. These decisions both stem from their inferences about the negative patterns they saw in the data they collected (f = 6) and organized (f = 9) for their system.

Overall, this student did not demonstrate significant gains in their concept knowledge based on the provided quantitative measure. However, their ability to accurately describe situations in their IEJ and interview demonstrated a high level of concept knowledge of patterns of association and lines of best fit, and is consistent with the analysis of their BDP pre/post scores.

Participant 30

P-30 was placed in the Low Change Sub-Group based on their low change in score from BDPre to BDPost (Table 22). This student only increased their score by 4 points (one-point increase on patterns of association items and three-point increase on lines of best fit items). However, the one-point increase on RQa items (10/11) and three-point increase on RQb items (8/9) allowed them to almost score a perfect score on the BDPost overall (18/20). The findings of their qualitative data sources (IEJ and interview) confirmed that although they did not demonstrate high gains quantitatively, they did possess high levels of concept knowledge relative to bivariate measurement data. Table 30 and Table 31 present initial coding frequency counts for the IEJ and semi-structured, individual interview for P-30.

Table 30

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P-30

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	10	19	4	4	0	5	8	16
Interview	9	15	7	0	0	18	16	16

Table 31

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-30

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	44	17	13	16	22
Interview	15	6	15	21	39

P-30 was able to describe all pattern types except non-linear (NLPR) patterns in their IEJ. In their interview they further confirmed that they had concept knowledge of patterns of association by clearly describing increasing (IPR), decreasing (DPR), and no patterns (NPR) of association. These experiences with different data types provides some evidence for why this student was able to increase their score to almost perfect on the BDPost RQa items.

This student demonstrated higher gains on lines of best fit (RQb) items on the BDPost than patterns of association (RQa) items. Clear descriptions were found in both the IEJ and interview responses documenting how this student constructed a scatter plot, drew a line of best fit for their negative data pattern (Figure 7), and used that line for predictive analysis. Qualitative findings confirm that this student increased their level of concept knowledge of lines of best fit through their experiences during the intervention.

P-30 was not only able to identify the decreasing pattern that emerged in their data but demonstrate understanding of what this pattern meant for the electricity production of their system. Specifically, this student acknowledged in both their IEJ and interview that their electricity production would eventually reach zero and that several changes would have to be made to the system to allow it to produce enough electricity to light a light bulb. This understanding demonstrates bivariate measurement data concept knowledge for patterns of association and lines of best fit.

The BDPre scores indicated this student possessed relatively high mathematical concept knowledge prior to the intervention. As such, it is unsurprising that the pre/post analysis showed low gains in concept knowledge following the intervention. However, their qualitative data does provide clear evidence that this student demonstrated improvement in specific areas of concept knowledge as a result of their experiences during the intervention.

Middle Change Sub-Group

Participant 22

P-22 demonstrated gains on the BDPost closest to the participant mean (5.96), placing them in the Middle Change Sub-Group. These moderate gains were seen as a two-point increase in patterns of association (RQa) items and a three-point increase in lines of best fit (RQb) items. Table 32 and Table 33 provide summaries of frequency counts for the IEJ and semi-structured, individual interview of P-22.

Table 32

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P- 22

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	0	17	0	3	0	8	2	10
Interview	1	6	0	0	0	2	5	5

Table 33

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-22

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	21	7	3	12	4
Interview	6	1	2	8	7

This student began with “moderate” understanding (BDPre) and after the intervention showed only a “moderate” improvement (BDPost) of their understanding. However, this can be attributed to a relatively high BDPre score of 14/20 points compared to a marginally higher BDPost score of 19/20 points. Given the initial a high prescore, there was minimal room for a post score (max six points) to demonstrate an increase in understanding. The class mean was 5.96 points.

P-22 achieved a perfect score (11/11) on the BDPost on items measuring patterns of association (RQa) concept knowledge. Analysis of both the IEJ and individual interview responses from P-22 confirmed that this student demonstrated improved understanding of patterns of association because of their experiences with mostly decreasing patterns of association (DPR). In both the IEJ and interview, P-22 described decreasing patterns most frequently because this is the pattern that emerged for their system's data. P-22 described two types of patterns in their IEJ (DPR, LPR) and in their interview (IPR, DPR). This student did not document any experiences with no patterns (NPR) and nonlinear patterns (NLPR) in either of their qualitative sources. Qualitative data provided documentation to confirm that this student had experiences with some, but not all pattern types during the intervention. These experiences, mostly with decreasing, increasing, and linear patterns, helped this student to increase in concept knowledge patterns of association overall.

P-22 demonstrated higher gains (3 points) for BDPost RQb items as is reflected in their IEJ and interview descriptions. Both the IEJ and interview data confirmed that this student gained concept knowledge from their experiences with constructing scatter plots, drawing lines of best fit (Figure 8), and conducting predictive analysis using that line. Their clear descriptions in both the IEJ and interview of these concepts provide evidence that although they did not demonstrate high gains quantitatively, they did show improvements in their concept knowledge relative to lines of best fit (RQb). Such improvements are further confirmed by their understanding that the data patterns demonstrated by their negative line of best fit meant that their system was not going to be successful in producing enough electricity to light a light bulb and therefore would most likely need to be rebuilt differently to complete a future design challenge.

Participant 12

P-12 demonstrated moderate gains (7 points) in their scores between the BDP pre/post, placing them in the Middle Change Sub-Group. IEJ data were used to confirm or disconfirm whether or not this student demonstrated a moderate level of understanding of bivariate measurement data concepts during their experiences throughout the intervention. Table 34 and Table 35 provide a summary of the pre-code frequencies for the IEJ and semi-structured, individual interview of P-12.

Table 34

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P- 12

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	8	9	1	4	0	4	5	7
Interview	7	2	1	0	0	1	1	5

Table 35

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-12

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	40	8	7	8	6
Interview	4	0	4	14	12

The IEJ data confirmed that during the intervention this student had experiences with all patterns of association (RQa) except for non-linear patterns (NLPR). The interview data were consistent in indicating that P-12 had a greater number of experiences with increasing (IPR) and decreasing patterns (DPR) than other types of patterns. Collectively, these qualitative data provide corroborating evidence that their moderate quantitative gains on RQa items (4 points) were associated with having experiences with select types of patterns of association and not all pattern types.

IEJ data provided evidence that P-12 had higher levels of understanding of lines of best fit (RQb) concepts than was demonstrated by their moderate gains (3 points) on the BDPost. In their IEJ, this student was able to accurately create a scatter plot, draw a correct line of best fit for their increasing data pattern (Figure 9), and interpret the meaning of that overall pattern by making the design decision not to change anything about their system because their data was "going up" (Appendix M). Interview data further supported this student's gains in understanding of RQb concepts through statements of decreasing data patterns early in their data collection and then made design decisions in the Solutions and Alterations Phase to stir the mud to try to produce more electricity.

Analysis of the qualitative data for this student clearly confirms the moderate gains as demonstrated quantitatively on the BDPre/post patterns of association (RQa) items. Qualitative data do not confirm moderate gains in concept knowledge of lines of best fit (RQb) concepts, but indicate that this student actually had high levels of understanding based on their IEJ drawings, descriptions, and explanations as well as their interview discussion about design decisions made due to their data patterns summarized by their line of best fit.

High Change Sub-Group

Participant 20

P-20 demonstrated high gains (8 points) between the BDP pre/post scores. Qualitative data were used to confirm this demonstration of high levels of concept knowledge of bivariate measurement data, and to identify any reasoning behind drastically higher gains on patterns of association (RQa) items (6 points) than lines of best fit (RQb) items (2 points). Table 36 and Table 37 present a summary of the frequency counts for pre-determined codes for RQa, RQb, and design decisions used in the initial coding round for the IEJ and individual interview of P-20.

Table 36

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P- 20

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	3	6	5	2	3	4	3	7
Interview	0	1	2	0	1	1	0	2

Table 37

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-20

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	25	5	4	20	7
Interview	3	1	4	2	3

The IEJ for P-20 documented their having several experiences with all data pattern types (increasing, decreasing, linear, non-linear, no pattern) throughout the intervention. In vivo coding provided further documentation that this student gained understanding of these patterns through their correct descriptions of each of these patterns during their interview (Appendix M). These IEJ findings for P-20 confirmed that the high gains on RQa items were strongly connected to their intervention experiences. Analysis of the individual interview responses from P-20 did not provide as much support for this inference given they did not discuss all pattern types. However, it is important to note that the interview was conducted after the intervention took place, while the IEJ was a continuous documentation of intervention experiences. Therefore, it is understandable why more data patterns were naturally recorded in this student's IEJ given they were discovering each type of pattern as their data emerged. While the interview did not provide documentation of experiences with many data pattern types, it did confirm that the experiences of the intervention as recorded in their IEJ was instrumental in their better understand the "no pattern" of association as one most discussed during their interview.

The experiences P-20 had during their intervention were clearly dominated by no and nonlinear patterns in their IEJ and interview. As a result, P-20 had fewer experiences drawing a line of best fit or using that line for predictive analysis for their own data. For this reason, they were placed in the High Change Sub-Group due to very high gains overall. Consequently, this was reflective of their high gains on patterns of association (RQa) items but not for their gains with lines of best fit (RQb) items. However, this student did gain some concept knowledge of lines of best fit as demonstrated in Figure 10 taken from their IEJ. In this figure, P-20 attempted to draw a line of best fit through their data points before they realized that they could not accurately draw one as their data did not have a pattern (Figure 11). This demonstrates that P-20 did have limied experiences with lines of best fit, and therefore leading them to minimal gains in concept knowledge relative to RQb.

The mathematical concept knowledge gained during the contextual experiences of the intervention can also be seen through the data analysis and data-driven design decisions demonstrated in the IEJ and interview of P-20. Throughout their IEJ, P-20 provided reasoning for their design decisions based on their data analysis records. Two examples of this lie with this student's reasoning behind the decline of their electricity. They stated reasons for why their electricity was decreasing as it fluctuated such as, "because the electrons stopped producing as much" and "I think it might be going down because the mu iis drying up" (Appendix M). These inferences provide the insight that this student knew, based on their decreasing pattern at that time during the intervention, that there was an issue with their system. They also knew that it had to be fixed, so they made the design decision to change the position of the wires in their system. They confirm these findings in their interview when they stated that based on their pattern, they did not think their system could eventually light a light bulb because the electricity production of their system “was going down” (Appendix O).

Overall, this student demonstrated understanding of patterns of association and lines of best fit concepts (how to collect and organize variable data and how to use data patterns for predictive analysis) leading them to make design decisions for increasing electricity production and thereby ensuring their system would be more successful. The qualitative data, provided by the IEJ and supported by the individual interviews, corroborates the quantitative findings that this student increased their mathematical concept knowledge through experiences with mathematical concepts during the intervention.

Participant 4

Analysis of the BDP pre/post data quantitatively demonstrated that P-4 had a high degree of change (doubling the number of correct questions on the BDPost) in levels of concept knowledge, thereby placing them in the High Change Sub-Group. Given there were no large discrepancies between correct RQa and RQb sub-items, the IEJ and individual interview responses from P-4 were examined for evidence of high gains in concept knowledge to confirm quantitative findings. Table 38 and Table 39 provide the frequency counts for pre-codes used during initial coding to analyze both the IEJ and individual interview of P-4.

Table 38

Summary of RQa and RQb Pre-Code Frequency Counts for Qualitative Data Sources for P- 4

Data Source	RQa Codes					RQb Codes		
	IPR	DPR	NPR	LPR	NLPR	LBSPC	DLB	LBPA
IEJ	11	8	1	5	0	4	4	8
Interview	8	5	1	0	0	2	1	4

Table 39

Summary of Design Pre-Code Frequency Counts for Qualitative Data Sources for P-4

Data Source	Design Codes				
	VI	DC	DO	DA	DD
IEJ	27	5	6	8	9
Interview	4	1	2	5	10

Entries in the IEJ of P-4 provided documentation of their concept knowledge of four types of patterns of association (IPR, DPR, NPR, LPR), while their interview provided documentation of understanding of three types of patterns (IPR, DPR, NPR). There was no evidence provided in either the IEJ or the individual interview to support the increase in concept knowledge of non-linear patterns during the intervention. However, the descriptions of these four types of patterns found through in vivo coding of both the IEJ and interview provided clear evidence that this student did increase their levels of RQa concept knowledge due to their intervention experiences.

IEJ data also provided documentation that P-4 increased concept knowledge of lines of best (RQb) fit due to their experience drawing a line of best fit through their data (Figure 12). Their interview responses further confirmed these findings through their descriptions of how to draw their line and its use in predictive analysis for electricity production on Day 10 of data collection which was outside of the intervention window.

The statement made by P-4 in their IEJ that, “We didn’t have to redesign because my system worked” epitomizes the high levels of concept knowledge this student was now able to demonstrate. Specifically, this statement clearly conveys that P-4 grasped the meaning of increasing data pattern. Although in their interview they state that their system “couldn’t power the light bulb”, their IEJ entries acknowledge that the system continued to increase in electricity production. In follow up prompts during the interview, P-4 stated that their system would eventually have been able to light a light bulb in about two months. This is further confirmation that P-4 understandood that the information reflected by the increasing data pattern indicates their system would have kept increasing in electricity production if allowed to do so.

Overall, P-4 IEJ and interview data confirmed their high levels of concept knowledge of both patterns of association (RQa) and lines of best fit (RQb) that were accurately demonstrated quantitatively on the BDPost.

Summary of Results

This research was guided by one research question with two parts (RQa and RQb), each addressing a different concept relative to bivariate measurement data:

RQ1 – What evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) documents a change in concept knowledge of:

c) patterns of association between bivariate measurement data on a scatter plot, and
d) lines of best fit used to model predictive relationships among two quantitative variables on a scatter plot

Quantitative data were collected to provide evidence of significant gains in mathematical concept knowledge between the pretest (BDPre) administered before the intervention and posttest (BDPost) administered after the intervention. Qualitative data were collected to corroborate quantitative findings and provide evidence of connections between changes in mathematical concept knowledge and experiences with T/E DBBL.

Research Question 1 – RQa

The quantitative data relative to measuring the concept knowledge of patterns of association (RQa) indicated significant gains ($p < .01$) between all participant scores on the BDPre and BDPost. To further investigate the connection between the intervention and these changes, six students were purposefully selected to represent three groups with low, middle, and high gains between BDPre and BDPost scores. The IEJs of these six students were initially coded for the frequency with which they were able to demonstrate concept knowledge of patterns of association in their journal. Interviews with all six students were then conducted to discuss their experiences, each of which were coded to establish frequencies of responses regarding demonstrations of concept knowledge of patterns of association. Table 40 provides a summary of data for the initial coding of the IEJs and individual interviews.

Table 40

Summary of IEJ and Interview RQa Pre-Code Frequency Counts

Data	Participant						Sum
Source	23	30	22	12	20	4	
IEJ	23	37	20	22	19	25	146
Interview	14	31	7	10	4	14	80

Collectively, these students were able to demonstrate experiences (f = 146) with concept knowledge of patterns of association with the range of instances for a single student between 19 and 37 throughout the entire intervention. A closer look at the IEJ initial coding data presented in Appendix G narrows the majority of these experiences to the Solutions and Alterations Phases of the intervention. It was during these days (9-14) that students responded to journal prompts about data collection and analysis for their microbial fuel cell design. The experiences that students had during these days provided data indicating a clear impact on their ability to document mathematical concept knowledge relative to patterns of association.

To support this inference, interview data were used to provide further insights into the ability of participants to discuss their experiences with data collection and analysis. Table 38 reveals that collectively, students provided 80 responses to interview questions documenting their understanding of patterns of association. Data provided in Appendix N provides detailed information about the frequency of statements concerning patterns of association when answering questions two through five of the interview protocol (Appendix J). The purpose of these four questions was to allow students to elaborate on the patterns they saw during data collection, organization, and analysis of their own bivariate measurement data.

In vivo codes (Appendix M and Appendix O) were used to determine specific language students used in their IEJ and individual interview for the researcher to develop key points about their patterns of association concept knowledge. Students using phrases such as “the energy kept increasing” or “it keeps going up” represented instances of increasing pattern recognition (IPR). Similarly, statements such as “our electricity is going down” or “ours was negative” signified a student expressing an understanding of decreasing pattern recognition (DPR). A phrase such as “I don’t see a pattern in our data” was used to represent no pattern recognition (NPR) while “I drew a positive line” was interpreted as an understanding of linear pattern recognition (LPR). Overall, these statements correlate with the questions on the BDP asking for students to identify patterns of “negative correlation”, “positive correlation”, or “linear association.”

Only one student was able to discuss a non-linear pattern in both their IEJ and their interview because this student was the only one among the purposefully selected sample participants to have collected data that produced a non-linear pattern with no association. As a result, in vivo codes for non-linear patterns included statements such as “our graph does not have a line” and “it didn’t have a line” in their IEJ and their interview both. The ability of this participant to provide these non-linear pattern recognition examples in both their IEJ and interview, supports the inference that their experiences during the intervention with data patterns led to an increase in their concept knowledge of this type of data pattern of association.

Identifying such patterns in the bivariate measurement data generated by their microbial fuel system, students presented a justification to account for their increased ability to recognize these patterns on the quantitative tests.

Research Question 1 – RQb

Nine items on the BDP were designed to quantitatively measure change in concept knowledge of lines of best fit (RQb) before and after the intervention. The participant Whole Group results demonstrated statistically significant gains ($p < .01$) between the BDPre and BDPost. To confirm that (1) students had the concept knowledge demonstrated by these results and (2) these gains were related to experiences during the intervention, six students were purposefully selected as Change Sub-Group participants for qualitative data collection. The IEJ of each Change Sub-Group participant was analyzed for demonstrations of lines of best fit concept knowledge including scatter plot construction (LBSPC), drawing a line of best fit (DLB), and predictive analysis using their line of best fit (LBPA). Table 41 provides a summary of initial coding frequencies (Appendix L and Appendix N) for all pre-codes relative to RQb collectively for each participant’s IEJ and individual interview.

Table 41

Summary of IEJ and Interview RQb Pre-Code Frequency Counts

Data Source	Participant 23	30	22	12	20	4	Sum
IEJ	21	29	20	16	14	16	116
Interview	12	50	12	7	3	7	91

These six participants collectively documented experiences (f = 116) with lines of best fit concepts in their IEJs throughout the intervention. Instances used as documentation to confirm the existence of this concept knowledge included descriptions and graphs drawn by the students. For example, descriptions such as, “There is a total of 2 dots on each side of my line,” “to get the dots on both sides to even amounts,” and, **“**making sure the same number of points were above and below my line” were stated by three different students to describe how they knew where to draw the line of best fit through their data. Further confirmation of the existence of this concept knowledge and its relationship to experiences during the intervention was evident through the scatter plots drawn by all students in their IEJs (Figures 6-12). In each of their hand-drawn scatter plots, students demonstrated their understanding of how to draw a scatter plot, how they drew a line of best fit (if possible), and how they located future data points on that line (if appropriate for their data). The student (P-20) with no data pattern to draw a line of best fit through provided evidence of their concept knowledge by explicitly stating in their IEJ that their graph did not have a pattern.

Individual, semi-structured interview responses from these students confirmed the existence of lines of best fit concept knowledge and the connection between the change in concept knowledge and the intervention. Students discussed this concept frequently (f =91) during their interviews. Specifically, these students described drawing lines of best fit as, “Mostly to where you had to have points above and below the line,” “we drew like a line through like between dots," and, "trying to find the middle point of all of our plo, all the plots on our scatter plot." These statements are examples of three students using different phrases to describe the same concept. They each drew a line between their data points, trying to make sure they kept the same number of points above and below their line on a scatter plot they created.

Each student was also able to provide a prediction of future electricity production based on points that would potentially lie on their line of best fit if they collected data for additional days outside of the intervention. For example, P-30 stated that "whenever it reaches 2000 I would take my finger and just go down to the day" to describe how they would determine what day their data would reach 2,000 millivolts collected, as required for their system to light a small 2-volt light bulb.

Overall, the qualitative data confirm the existence of concept knowledge of lines of best fit, determined by the quantitative measure, in connection to student experiences during the intervention.

Design

Design pre-codes were used to investigate student understanding of mathematical bivariate measurement data foundational concepts. These codes were created to account for the frequency with which students identified variables (VI), collected data (DC), organized data (DO), analyzed data (DA), and made design decisions (DD) based on their data patterns. Table 42 provides a summary of the frequency counts for these pre-codes in each of the six qualitative participants' IEJs and individual interviews.

Table 42

Summary of IEJ and Interview Design Pre-code Frequency Counts

Data Source	Participant 23	30	22	12	20	4	Sum
IEJ	52	41	47	30	51	55	276
Interview	35	95	24	34	13	23	224

The mathematical concepts of patterns of association and lines of best fit are based on the original data that students collected, organized, and analyzed. The frequency with which students worked with their own data in their IEJ (*f* =276) provides further confirmation that the quantitative gains on the BDP were made in relation to student experiences with data during the intervention. Examples of student interactions with data were found in identification of variables as “electricity”, “days”, or “millivolts” and tables drawn in all students’ IEJs. Students also demonstrated understanding of mathematical concepts through their data analysis statements such as “I think it dropped because the electrons stopped producing as much” and “our system may not have been set up properly and that might have caused it to go down” (Appendix M). These statements indicate that students can not only identify patterns in their data but attempt to reason why their data showed the patterns it did. This connection between identification and reasoning lead to the design decisions students made such as “add more mud” (Appendix M) When students made design decisions, they used higher level thinking, representative of understanding what their data patterns meant in conjunction to the performance of their system.

The frequency (*f* = 224) with which students discussed their design decisions during their individual interviews provided further evidence that gains in bivariate measurement data concept knowledge were connected to experiences during the intervention. Again, students were able to recognize the variables they measured as “voltage”, “electricity”, or “day one” (Appendix O). Most students (4/6) discussed how they collected and organized it on a table or graph. All students were able to discuss the success of their system based on its ability to produce enough electricity to light a small two-volt light bulb based on the patterns in their data or judging by the direction of their line of best fit. Students also recalled the design decisions they made during the intervention or discussed changes they would make to a future system to increase electricity production. For example, students suggested using bigger containers or stirring the mud to try to increase electricity production.

Summary of Findings

Quantitative data were collected through the BDPre/posttest to determine if students demonstrated change in concept knowledge of bivariate measurement data after participating in a DBBL intervention. Quantitative data indicated that students demonstrated statistically significant ($p < .01$) gains in concept knowledge of patterns of association relative to RQA and lines of best fit relative to RQb.

A small Change Sub-Group of six individuals was purposefully selected to represent the participant population. Two students with low, middle, and high changes in scores were selected to participate in qualitative data collection. The Interactive Engineering Journals (IEJ) of each of the six Change Sub-Group participants were analyzed for demonstrations of bivariate measurement data concept knowledge to confirm or disconfirm gains found through the corresponding student's pre/posttest scores. After IEJ analysis, each of the six qualitative participants were then individually interviewed to clarify the findings of their IEJ. The individual interviews were used to further confirm or disconfirm the quantitative and IEJ findings about the concept knowledge of patterns of association (RQa) and lines of best fit (RQb) for each of the six students.

The qualitative data findings confirmed the existence of mathematical bivariate measurement data concept knowledge of patterns of association and lines of best fit for each the six Change Sub-Group participants. The design decisions students made, documented in their IEJ and interview, during the intervention based on the patterns in the data they collected and organized provided evidence of higher order thinking indicative of understanding. Overall, the qualitative data findings confirmed the existence of high levels of bivariate measurement data concept knowledge for each of these six students and connected the quantitative gains demonstrated by the BDP to their experiences during the intervention.

CHAPTER FIVE: CONCLUSIONS

The purpose of this research was to document the ways in which the pedagogical approaches of T/E DBL are shown to promote change in concept knowledge of eighth grade mathematics students. In this chapter, conclusions, derived from the findings of the previous chapter, are discussed for each research question part (a and b respectively). Also included in this chapter are implications, limitations, delimitations, and recommendations for future research.

Conclusions

The overall gains (83%) demonstrated by the Whole Group on the Bivariate Data Pretest/Posttest (BDP) indicate that students' concept knowledge of patterns of association and lines of best fit increased after participation in the T/E DBBL intervention. On patterns of association (RQa) items specifically, the Whole Group increased their scores by 57 percent and on lines of best fit (RQb) items, the Whole Group increased their scores by 139 percent. These significant gains demonstrated by all three data sets indicate that teaching mathematical concepts through T/E DBBL has the potential to increase mathematical concept knowledge, specifically bivariate measurement data concept knowledge.

Qualitative data sources were used to (1) confirm that there was evidence of students having the bivariate measurement data concept knowledge that the BDPost results showed they had and (2) that the gains demonstrated quantitatively were related to experiences students had during the T/E DBBL intervention. Qualitative data analyses of the IEJs for each of the six qualitative participants (Change Sub-Group) confirmed that students demonstrated the concept knowledge implied from BDP findings and that knowledge was connected to their documented experiences during the intervention. Individual interview data further strengthened that implication and supported that student experiences with collecting, organizing, and analyzing their original data influenced their increase in bivariate measurement data concept knowledge.

The following research question will be discussed in upcoming sections:

RQ1 – What evidence derived from student engagement in Technological/Engineering Design Based Biotechnical Learning (T/E DBBL) documents a change in concept knowledge of:

e) patterns of association between bivariate measurement data on a scatter plot, and

f) lines of best fit used to model predictive relationships among two quantitative variables on a scatter plot

Research Question, Sub-Question One (RQa)

Data collected from the quantitative measure (BDP) indicated that student concept knowledge of patterns of association between bivariate measurement data on a scatter plot increased significantly following the intervention. Data collected from each qualitative participant's IEJ and individual interview provided evidence that each student demonstrated concept knowledge of patterns of association through their recognition of data patterns. Student IEJ and interview data analysis led to the following key points which resonated throughout their collective qualitative data sources: increasing, decreasing, no, and linear patterns. Only one of the six qualitative participants was able to discuss non-linear patterns. These key points were either documented in each student's IEJ or discussed in their interview.

Collectively, these qualitative data indicate that the original data collected by students from their microbial fuel cell systems provided them with a variety of experiences with data patterns. The types of patterns they were exposed to during the design challenge influenced the types of patterns they were able to document in their IEJ or discuss in their interview. Overall, the BDP indicated significant changes in concept knowledge. Qualitative data provided evidence that these significant changes were connected to student engagement in the T/E DBBL intervention.

During the design challenge, students were able to make design decisions on different aspects of their system's design based on the data patterns that they saw. Many of their data patterns fluctuated until they had collected enough data points to see a stronger overall pattern. Meanwhile, when their system demonstrated a decrease in energy, students made some sort of design decision to change something about their design in an attempt to increase their energy production. These design iteration decisions made based on their data patterns provide additional evidence of changes in patterns of association concept knowledge. As students saw changes in their data patterns, they had greater clarity and understanding regarding the meaning of the increasing or decreasing pattern. If they saw a decrease, they made a design decision to change something. If they saw an increase, they did not change anything because their system was working as designed. These contextual connections between patterns of association and design decisions while engaged in T/E DBBL indicate that students increased their understanding of this mathematical concept as a result of their need to know. Students' intrinsic drive to achieve a successful biotechnical system during the intervention ultimately provided the intentional experiences that would lead students to increased mathematical concept knowledge of patterns of association.

Research Question, Sub-Question Two (RQb)

Quantitative data analyses revealed significant gains in concept knowledge of lines of best fit between the BDPre and BDPost. All six student IEJs examined during qualitative data analyses included evidence of lines of best fit concept knowledge through the following key points illuminated during qualitative coding: creating a scatter plot of their data, drawing a line of best fit through their data, and using that line for predictive analysis. Only one student had a data pattern not warranting a line of best fit and that student acknowledged in their interview that their data did not have a pattern so they could not draw a line of best fit. Interview data further confirmed increased levels of concept knowledge through student descriptions of those same key points. Specifically, students were able to describe how to create a scatter plot, draw a line of best fit through their data (if possible), and use their line of best fit for predicting future data points on their line.

The line of best fit drawn by students for the data collected on their system was also an indicator of the success of their system in terms of meeting the design criteria which required the of lighting a small (two-volt) light bulb. Students were able to predict if or when their system might be able to produce enough electricity in the future (outside of the intervention window) to light a small bulb. Throughout the interviews, students were able to describe how to use their line to predict whether their system would eventually reach zero millivolts of electricity or continue to rise. They also discussed design decisions for each design iteration during the challenge or choices they would make if they were able to create a new design. The ability of students to alter their system based on the pattern summary presented by their line of best fit further confirms the gains in concept knowledge seen on the BDP. Students who possessed conceptual understanding and high levels of concept knowledge were not only able to recognize how to construct a line of best fit, but were able to verbalize the meaning of that line within the context of their design. This was the case for all six qualitative participants each of whom provided evidence of high levels of concept knowledge through their IEJ documentation or individual interview responses.

Overall, the qualitative data collected from the IEJ and individual interviews of the six qualitative participants confirmed the findings of the Whole Group BDP data. These students represented the Whole Group participants with low, middle, and high gains on the BDP. All qualitative participants, regardless of their Change Sub-Group, demonstrated high levels of concept knowledge regarding lines of best fit through their qualitative data sources. These findings support the conclusion that student experiences during the intervention were influential towards the increase of mathematical concept knowledge.

Implications

Mathematics Educators

This study indicates that students can learn mathematical concepts through engagement in technology/engineering design-based learning (T/E DBL). By promoting student learning of mathematical concepts through authentic, contextual T/E DBL experiences where the need to know is imposed by the design challenge, students achieve deep learning of targeted concepts. Specifically, they not only know the targeted mathematical concepts, but can use that understanding to design a viable solution for the technological problem presented to them. Mathematics educators can use this study as a guide for an alternative pedagogical approach demonstrated to promote student gains in the learning of mathematics concepts in the classroom.

This study showed the potential for T/E DBL to be utilized in the mathematics classroom. This technology/engineering design based biotechnical learning (T/E DBBL) microbial fuel cell design challenge was selected for teaching and learning bivariate measurement data specifically. Furthermore, mathematics educators can draw on this study to guide their use of T/E DBL for teaching other mathematics concepts. The design challenge used by the mathematics educator should be intentionally selected based on the specific concept to be taught.

The Interactive Engineering Journal (IEJ) kept by individual students throughout this intervention was a powerful tool for having students reflect on their own thinking and learning as well as for the teacher to reflect on the thinking and learning that was happening in the classroom. IEJs are similar to traditional mathematics journals because they promote student metacognition through self-reflection (Benson-O'Connor et al., 2019). However, IEJs are different from traditional mathematics journals where students are encouraged to provide examples and notes from math concepts explicitly taught. In an IEJ, students follow the eight phases of design presented in the PIRPOSAL pedagogical model (without being instructed explicitly on this model) as they explore information independently to design a solution to a real-world problem (Wells, 2016c). The purpose of the IEJ is to document information needed to complete the design challenge. The mathematics concepts documented in the IEJ come from students' own research, ideas, and data generated from their design.

The PIRPOSAL model is a pedagogical model for use by the educator in guiding students through the journey of designing a solution to their model. In this study, the PIRPOSAL model was used to create IEJ prompts during all eight phases of design which helped guide students through the design challenge and learn the targeted mathematics concepts intentionally selected as learning outcomes.

Curriculum Development

This study can be used as a guide for implementing the T/E DBL pedagogy that allows students to learn through contextual experiences. Using real-world problems that immerse students in the need-to-know information to solve them can be a powerful tool. When students are in control of their own learning, they are able to document their ideas and discuss their learning first hand. T/E DBL provides students with these opportunities to be engaged in a learning environment that provides concrete, contextual experiences intentionally designed to promote changes in concept knowledge by developing habits-of-mind through habits-of-hand (Wells, 2019).

The microbial fuel cell (MFC) biotechnical design challenge was employed with the end in mind. Specific eighth-grade content standards were selected to be targeted through development of the solutions for the design challenge. The MFC design challenge was specifically chosen to impose on students the need to collect and organize original data from their microbial fuel cell system in order to see various patterns of association necessary for making changes to their design to achieve the desired level of electricity produced. The IEJ daily prompts created by the teacher were intentionally designed to immerse students in the targeted mathematical concepts of patterns of association and lines of best fit. Students were asked to include specific information in their IEJs to guide their thinking and learning of mathematics.

As curriculum developers consider this pedagogical approach, careful consideration of the concepts being intentionally taught should guide the design challenge selected. IEJ prompts, carefully crafted following the PIRPOSAL model (Wells, 2016c) can be used to guide learning in the direction of the targeted mathematical concepts.

Limitations

Time

This intervention took place over fifteen instructional days. Students did not have the time necessary to completely re-design their system. They were only able to make modifications to the system they built. Additional time would have allowed them the opportunity to explore the re-design ideas they had for increasing electricity production.

Furthermore, students only collected data for six instructional days. Additional days for data collection may have revealed additional data patterns and lead to increased concept knowledge.

This study also conducted a single design challenge. More time could have allowed students to complete additional design challenges to be used to determine the influence of T/E DBL on change in the mathematical concepts of patterns of association and lines of best fit.

Materials

Materials used for the design challenge were limited to what the students and researcher brought to the classroom. Additional materials would have allowed for more design iterations leading to different system outputs, which in turn would have impacted the data collected, organized, and analyzed by students.

Assessments

Only one quantitative assessment was used for this study. The assessment used was largely based on a single, high stakes testing source. The source used provided a limited bank of sample questions from which to model test questions for this study. Using multiple assessment sources with larger banks of questions could have allowed for assessment of these mathematical concepts at a finer grain.

Participants

Another limitation for this research was the participant size. The small participant size was due to the convenience sample available at the researcher's home school. There were only 42 students in the eighth-grade population at this school to be possible participants in this study. Thirty of these 42 students returned permission and assent forms to participate in the study. A larger number of participants could increase the reliability of the study outcomes.

A limited number of participants were selected for qualitative data collection and analysis. This small number was identified as sufficient for this study; however, a larger number of participants could have enhanced the scope of the qualitative findings.

Delimitations

Eighth-grade students were specifically selected as potential participants for this study because of the bivariate measurement data standards introduced in the eighth grade. To conduct this study in an older group of students could have increased the chances that students were more familiar with bivariate measurement data concepts. Younger students may not have had the background knowledge on coordinate planes or linear functions which were helpful for these eighth-grade students to learn the bivariate measurement data concepts.

The microbial fuel cell design challenge selected was intentionally chosen to allow students to collect, organize, and analyze original data that would provide them with experiences with different types of data patterns. Some systems were designed well and were successful, and some designs had issues that led them to fluctuate or decrease in electricity production. It is important for students to experience all types of data patterns. Therefore, it is also important for some systems to initially not work well so students have a need for engaging in design iterations and decision-making based on their fluctuating or negative data patterns. This specific design challenge provided the necessary experiences with a variety of data patterns to expose students to multiple patterns of association and lines of best fit directions.

Recommendations for Future Research

This study indicates the potential for T/E DBL to be used to teach mathematical concepts. The scope of this study was limited to two mathematical concepts, patterns of association and lines of best fit, to thoroughly investigate the effects of this pedagogical approach on each concept independently. Future research should maintain a limited number of concepts, but should expand the types of mathematical concepts to be taught through T/E DBL. Each grade level has different key concept outcomes students in that grade level are expected to come to know. Future research should explore the use of the T/E DBL pedagogical approach for instruction of different mathematical concepts in different grade levels.

This study was limited to the small number of participants used. Conducting a similar study with a larger participant population would better document the efficacy of T/E DBL as a viable pedagogical option in the mathematics classroom. In a future study where additional time is allotted, multiple design challenges conducted to enhance the same concepts would also be beneficial to support the reliability of the findings of this research.

Previous studies have explored the use of various types of design-based learning to teach multiple mathematics concepts. Most studies utilizing design-based learning either focus entirely on the increase of science knowledge (Wells, 2016a; Mamlock et al., 2001; Fortus, et al., 2004; Fortus et al., 2005; Holbrook et al. 2001; Kolodner, Gray, & Fasse, 2003; Doppelt et al., 2008; Mehalik et al., 2008; Schnittka, 2009) or the simultaneous increase of science and mathematics knowledge (Akins and Burghardt, 2006; Kelley and Sung, 2017). Even fewer have utilized design-based learning for explicitly increasing mathematics concept knowledge (Burghardt et al., 2010), and this study is the first to specifically investigate the use of T/E DBL pedagogy to increase the bivariate measurement data concept knowledge of eighth grade students.

While this study was small in scale, it demonstrates the potential of T/E DBL to be used for increasing the mathematical concept knowledge of eighth grade students. However, future research is needed to continue investigating the potential of T/E DBL to teach additional mathematics concepts to students in different grade levels in schools around the world.

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APPENDICES

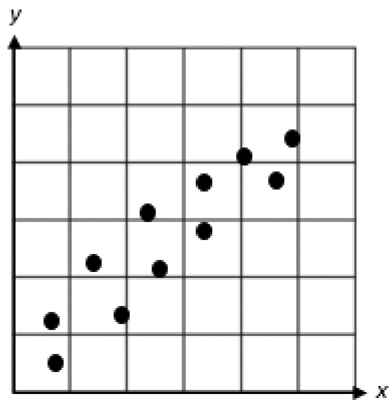
Appendix A

Bivariate Data Pretest

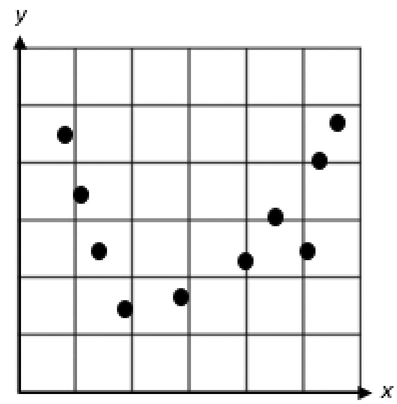
DO NOT PUT YOUR NAME Number: ______________________

1. Circle the letter of the scatter plot showing a linear relationship with a negative correlation.

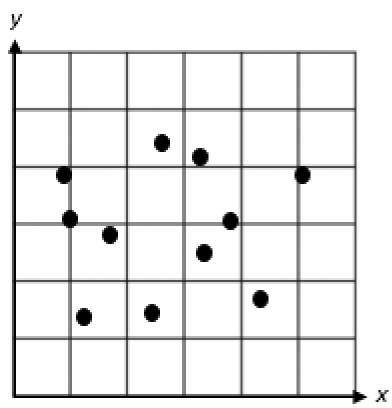
a.



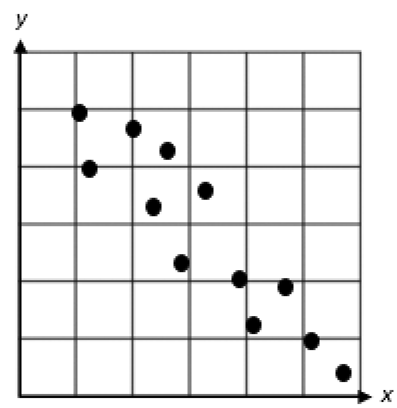
b.



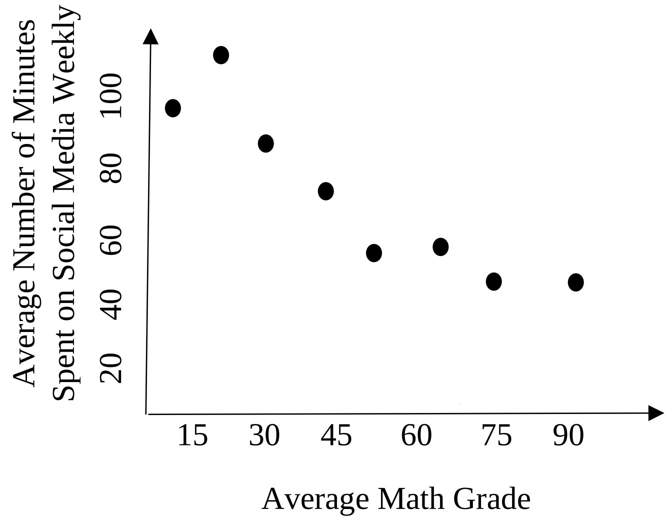
c.



d.



2.



For a science project, Jarren creates a scatter plot for the average time students in his math class spend on social media and their average math grade. According to the scatterplot, what is the relationship between the time spent on social media and the average math grade?

a. There appears to be no relationship.

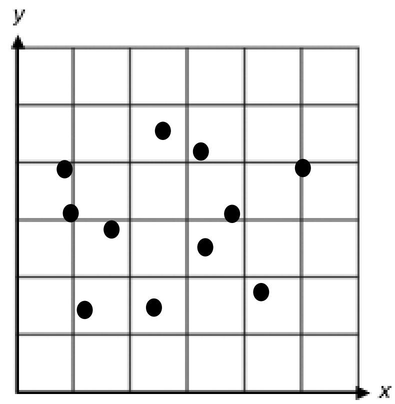
b. Students who spend more time on social media have a higher average math grade.

c. Students who spend more time on social media have a lower average math grade.

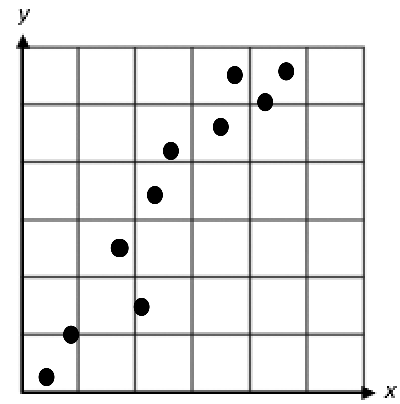
d. Students who spend 40 – 60 minutes on social media have a higher average math grade than students who do not spend any time on social media.

3. Circle the letter of the scatter plot showing a linear relationship between data.

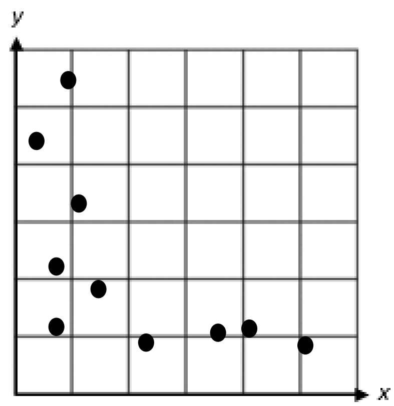
a.



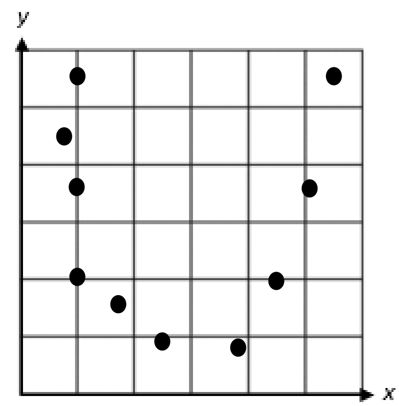
b.



c.

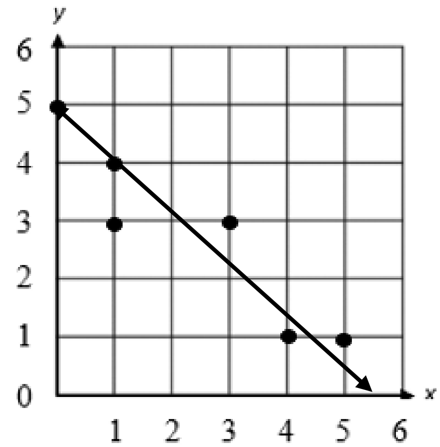


d.

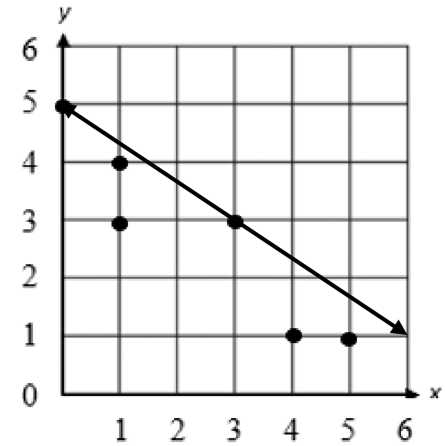


4. Circle the letter of the graph showing a trendline that **best** fits the data.

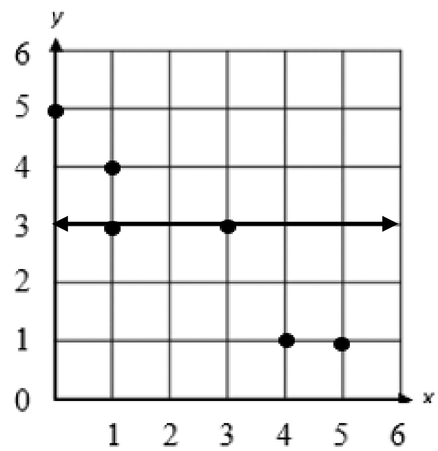
a.



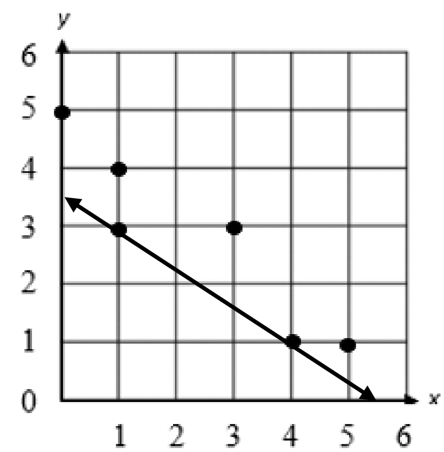
b.



c.



d.

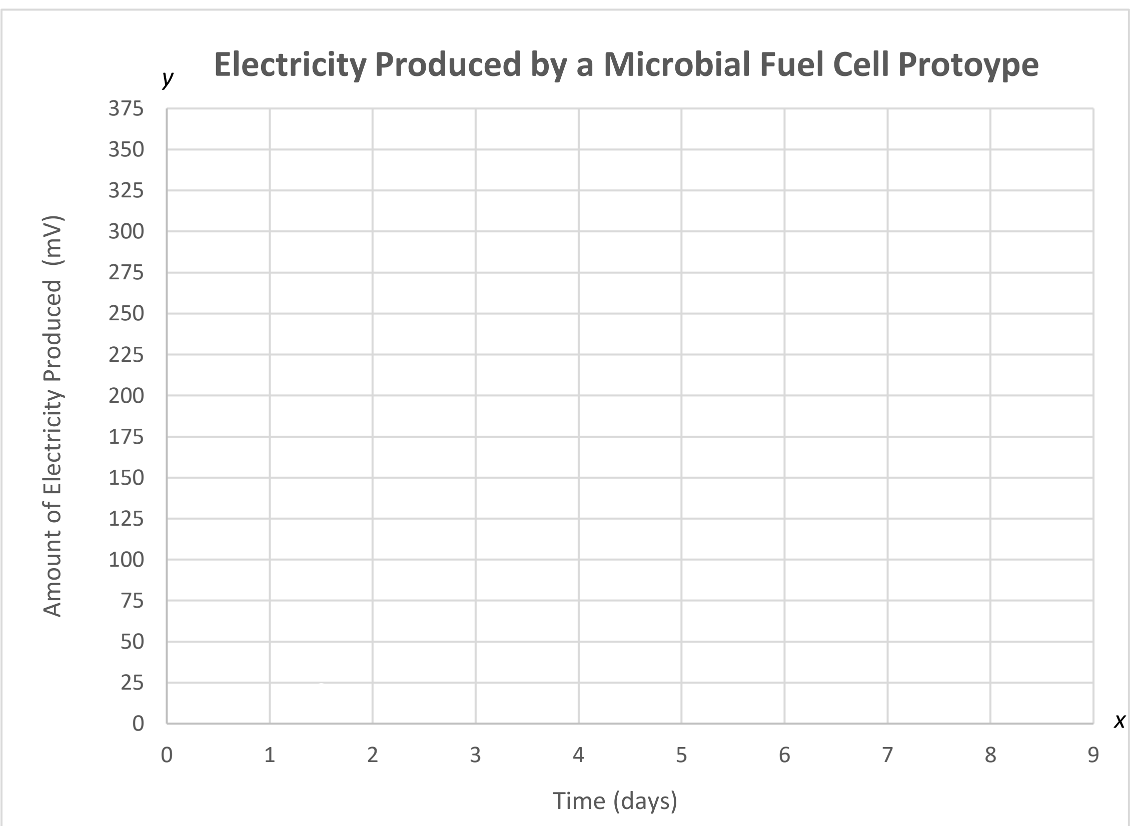


5. A BioTech company has asked you to build a prototype of a microbial fuel cell (MFC). The MFC prototype must generate enough electricity to power a small light bulb requiring 2,000 millivolts (mV) of electricity. The MFC will generate electricity slowly over time. The table below shows the amount of electricity (y) in millivolts (mV) produced each day (d) in the first week.

The table below shows the total amount of electricity (y) generated in millivolts (mV) each day (d) during the week the MFC was allowed to run.

d	***y***
0	95
1	123
2	137
5	195
6	235
7	295

Use the data in the table to graph the relationship between the number of days the MFC was allowed to run and the total amount of electricity it produced.



Use the scatter plot you created to respond to items a, b, c, and d.

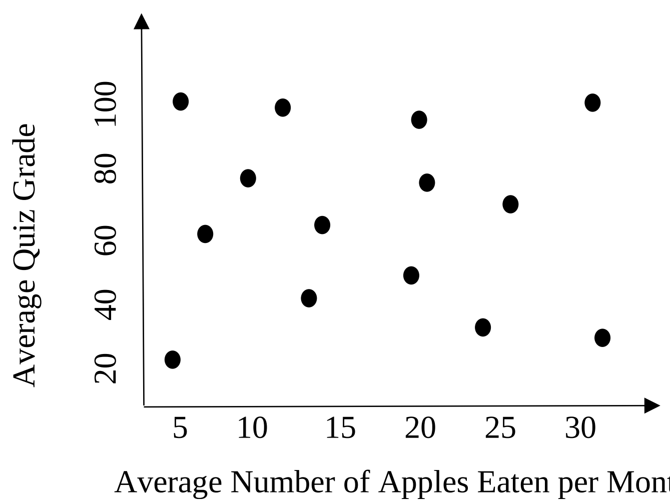
(a) Is there a positive, negative, or no association between the time (days) and electricity produced (mV)?

(b) Is there a linear or non-linear association between the time (days) and electricity produced (mV)?

(c) Draw a trendline that best fits the data in the scatter plot above.

(d) Based on the trendline you drew, if electricity continues to be generated at the same rate, how much electricity would be generated by day 8.

6.



For a science project, Charlie made the scatterplot above providing the average quiz grade and corresponding average number of apples students in her class eat per month. According to the scatterplot, what is the relationship between quiz grades and the average number of apples eaten per month?

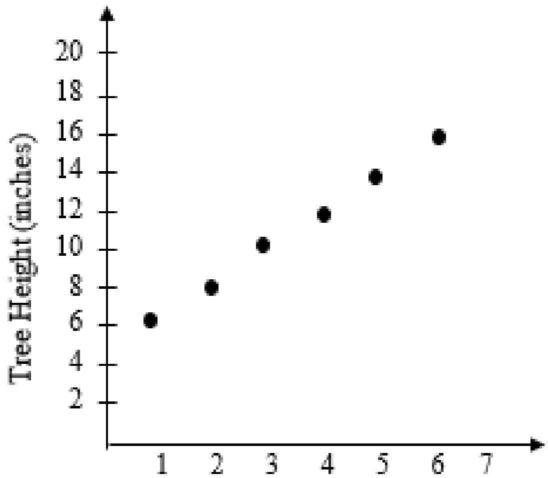
a. There appears to be no relationship.

b. Students who eat apples more often score higher on quizzes.

c. Students who eat apples less often score higher on quizzes.

d. Students who eat 20-25 apples a month score higher on quizzes than students who do not eat apples that often.

7. The graph shows the growth rate of a tree for several weeks.



If the growth rate stays the same, what will the height of the tree be by week 7? Circle your answer.

a. 14

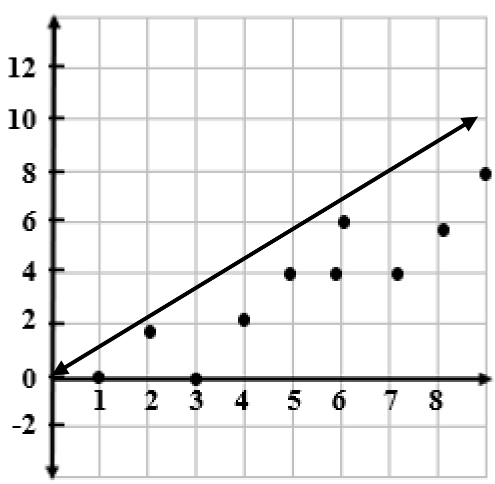
b. 16

c. 18

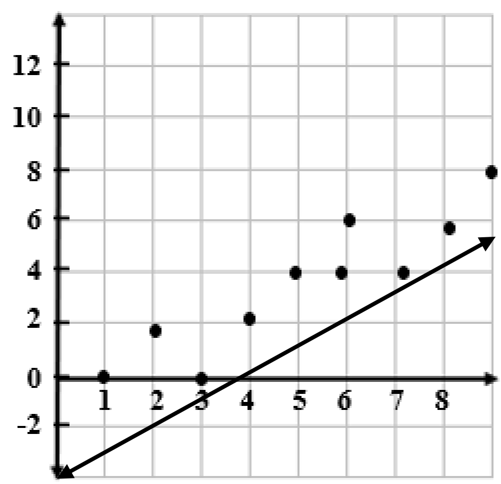
d. 20

8. Circle the letter of the graph showing a trendline that best fits the data.

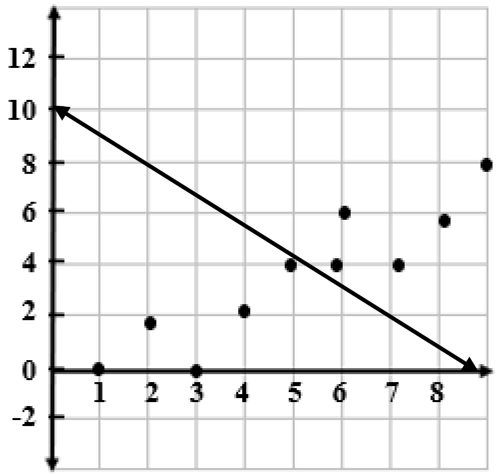
a.



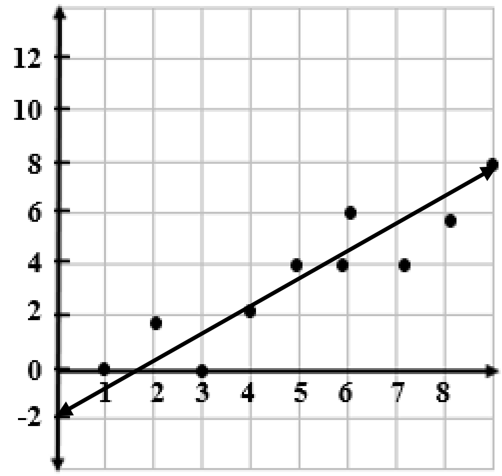
b.



c.

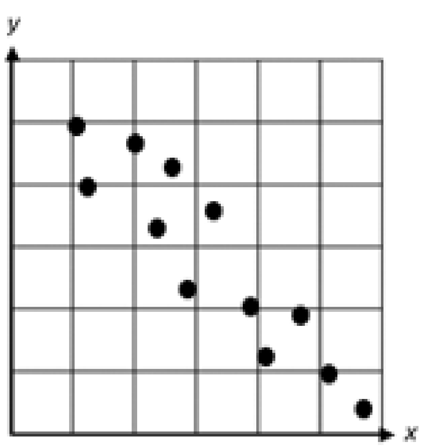


d.

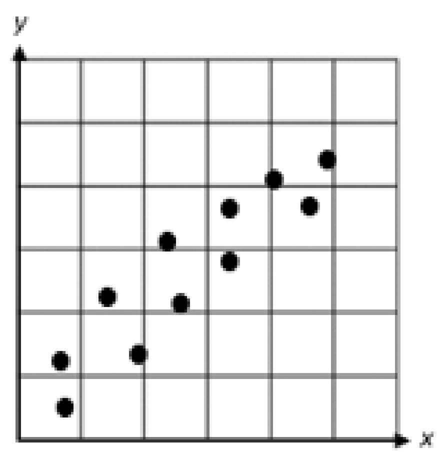


9. Circle the letter of the scatter plot showing a linear relationship with a positive correlation.

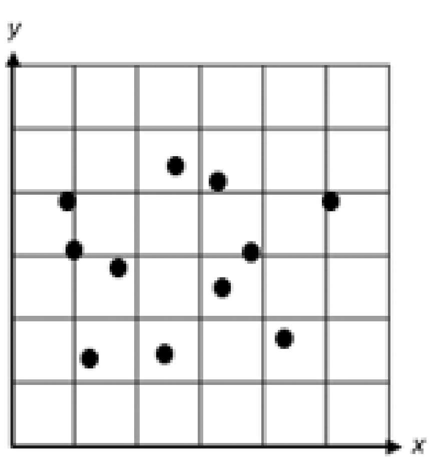
a.



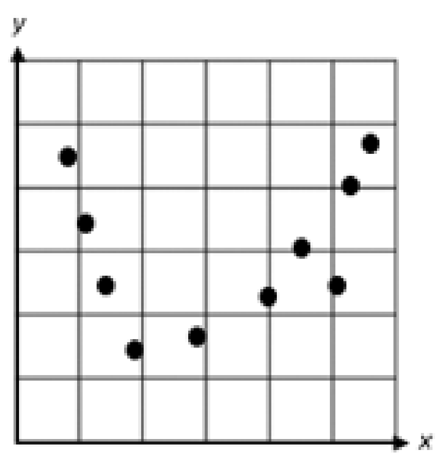
b.



c.

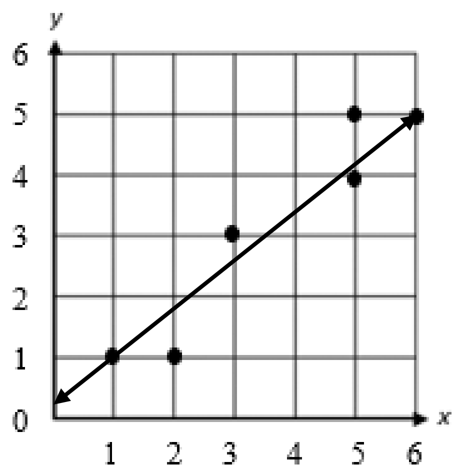


d.

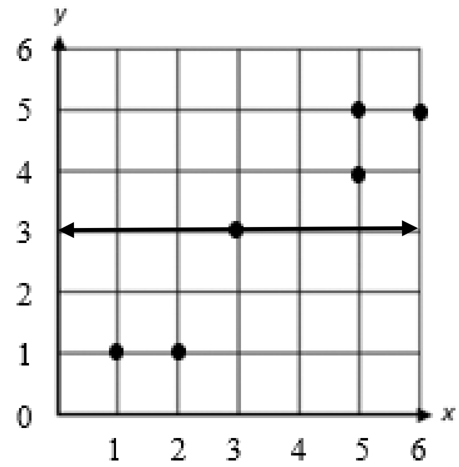


10. Circle the letter of the graph showing a trendline that **best** fits the data.

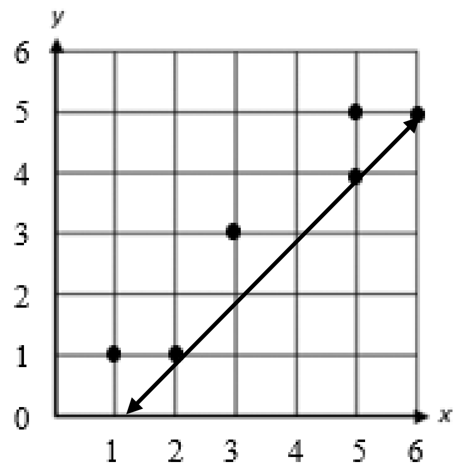
a.



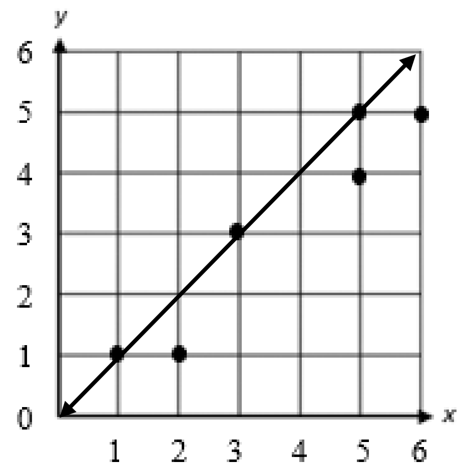
b.



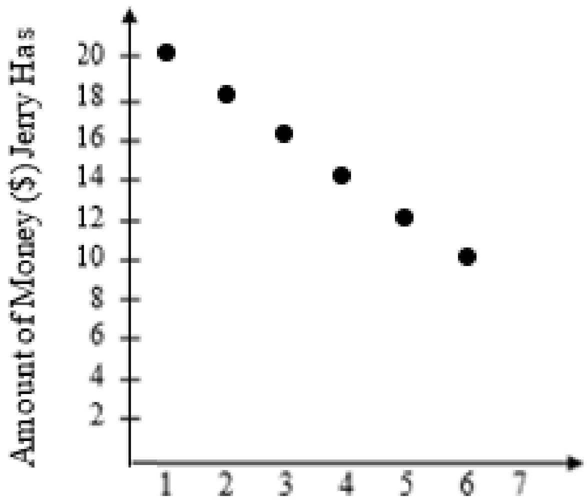
c.



d.



11. The graph below shows the amount of money Jerry spends each day at lunch.



If his spending rate stays the same, what amount of money will Jerry have left on day 7? Circle your answer.

a. 2

b. 4

c. 6

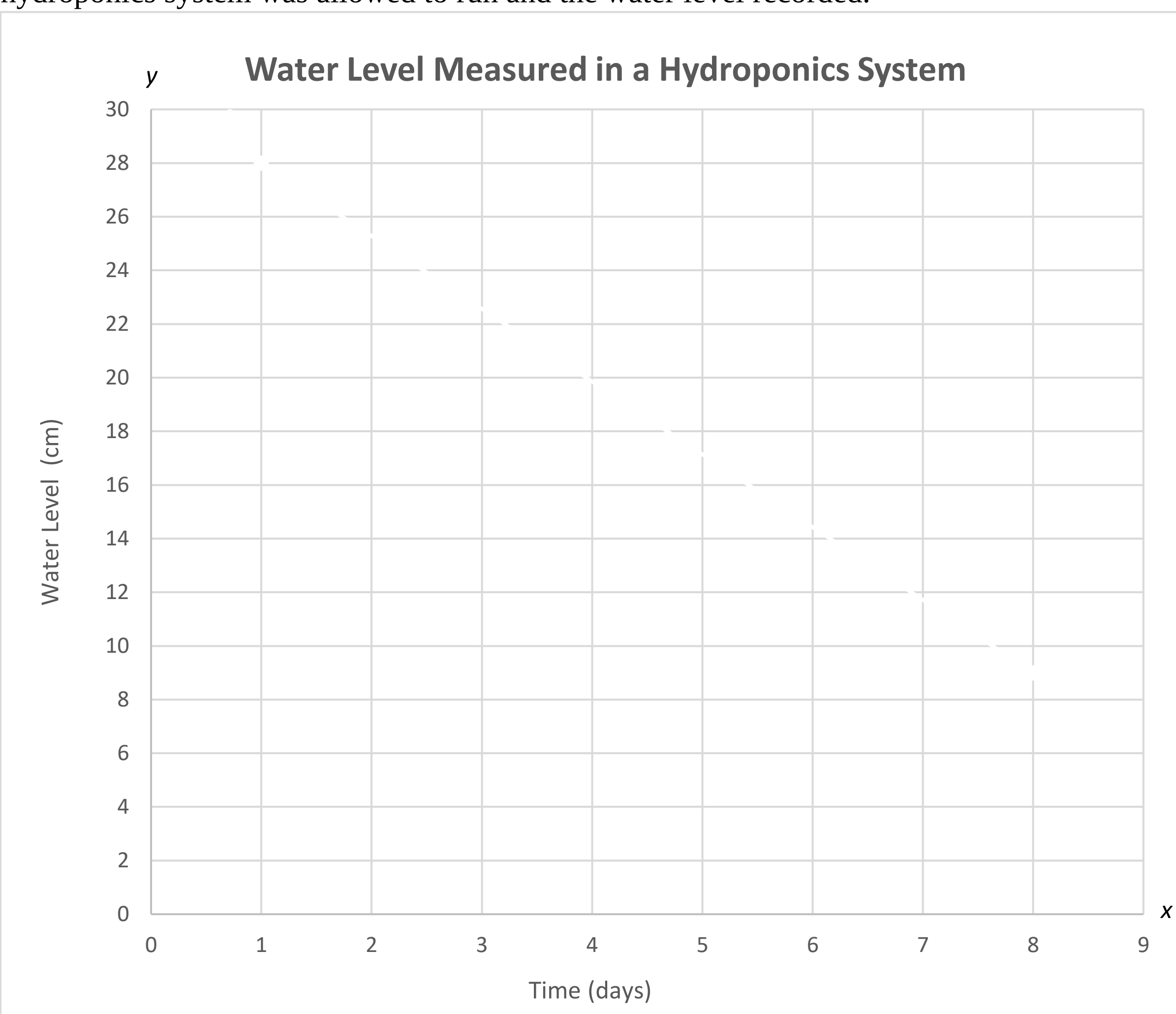
d. 8

12. A HydroPlant company has asked you to build a prototype of a hydroponics system. The prototype must be capable of keeping a plant growing at a healthy rate for at least two weeks to demonstrate its potential to grow plants for a longer period of time. To determine how much water the system requires, the water level in the 2 gallon reservoir must be measured daily.

The water level (*w*), in centimeters (cm), for the number of days (*d*) the hydroponics system was allowed to run is shown in the table.

d	***w***
0	29
1	28
5	26
6	21
7	19
8	16

Use the information in the table to graph the relationship between the number of days the hydroponics system was allowed to run and the water level recorded.



(a) Is there a positive, negative, or no association between the time (days) and water level (cm)?

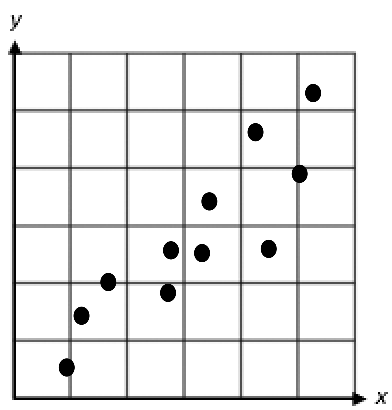
(b) Is there a linear or non-linear association between the time (days) and water level (cm)?

(c) Draw a trendline that best fits the data above.

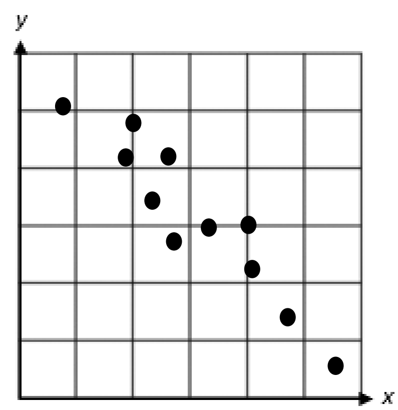
(d) Based on the trendline you drew, if electricity continues to be generated at the same rate, what will the water level be by day 9?

13. Circle the letter of the scatter plot showing a non-linear relationship between data.

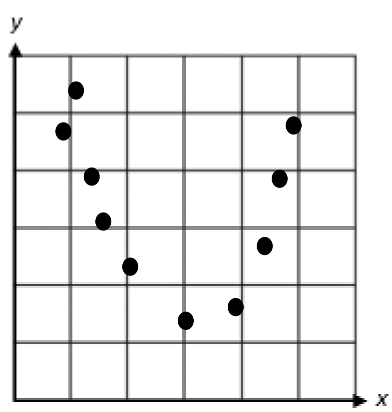
a.



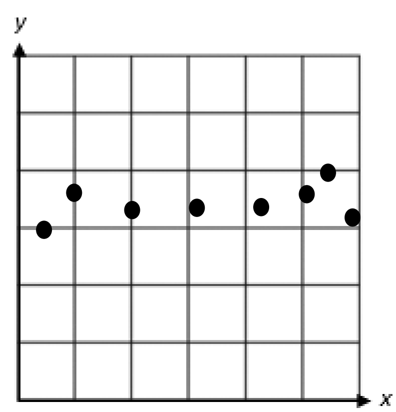
b.



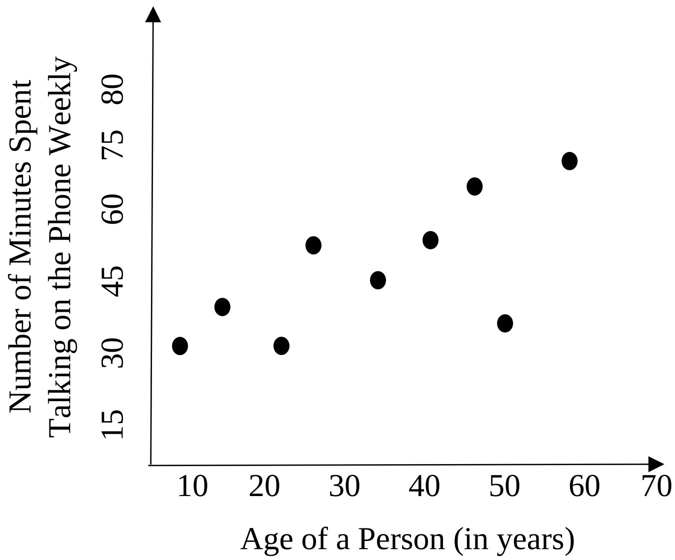
c.



d.



14.



For a science project, Hailey made a scatter plot for the age of her friends and family and how many minutes they spend talking on the phone per week. According to the scatterplot, what is the relationship between the age of a person and how many minutes they spend talking on the phone?

a. There appears to be no relationship.

b. People who are older often spend more time talking on the phone.

c. People who are older often spend less time talking on the phone.

d. People who are 13 years old talk less on the phone than people who are 53 years old.

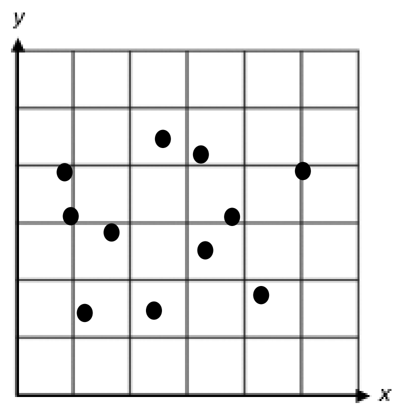
Appendix B

Bivariate Data Posttest

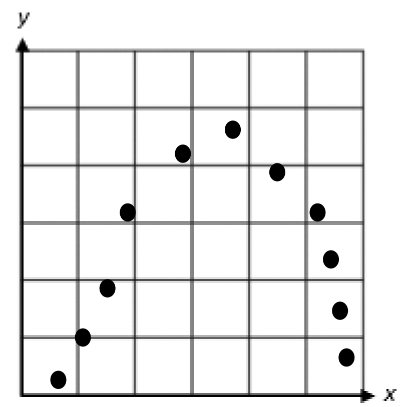
DO NOT WRITE YOUR NAME Number: ______________

1. Which scatter plot shows a linear relationship?

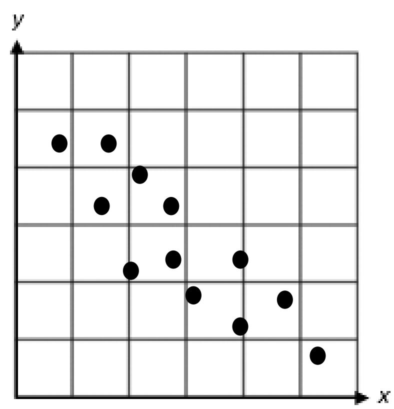
b.



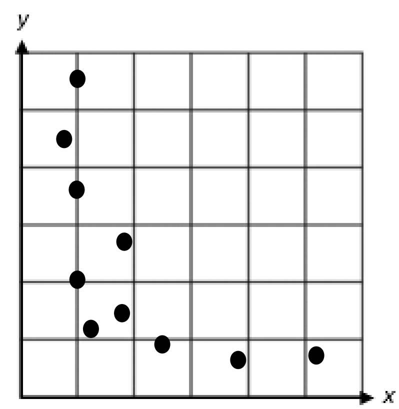
b.



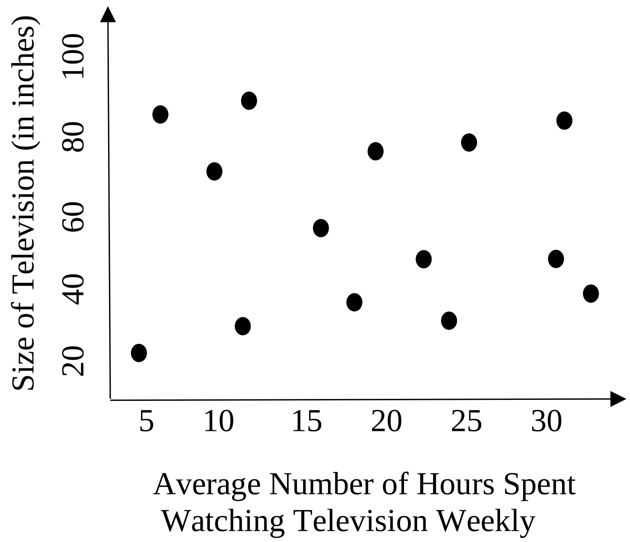
c.



d.



2.



For a science project, Andres made the scatterplot above providing the average size of the televisions owned by his classmates and the average number of hours they watch television per week. According to the scatterplot, what is the relationship between the size of the television and the average number hours of television watched per week?

a. There appears to be no relationship.

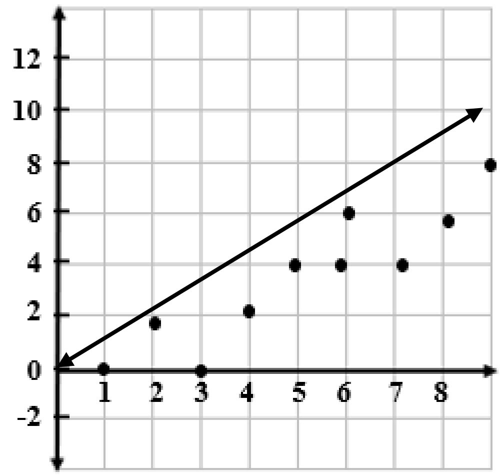
b. Students who watch more television often have larger televisions.

c. Students who watch more television often have smaller televisions.

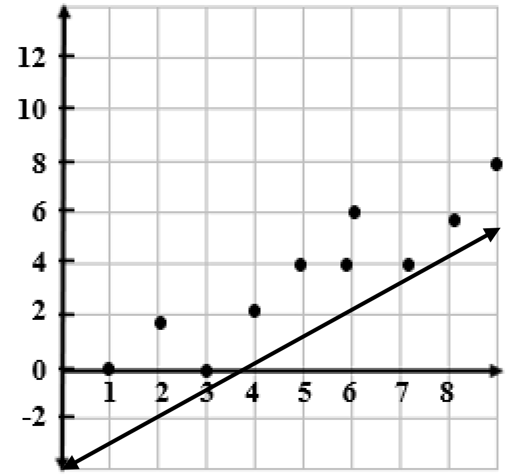
d. Students who watch television for 10 to 15 hours a week often have a larger television than those who watch television for 25 to 30 hours a week.

3. Circle the letter of the graph showing a trendline that best fits the data.

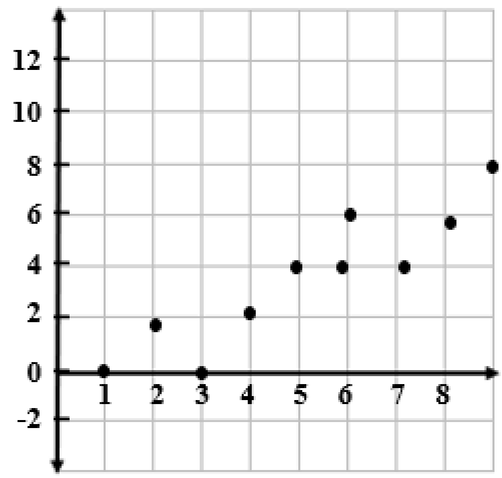
a.



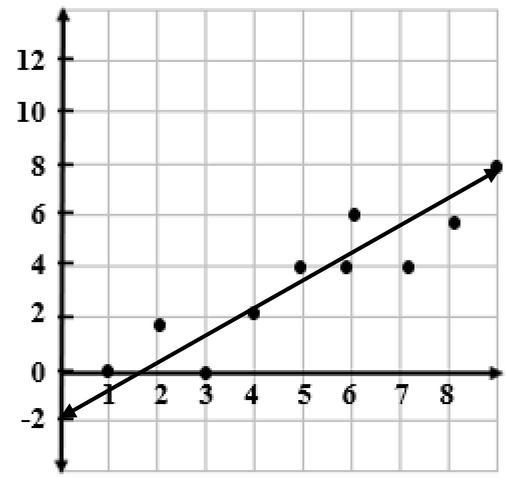
b.



c.



d.

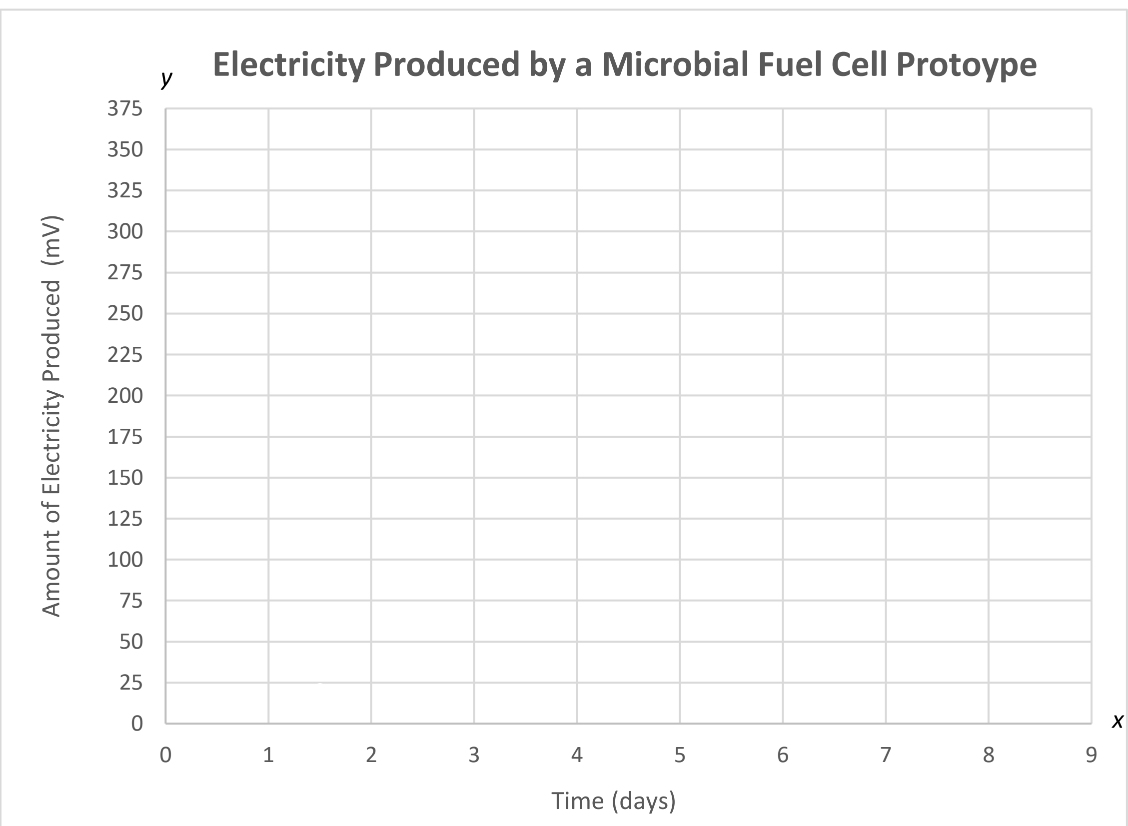


4. A BioTech company has asked you to build a prototype of a microbial fuel cell (MFC). The MFC prototype must generate enough electricity to power a small light bulb requiring 2,000 millivolts (mV) of electricity. The MFC will generate electricity slowly over time. The table below shows the amount of electricity (*y*) in millivolts (mV) produced each day *(d*) in the first week.

The table below shows the total amount of electricity (*y*) generated in millivolts (mV) each day (*d*) during the week the MFC was allowed to run.

d	***y***
0	97
1	125
2	139
5	197
6	238
7	294

Use the data in the table to graph the relationship between the number of days the MFC was allowed to run and the total amount of electricity it produced.



Use the scatter plot you created to respond to items a, b, c, and d.

(a) Is there a positive, negative, or no association between the time (days) and electricity produced (mV)?

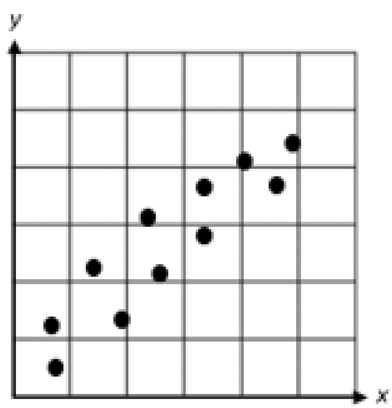
(b) Is there a linear or non-linear association between the time (days) and electricity produced (mV)?

(c) Draw a trendline that best fits the data in the scatter plot above.

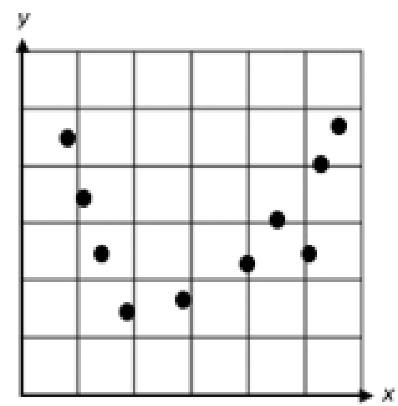
(d) Based on the trendline you drew, if electricity continues to be generated at the same rate, how much electricity would be generated by day 8.

5. Which scatter plot shows a linear relationship that has a positive correlation?

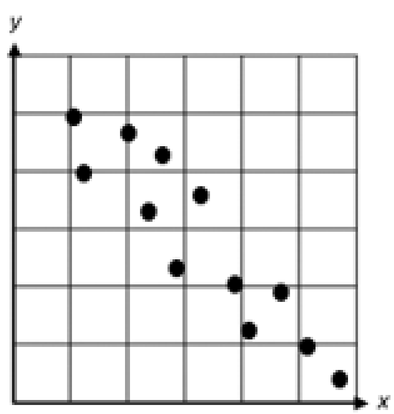
a.

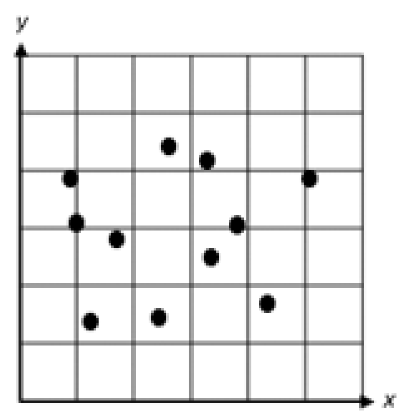


b.

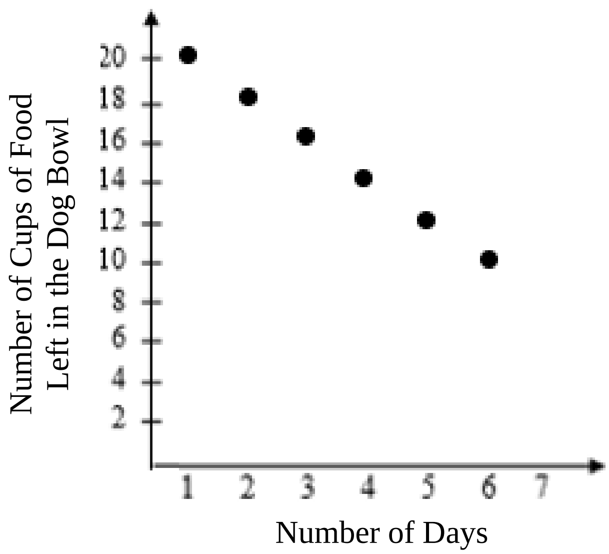


c.





6. The graph below shows the amount of food Olivia's dog eats each day.



If Olivia's dog eats food at the same rate, how many cups will be left in her dog's bowl on day 7? Circle your answer.

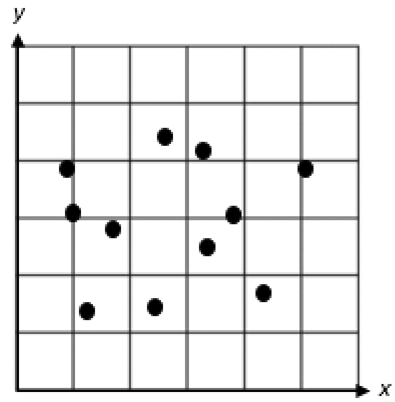
a. 10

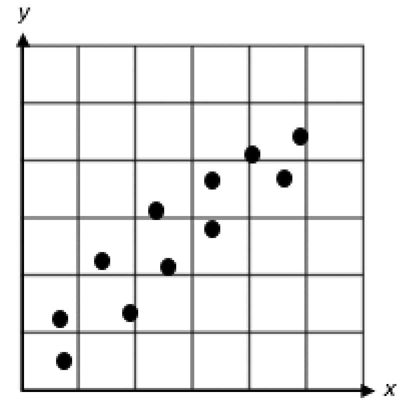
b. 8

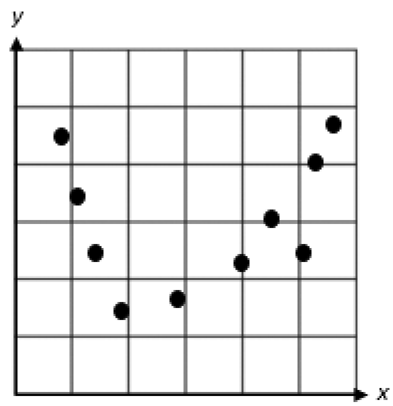
c. 6

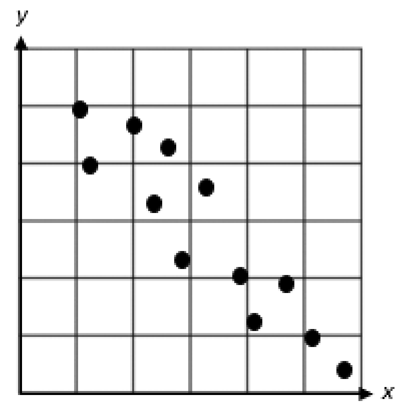
d. 4

7. Which scatter plot shows a linear relationship that has a negative correlation?

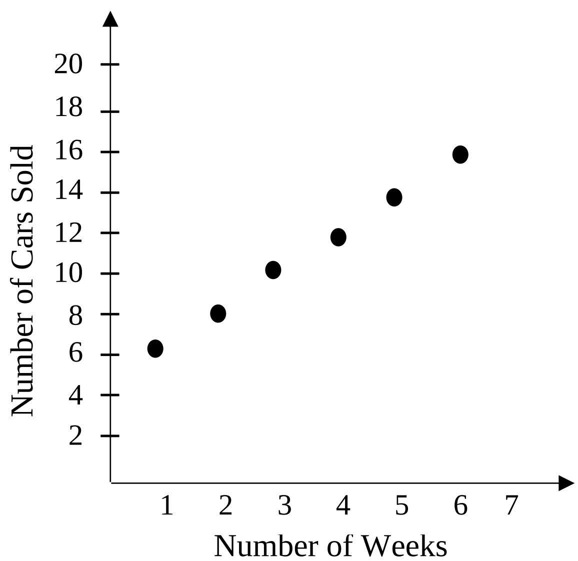
a.


b.


c.


d.


8. The graph shows the growth rate of car sales for several weeks.



If the growth rate stays the same, how many cars will be sold by week 7?

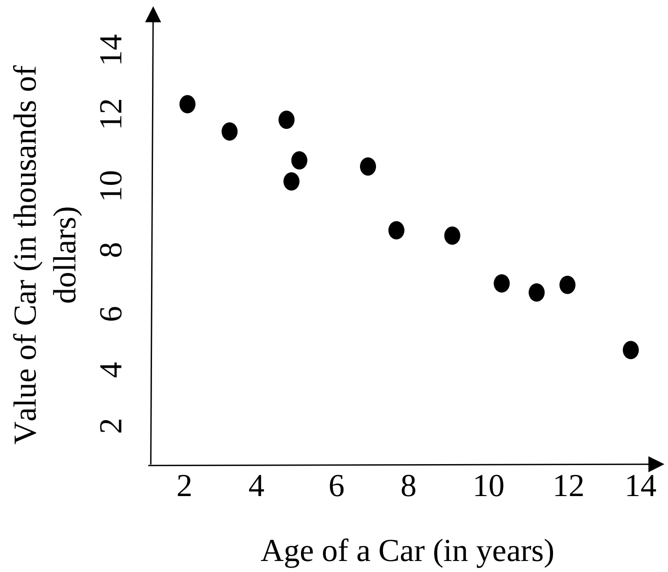
a. 20

b. 18

c. 16

d. 14

9.



Chase wants to know if there is a relationship between the price of a car and the age of that car on a used car lot. He creates a scatter plot for the age and price of corresponding cars on a local used car lot. According to the scatterplot, what is the relationship between the price and ago a car on the local car lot?

a. There appears to be no relationship.

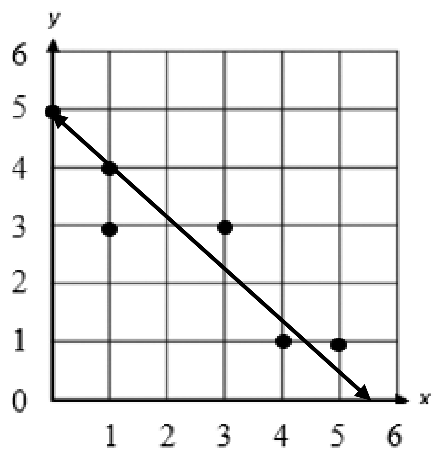
b. As a car gets older, it is often worth more.

c. As a car gets older, it is often worth less.

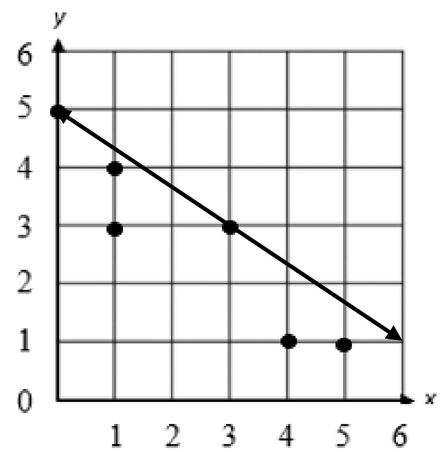
d. If a is 8 to 10 years old, it will be worth more than a car that is 6 to 8 years old.

10. Circle the letter of the graph showing a trendline that **best** fits the data.

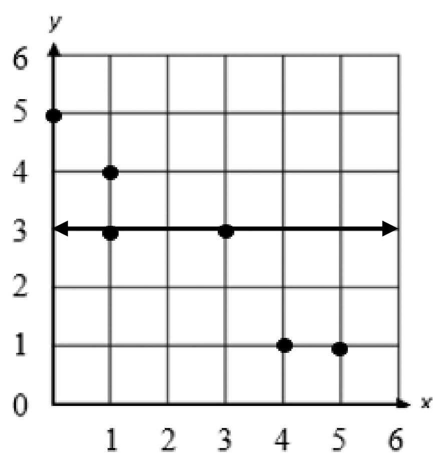
a.



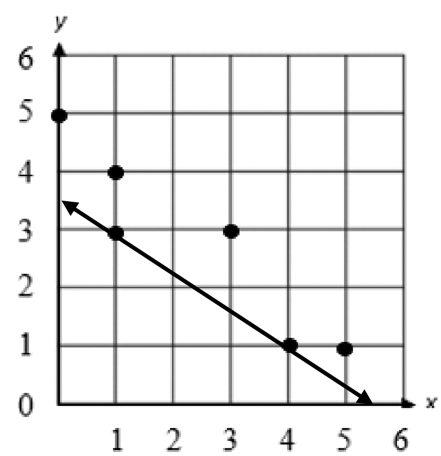
b.



c.



d.

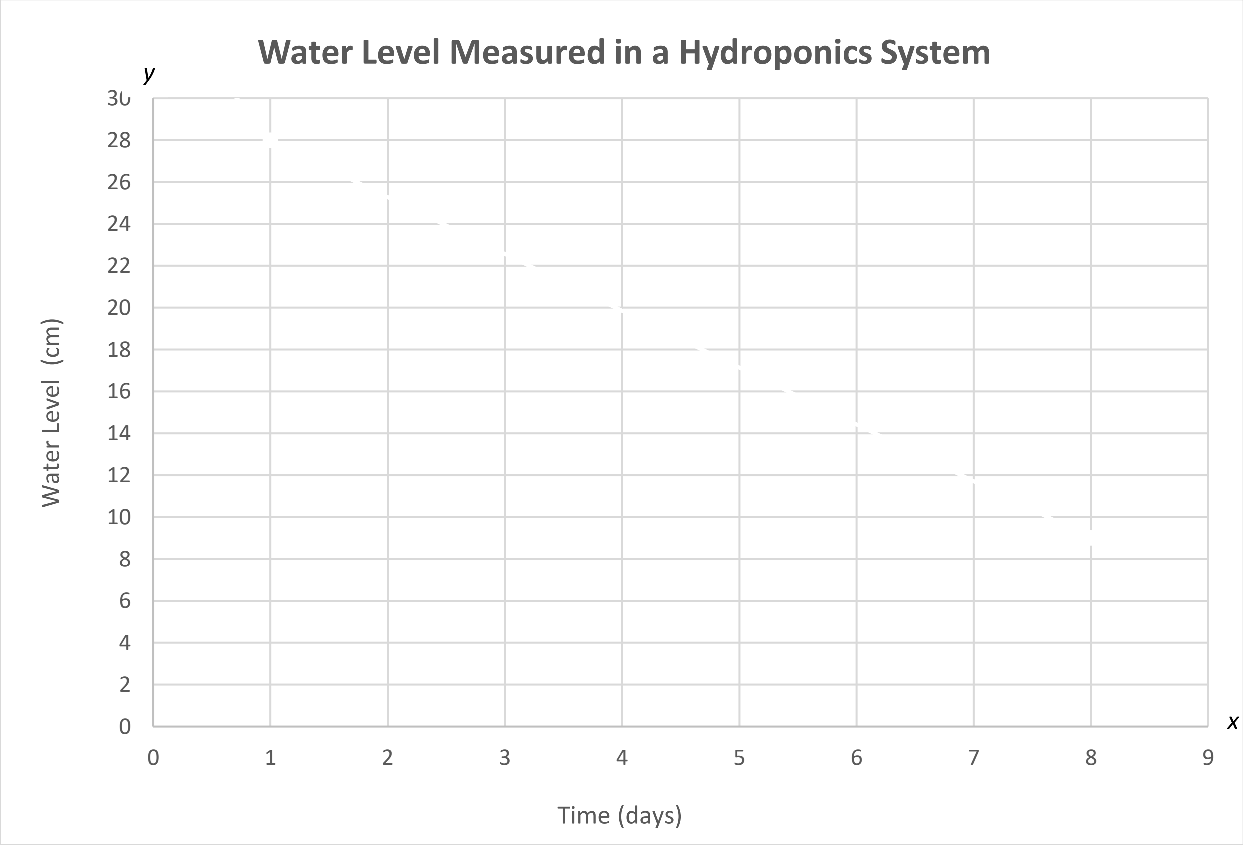


11. A HydroPlant company has asked you to build a prototype of a hydroponics system. The prototype must be capable of keeping a plant growing at a healthy rate for at least two weeks to demonstrate its potential to grow plants for a longer period of time. To determine how much water the system requires, the water level in the 2 gallon reservoir must be measured daily.

The water level (*w*), in centimeters, for the number of days (*d*) the hydroponics system was allowed to run is shown in the table.

d	*w*
0	30
1	28
5	22
6	20
7	19
8	17

Use the information in the table to graph the relationship between the number of days the hydroponics system was allowed to run and the water level recorded.



(a) Is there a positive, negative, or no association between the time (days) and water level (cm)?

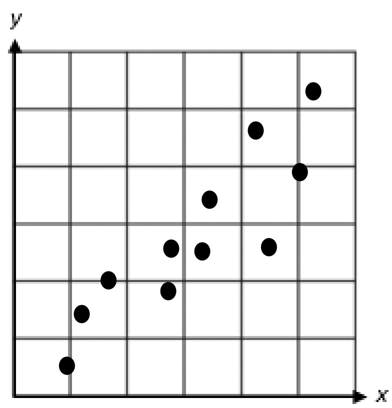
(b) Is there a linear or non-linear association between the time (days) and water level (cm)?

(c) Draw a trendline that best fits the data above.

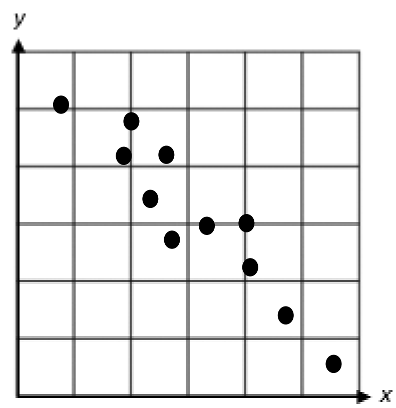
(d) Based on the trendline you drew, if electricity continues to be generated at the same rate, what will the water level be by day 9?

12. Circle the letter of the scatter plot showing a non-linear relationship between data.

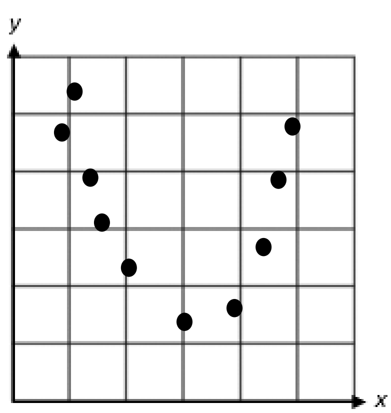
b.



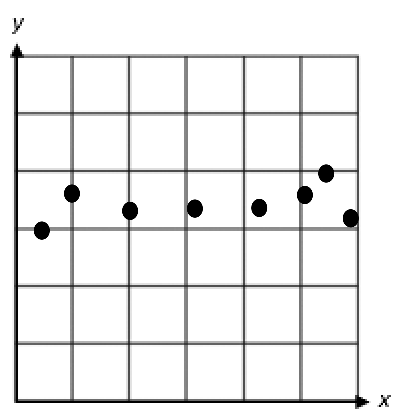
b.



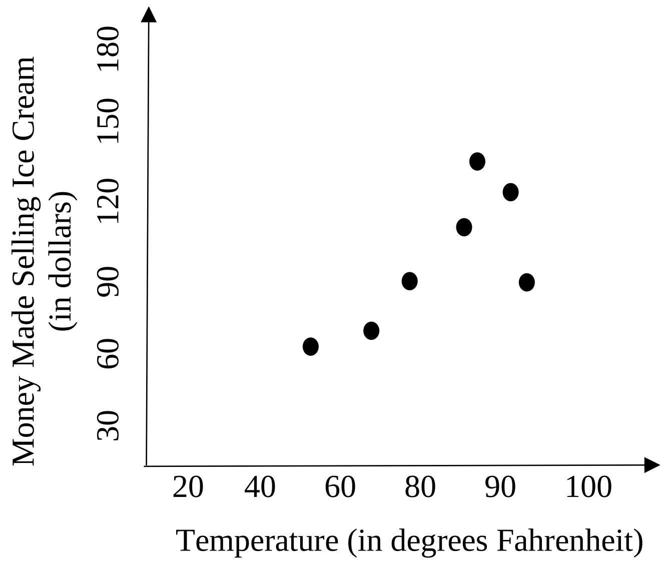
c.



d.



13.



Carlotta wants to know if there is a relationship between the temperature outside and ice cream sales at her job. She creates a scatter plot of the temperature and ice cream sales for one week. According to the scatterplot, what is the relationship between the temperature and ice cream sales?

a. There appears to be no relationship.

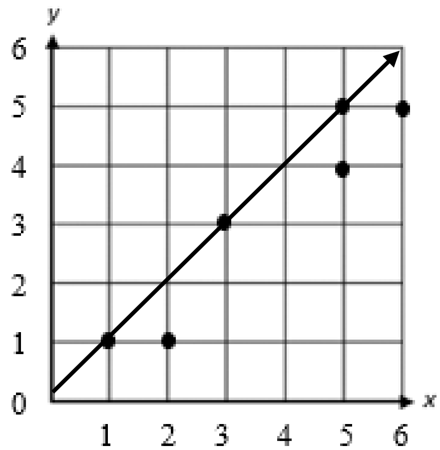
b. The higher the temperature, the more money is made from ice cream sales.

c. The higher the temperature, the less money is made from ice cream sales.

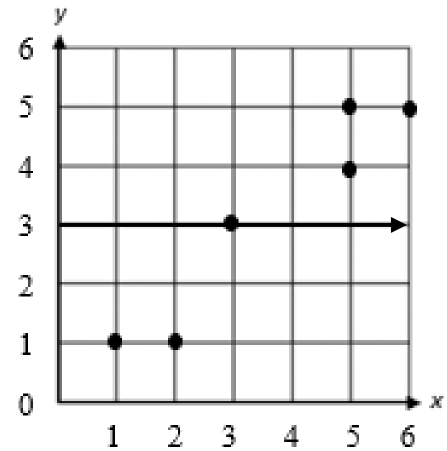
d. When the temperature is 60 degrees, people buy more ice cream.

14. Which graph shows a trendline that **best** fits the data?

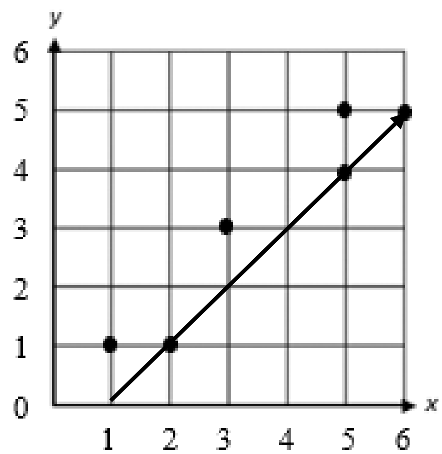
a.



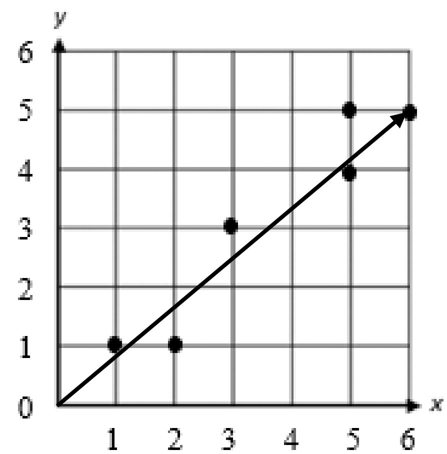
b.



c.



d.



Appendix C

Panelist Rubric for Determining Face and Content/Construct Validity

Dear Panelist,

Thank you for agreeing to analyze the face and content/construct validity of the Bivariate Data Pretest (BDPre) and Bivariate Data Posttest (BDPost) assessments. These tests are designed to measure concept knowledge of 8^{th} grade mathematics students. Each question should measure either mathematical concept knowledge of patterns of association or lines of best fit (trendlines). The table below lists the questions in order of the BDPre while providing the corresponding question number for the BDPost.

Directions:

1. Please use the table below to check a box indicating whether each equation measures concept knowledge of patterns of association OR lines of best fit (trendlines).

2. Please check a box to indicate your suggested acceptance, conditional acceptance (with modifications), or removal for each question. If additional room is needed for modification descriptions, please add comments in the specified area below the table.

Again, your participation on this panel is appreciated. Any questions can be forwarded to afeldes@k12.wv.us.

Thank you,

Amanda Feldes

Virginia Tech Doctoral Candidate

Panelist Rubric for Determining Face and Content/Construct Validity

Item #		Concept Knowledge Measured (Check One)		Decision (Check one)		
Pre	Post	Patterns of Association	Lines of Best Fit	Accept	Modify	Remove
1	7	☐	☐	☐	☐ ___	☐
2	9	☐	☐	☐	☐ ___	☐
3	1	☐	☐	☐	☐ ___	☐
4	10	☐	☐	☐	☐ ___	☐
5a	4a	☐	☐	☐	☐ ___	☐
5b	4b	☐	☐	☐	☐ ___	☐
5c	4c	☐	☐	☐	☐ ___	☐
5d	4d	☐	☐	☐	☐ ___	☐
6	2	☐	☐	☐	☐ ___	☐
7	8	☐	☐	☐	☐ ___	☐
8	3	☐	☐	☐	☐ ___	☐
9	5	☐	☐	☐	☐ ___	☐
10	14	☐	☐	☐	☐ ___	☐
11	6	☐	☐	☐	☐ ___	☐
12a	11a	☐	☐	☐	☐ ___	☐
12b	11b	☐	☐	☐	☐ ___	☐
12c	11c	☐	☐	☐	☐ ___	☐
12d	11d	☐	☐	☐	☐ ___	☐
13	12	☐	☐	☐	☐ ___	☐
14	13	☐	☐	☐	☐ ___	☐

Modification descriptions/comments continued:

Appendix D

Individual Semi-Structured Interview Questions

1. Tell me about the purpose of the design challenge.
    a. Why did you choose your particular design?
    b. Describe the parts of the MFC and how they worked.
2. What criteria did your design have to meet?
    a. Do you think your MFC met the criteria? Why or why not?
    b. How did you know if your MFC was performing well or not?
    c. What variables did you have to measure to know how well your MFC was performing?
    d. How did collecting data from your variables tell you if the MFC was performing well or not?
3. What did you do with your data when you collected it?
    a. What did the data tell you?
    b. What patterns did you see in your data?
    c. How did you organize your data to help you see those patterns?
    d. Describe to me how you constructed your scatter plot.
    e. What patterns emerged in the data when you put it on a scatter plot?
    f. What direction was the data going in your scatter plot?
    g. What was the difference between what patterns you saw you're the table and what patterns you saw on the scatter plot?
    h. How did the patterns you saw in your data affect your design decisions throughout the design challenge?

i. What design decisions did you have to make? Why did you make them?

4. How did you predict how much electricity your MFC would produce on day 10?

a. What was the most helpful thing you did to see how well your MFC was working?
b. Do you think your MFC prototype could eventually light a small light? How do you know?
c. How could you use your data to figure out if it would light a small light?
d. How could you use your scatter plot to figure out if it would light a small light?
e. Describe to me how you constructed your trendline for your data.
f. How could you use your trendline to figure out if your MFC prototype could light a small light in the future?
g. When do you think it would take for your prototype to light a small light?
h. How can you use your trendline to figure out how long it would take to light a small light?

5. Now that you have built your first MFC, if you did this design challenge again what data would you collect to see if it was successful?

a. How did your data help you to make design decisions during this design challenge?
b. How could your data help you to make future design decisions?
c. What patterns would you look for to make design decisions?
d. Based on your data, what would you do differently to your design next time to increase the amount of electricity it produces?
e. What did you do that was the most helpful for you to complete the design challenge?

6. Is there anything else you would like to tell me about your experiences during the design challenge?

Appendix E

IRB Approval Letter

VIRGINIA TECH

Division of Scholarly Integrity and Research Compliance
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732

MEMORANDUM

DATE: April 5, 2023

TO: John Wells, Amanda Marie Feldes

FROM: Virginia Tech Institutional Review Board (FWA00000572)

PROTOCOL TITLE: Analyzing the Use of Technological/Engineering Design-Based Biotechnical Learning Pedagogical Approaches to Promote Change in Concept Knowledge of Eighth Grade Mathematics Students

IRB NUMBER: **23-236**

Effective April 5, 2023, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104(d) category (ies)1.

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Determined As: **Exempt, under 45 CFR 46.104(d) category(ies) 1**
Protocol Determination Date: **April 5, 2023**

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

SPECIAL INSTRUCTIONS:

***Please note: The HRPP office has stopped stamping documents for Exempt protocols. It is your responsibility to maintain these documents and make current versions available on request.

***Please obtain required permission from [redacted] Public Schools prior to conducting any human subjects research activities.

Date*	OSP Number	Sponsor	Grant Comparison Conducted?

* Date this proposal number was compared, assessed as not requiring comparison, or comparison information was revised.

If this protocol is to cover any other grant proposals, please contact the HRPP office (irb@vt.edu) immediately.

Appendix F

District Support Letter

District Support Template – Letter from Superintendent

March ___, 2023

Dear Virginia Tech Institutional Review Board:

On behalf of [redacted] Public Schools, I would like to express our support for the research proposal, Analyzing the Use of Technological/Engineering Design-Based Biotechnical Learning Pedagogical Approaches to Promote Change in Concept Knowledge of Eighth Grade Mathematics Students. The proposed research study is designed to examine the role that technological and engineering design-based learning challenges could serve in supporting the instruction of eighth grade mathematics concept knowledge, specifically of patterns of association and lines of best fit. In turn, results of the study will have the potential to broaden our understanding of both pedagogical strategies teaching eighth grade mathematics concept knowledge and the role technology and engineering can play in the eighth-grade mathematics classroom. We view this as a worthy activity in which to participate.

It is our understanding that:

- student participation in this research study will take place over a 4-week period.
- student participants will be asked to complete various mathematics concept assessments
- student participants will engage in a technological and engineering design-based learning challenge
- six student participants will be audio recorded during interviews for the purpose of gathering information about their mathematics concept knowledge and experiences during the design-based learning challenge, this recording will not be heard by anyone outside of the research team

To support this proposed research, and to ensure the successful implementation of this research study, we have agreed to assist Amanda Feldes (graduate researcher) and her research team by:

- Allowing the subject pool to be drawn from the approximately 45 eighth grade students at [redacted] High School.
- Allowing potential subjects to receive recruitment packets containing informed consent documents (parent consent and student assent forms) providing information (rationale, purpose, procedures, and requirements) about the research study, which will be distributed by, and returned to, the graduate researcher through the students' regularly scheduled science or math class.

Furthermore, it is understood that the decision to provide permission to recruit for this opportunity does not in any way obligate students to participate. Moreover, students are free to discontinue participation at any time. It is with this understanding that I support, and look forward to working with, Ms. Feldes and her team on this research project.

Sincerely,

X__________________________

[redacted], District Superintendent

Appendix G

Parental Permission Form

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Permission to Take Part in a Research Study

Title of research study: Analyzing the Use of Technological/Engineering Design-Based Biotechnical Learning Pedagogical Approaches to Promote Change in Concept Knowledge of Eighth Grade Mathematics Students

Principal Investigator: Dr. J. G. Wells, [redacted], jgwells@vt.edu

Other study contact(s): Amanda Feldes, [redacted], afeldes@k12.wv.us

Key Information: The following is a short summary of this study to help you decide whether or not to provide permission for your child to be a part of this study. More detailed information is listed later in this form.

My name is Amanda Feldes. I am the eighth-grade mathematics teacher here at Montcalm High School. I am also a doctoral student at Virginia Tech and beginning my research study on 8th grade mathematics concept knowledge. I will be working under the advisement of Dr. John G. Wells, Virginia Tech.

We are inviting your child to participate in this research because they are enrolled as an 8th grade student at Montcalm High School. The study will last four weeks and will involve working on tasks during your child's normally scheduled math and science classes. Those students selected for this research will be given math tests before and after the study to assess their math concept knowledge. The participants will complete one engineering design challenge with a small group of students. Students will be asked to keep a journal throughout their experiences with the design challenge. At the end of the study, six students will be selected to be interviewed about their experiences with the design challenge. These interviews will be audio recorded and only listened to by the research team.

Why is my child being invited to take part in a research study?

We invite your child to take part in a research study because they are enrolled in an 8th grade mathematics course at Montcalm High School.

What should I know about my child being in a research study?

- Someone will explain this research study to you and your child
- Whether or not you provide permission is up to you
- You can choose not to provide permission
- You can provide permission and later change your mind
- Your decision will not be held against you
- You can ask all the questions you want before you decide

Why is this research being done?

The purpose of this research is to analyze teaching strategies that could potentially increase math concept knowledge for 8th grade students.

How long will the research last and what will my child need to do?

We expect that your child's participation in this research study will last four weeks and take place during their normally scheduled math and science class times.

Your child will be asked to take a math test before and after completing an engineering design challenge. They will be asked to write in a journal throughout the challenge. They could be interviewed about their experiences at the conclusion of the challenge.

More detailed information about the study procedures can be found under ***"What happens if I say yes, I want my child to be in this research?"***

Is there any way being in this study could be bad for my child?

Risks are no more than would be expected in everyday life.

More detailed information about the risks of this study can be found under ***"Is there any way being in this study could be bad for my child? (Detailed Risks)"***

Will being in this study help my child in any way?

We cannot promise any benefits to your child or others from their taking part in this research. However, we may learn something that will help other children with may concept knowledge in the future.

What happens if I do not want my child to be in this research?

Taking part in research is completely up to you and your child. You can decide to provide permission or not provide permission to participate. Your child's grades will not be affected by participating or not participating in this study.

Detailed Information: The following is more detailed information about this study in addition to the information listed above.

Who can I talk to?

If you have questions, concerns, or complaints, or think the research has hurt your child, talk to the research team at

Dr. J.G. Wells, 540-231-8471, jgwells@vt.edu

Amanda Feldes, 304-589-3719, afeldes@k12.wv.us

This research has been reviewed and approved by the Virginia Tech Institutional Review Board (IRB). You may communicate with them at 540-231-3732 or irb@vt.edu if:

- You have questions about your child's rights as a research subject
- Your questions, concerns, or complaints are not being answered by the research team
- You cannot reach the research team
- You want to talk to someone besides the research team to provide feedback about this research

How many people will be studied?

We plan to include about 45 people in this research study.

We plan to include about 45 people at this location out of 45 people in the entire study nationally.

What happens if I say yes, I want my child to be in this research?

If you agree to allow your child to participate in this study, they will be asked to complete mathematics assessments. They will participate in an engineering design challenge in a small group. They will also be asked to complete a journal throughout the design challenge. They could possibly be interviewed about their experiences during the design challenge. Participation in these activities will follow a schedule as follows:

- Week 1
    - Complete a 60-minute math pretest.
    - Complete daily tasks for the engineering design challenge during science and math classes.
- Week 2
    - Complete daily tasks for the engineering design challenge during science and math classes.
- Week 3
    - Complete daily tasks for the engineering design challenge during science and math classes.
- Week 4
    - Complete a 60-minute math posttest.
    - Six students will complete a 20-minute interview.

Assessments will be given by Amanda Feldes. They will take place during the normally scheduled school day. Participants will complete the design challenge in a small group.

What happens if I say yes, but I change my mind later?

You can withdraw your permission for your child's participation in this research at any time, for any reason, and it will not be held against you.

If you decide you no longer want your child to participate in the research, contact the investigator so that any data collected up to the point of withdrawal will be deleted.

Is there any way being in this study could be bad for my child? (Detailed Risks)

There are no known risks to participating in this study.

What happens to the information collected for the research?

We will make every effort to limit the use and disclosure of your child's personal information, including research study and medical records, only to people who have a need to review this information. We cannot promise complete confidentiality. Organizations that may inspect and copy your child's information include the IRB, Human Research Protection Program, and other authorized representatives of Virginia Tech.

Your child's information or samples that are collected as part of this research will not be used or distributed for future research studies, even if all of your identifiers are removed.

The results of this research study may be presented in summary form at conferences, in presentations, reports to the sponsor, academic papers, and as part of a thesis/dissertation.

The research team will not share any information that identifies the participants, school, or school district participating in this research study. All non-identifying collected data will be maintained confidentially. It will also be protected from unauthorized disclosure.

Can my child be removed from the research without my OK?

The person in charge of the research study or the sponsor can remove your child from the research study without your approval. Possible reasons for removal include excessive absences during the engineering design challenge.

What else do I need to know?

Your child's information and samples (both identifiable and de-identified) might be used to create products or to deliver services, including some that may be sold and/or make money for others. If this happens, there are no plans to tell you, or to pay you, or to give any compensation to you or your family.

We will offer to share your child's individual test results with you or your child. You may accept or decline these results.

Signature Block for Capable Adult

Your signature documents your permission for your child to take part in this research. We will provide you with a signed copy of this form for your records.

Signature of parent/legal guardian/legally authorized representative	Date
Printed name of parent/legal guardian/legally authorized representative	
Signature of person obtaining permission	Date
Printed name of person obtaining permission	

Appendix H

Student Assent Form

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

Assent to Take Part in a Research Study

Title of research study: Analyzing the Use of Technological/Engineering Design-Based Biotechnical Learning Pedagogical Approaches to Promote Change in Concept Knowledge of Eighth Grade Mathematics Students

Principal Investigator: Dr. J. G. Wells, [redacted], jgwells@vt.edu
Other study contact(s): Amanda Feldes, [redacted], afeldes@k12.wv.us

What Is A Research Study?

We want to tell you about a research study we are doing. A research study is a way to learn new information about a topic.

Why Are We Doing This Research?

For this research study, we would like to learn more about how to help mathematics concept knowledge for eighth grade math students.

Why Am I Being Asked to Join This Research?

You are being asked to take part in this research study because you are learning math concepts in 8th grade math class.

What Would Happen If I Join This Research?

If you agree to be in the study, you will be asked to do some tasks. You will complete an engineering design challenge with a small group. You will create designs that solve problems. You will be completing these tasks as a part of your regular science and math class. By agreeing to be in the study, you will allow us to collect your test scores and journal kept during the study as data sources. You may also be interviewed at the end of the study. During the interview you will only be asked questions about your experiences during the engineering design challenge. Your test, journal, and interview will be assigned a number that will be used instead of your name. The study will last 4 weeks.

Could Bad Things Happen If I Join This Research?

Possible risks involved with this research study include: no more than those found in everyday life.

Could The Research Help Me?

We do not know if you will be helped by being in this study. We may learn something that will help other children with mathematics concept knowledge in the future.

What If I Have Questions About The Research?

You can ask Amanda Feldes or Dr. Wells questions at any time about anything in this study. You can also ask your parent or guardian any questions you might have about this study.

If you have questions, are angry or are upset about something that happened while in the study, and/or are unable to reach the researchers, please tell your parent or guardian to contact the Virginia Tech Institutional Review Board ("IRB") at 540-231-3732 or irb@vt.edu.

What If I Don't Want to Join This Research?

You do not have to join this research study. It is up to you. You can change your mind or stop at any time. No one will be upset if you do not sign this paper or if you change your mind later. If you decide not to join, your grades will not be changed in any way.

What Else Should I Know About This Research?

Only six students will be chosen to participate in the interviews. If you are chosen, the interviews will be audio recorded only. These recordings are only for the researcher's use. They will help her understand what choices the participants make during the design challenges. No one outside of the research team will hear the recording of the interview.

If you would like to be in this study, please print and sign your name in the spaces below. We will give you a copy of this form to keep for yourself.

Signature Block for Children

____
Participant's Printed Name

____ ____________________
Participant's Signature Date

____ ____________________
Printed name of person obtaining assent

Signature of person obtaining assent | Date

Appendix I

Bivariate Data Pre/Posttest Administration Script

Script: Directions for PRE-Assessment and POST-Assessment (Bivariate Data Pre/Posttest)

Read aloud to students:

Today, you will be taking a math test. Please make sure you do not write your name on this test and that you have the correct identification number at the top. You will have one, 60-minute class period to complete this test. Answer all questions to the best of your ability. Please do not leave any questions blank. When you are finished, please turn your test over and I will collect your test. You may begin.

Appendix J

Prepared Individual, Semi-Structured Interview Protocol and Script

1. Individual student parental permission and student assent forms collected
2. Student enters the room
3. Password protected device accessed
4. Audio-recording turned on
5. **Script read aloud to student:**

   Today, I am conducting research about your experiences with technology/ engineering design-based learning and mathematics concept knowledge. I am interested in your experience as an eighth-grade math student. The purpose of this research is to learn about how your experiences affect your math knowledge. This research has no known risks. This research will benefit the academic community because it helps us to understand learning in mathematics. Please know I will do everything I can to protect your privacy. Only your voice will be recorded today. Please do not say your name or the names of others during this recording. Your identity and personal information will not be disclosed in any publication that may result from the study. All interview audio-recordings and transcripts will be stored in a secure location. Choosing to participate in the study or not to participate will not affect your grade in any way. I am going to ask you a few questions about your experiences with your design challenge. This interview will last about 20 minutes. Please answer all questions to the best of your ability.

6. **Interview questions read aloud to student:**

   Tell me about the purpose of the design challenge.

   - *Why did you choose your particular design?*

- *Describe the parts of the MFC and how they worked.*

What criteria did your design have to meet?

- *Do you think your MFC met the criteria? Why or why not?*
- *How did you know if your MFC was performing well or not?*
- *What variables did you have to measure to know how well your MFC was performing?*
- *How did collecting data from your variables tell you if the MFC was performing well or not?*

What did you do with your data when you collected it?

- *What did the data tell you?*
- *What patterns did you see in your data?*
- *How did you organize your data to help you see those patterns?*
- *Describe to me how you constructed your scatter plot.*
- *What patterns emerged in the data when you put it on a scatter plot?*
- *What direction was the data going in your scatter plot?*
- *What was the difference between what patterns you saw you're the table and what patterns you saw on the scatter plot?*
- *How did the patterns you saw in your data affect your design decisions throughout the design challenge?*
- *What design decisions did you have to make? Why did you make them?*

How did you predict how much electricity your MFC would produce on day 10?

- *What was the most helpful thing you did to see how well your MFC was working?*

- *Do you think your MFC prototype could eventually light a small light? How do you know?*
- *How could you use your data to figure out if it would light a small light?*
- *How could you use your scatter plot to figure out if it would light a small light?*
- *Describe to me how you constructed your trendline for your data.*
- *How could you use your trendline to figure out if your MFC prototype could light a small light in the future?*
- *When do you think it would take for your prototype to light a small light?*
- *How can you use your trendline to figure out how long it would take to light a small light?*

Now that you have built your first MFC, if you did this design challenge again what data would you collect to see if it was successful?

- *How did your data help you to make design decisions during this design challenge?*
- *How could your data help you to make future design decisions?*
- *What patterns would you look for to make design decisions?*
- *Based on your data, what would you do differently to your design next time to increase the amount of electricity it produces?*
- *What did you do that was the most helpful for you to complete the design challenge?*

Is there anything else you would like to tell me about your experiences during the design challenge?

7. Audio-recording turned off

8. Student dismissed
9. Interview saved on a password-protected device to a password-protected web repository
10. Interview transcribed

Appendix K

Microbial Fuel Cell Design Challenge

Microbial Applications

ProbScen 4C

Student ProbScen

BIOPROCESSING

Microbial Fuel Cell

Context:

In our technological world portable power plays a significant role in nearly every aspect of our daily activities. Batteries are a common portable energy source and an important part of everyday life. They make our lives more convenient by providing a portable electric source that is small and relatively long-lasting. Portable electricity is ubiquitous in our high-tech societies, especially given today's extensive use of hand-held devices that require a mobile source of electric energy. Batteries are necessary for powering countless personal technologies such as toys, radios, cell phones, household appliances, computers, and even crucial medical devices that people depend upon to live a normal life. Found in homes everywhere batteries store chemical energy ready to delivery electricity when and where needed.

One of the negative features of dry cell batteries is that they contain chemicals that are hazardous and to varying degrees toxic to living things. And because of this, disposing of them in a safe manner presents challenges. They are not safe to burn since they explode when exposed to extreme heat, and throwing them in the garbage is not a good option either because as they age their casings deteriorate and leak. Putting batteries in a landfill is environmentally irresponsible. Biotechnology however offers some solutions in developing new batteries that provide portable electricity and are environmentally friendly.

Researchers have discovered that common microbes such as yeast and bacteria actually generate electricity when they metabolize (digest) organic waste. Biotechnologists use this knowledge in harnessing energy from *microbial fuel cells* (MFC) that use microbes instead of chemicals to generate electricity. Moreover, the microbes in MFCs are able to digest both naturally occurring and human generated organic waste, making bioremediation a viable concurrent option for the treatment of wastewater.

Challenge:

The microbial fuel cell company BioCell, Inc. selected you to a team of researchers asked to develop a prototype battery that uses microbes to generate a portable power source, with the potential for large scale applications such as wastewater treatment. To design the prototype your team must understand how microbes generate electricity when they metabolize (digest) organic matter, what types of microbes are most appropriate for use in a microbial fuel cell, and what living/growth requirements the technological system must provide the microbes selected. This understanding is essential to design and develop an MFC that can transform microbial electricity into usable current and power an electrical device. The Team has been tasked with constructing a prototype MFC able to illuminate a small light or run a small electric motor and presenting/explaining their solution to the Board of Directors of Bio-Cell, Inc. Use the checklist below as starting points for completing the task of developing a microbial fuel cell.

- Research and document the ways in which microbes can produce electricity.
- Select an appropriate microbe for your battery and determine life requirements.
- Construct a fuel cell that is able to transform microbial electricity into current.
- Present your prototype battery and provide an explanation of how it works.
- Discuss the potential for your solution to be used in large scale applications such as waste water treatment.

Appendix L

IEJ Pre-Code Frequency Counts Per Participant

IEJ: Frequency Counts of Pre-Codes – Participant 23

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	2	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	14	1
	No pattern recognition (NPR)	0	0	0	0	0	2	0
	Linear pattern recognition (LPR)	0	0	0	0	0	4	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0	0
	Summary	0	0	0	0	0	22	1
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	3	0
	Drawing line of best fit (DLB)	0	0	0	0	0	4	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	13	1
	Summary	0	0	0	0	0	20	1
Design Decisions	Variable identification (VI)	2	2	1	0	1	27	0
	Data collection (DC)	0	0	0	0	0	6	0
	Data organization (DO)	0	0	0	0	0	7	0
	Data Analysis (DA)	0	0	0	0	0	3	1
	Design Decision (DD)	0	0	0	0	0	1	1
	Summary	2	2	1	0	1	44	2

IEJ: Frequency Counts of Pre-Codes - Student 30

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	10	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	17	2
	No pattern recognition (NPR)	0	0	0	0	0	4	0
	Linear pattern recognition (LPR)	0	0	0	0	0	4	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0	0
	Summary	0	0	0	0	0	35	2
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	5	0
	Drawing line of best fit (DLB)	0	0	0	0	0	8	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	15	1
	Summary	0	0	0	0	0	28	1
Design Decisions	Variable identification (VI)	0	0	0	0	4	40	0
	Data collection (DC)	0	0	0	0	0	17	0
	Data organization (DO)	0	0	0	0	0	13	0
	Data Analysis (DA)	0	0	0	0	0	10	6
	Design Decision (DD)	0	0	0	0	1	14	7
	Summary	0	0	0	0	5	23	13

IEJ: Frequency Counts of Pre-Codes – Participant 22

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	0	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	15	2
	No pattern recognition (NPR)	0	0	0	0	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	3	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0	0
	Summary	0	0	0	0	0	18	2
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	8	0
	Drawing line of best fit (DLB)	0	0	0	0	0	2	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	8	2
	Summary	0	0	0	0	0	18	2
Design Decisions	Variable identification (VI)	0	0	0	0	0	21	0
	Data collection (DC)	0	0	0	0	0	7	0
	Data organization (DO)	0	0	0	0	0	3	0
	Data Analysis (DA)	0	0	0	0	0	9	3
	Design Decision (DD)	0	0	0	0	0	2	2
	Summary	0	0	0	0	0	42	5

IEJ: Frequency Counts of Pre-Codes – Participant 12

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	8	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	9	0
	No pattern recognition (NPR)	0	0	0	0	0	1	0
	Linear pattern recognition (LPR)	0	0	0	0	0	4	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0	0
	Summary	0	0	0	0	0	22	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	4	0
	Drawing line of best fit (DLB)	0	0	0	0	0	5	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	7	0
	Summary	0	0	0	0	0	16	0
Design Decisions	Variable identification (VI)	0	1	0	0	2	34	3
	Data collection (DC)	0	0	0	0	0	8	0
	Data organization (DO)	0	0	0	0	0	7	0
	Data Analysis (DA)	0	0	0	0	0	4	4
	Design Decision (DD)	0	0	0	0	0	6	0
	Summary	0	1	0	0	2	23	4

IEJ: Frequency Counts of Pre-Codes - Participant 20

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	3	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	6	0
	No pattern recognition (NPR)	0	0	0	0	0	4	1
	Linear pattern recognition (LPR)	0	0	0	0	0	2	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	3	0
	Summary	0	0	0	0	0	18	1
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	4	0
	Drawing line of best fit (DLB)	0	0	0	0	0	3	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	5	2
	Summary	0	0	0	0	0	12	2
Design Decisions	Variable identification (VI)	0	0	0	0	3	21	1
	Data collection (DC)	0	0	0	0	0	5	0
	Data organization (DO)	0	0	0	0	0	4	0
	Data Analysis (DA)	0	0	0	0	0	8	2
	Design Decision (DD)	0	0	0	0	0	5	2
	Summary	0	0	0	0	3	43	5

IEJ: Frequency Counts of Pre-Codes - Participant 4

RQ	Pre-Determined Codes	Frequencies of Codes per PIRPOSAL Design Phase						
		P	I	R	P	O	S & A	L
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	11	0
	Decreasing pattern recognition (DPR)	0	0	0	0	0	7	1
	No pattern recognition (NPR)	0	0	0	0	0	1	0
	Linear pattern recognition (LPR)	0	0	0	0	0	5	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0	0
	Summary	0	0	0	0	0	24	1
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	0	0	4	0
	Drawing line of best fit (DLB)	0	0	0	0	0	4	0
	Line of best fit predictive analysis (LBPA)	0	0	0	0	0	8	0
	Summary	0	0	0	0	0	16	0
Design Decisions	Variable identification (VI)	2	0	0	0	3	20	2
	Data collection (DC)	0	0	0	0	0	5	0
	Data organization (DO)	0	0	0	0	0	6	0
	Data Analysis (DA)	0	0	0	0	0	7	1
	Design Decision (DD)	0	0	0	0	1	6	2
	Summary	2	0	0	0	4	44	5

Appendix M

IEJ: In Vivo Codes and Key Points

In Vivo Codes per Student 23	30	22	12	20	4	Key Points	RQ
-today they went up	-the energy kept increasing -energy still going up	N/A	-we went up 119 from yesterday -I have a positive association	-by forty five mullibolts it went up -points are mostly going up	-we went up 110 mvs from yesterday -my data is mostly positive	Increasing pattern recognition (IPR)	
-our data went down -our MV went down -my points are mostly decreasing	-energy decreased -the electricity went down	-it went down by 5mv -goes down just a little every day	-it dropped more down to 40 millivolts -our electricity is going down	-it went down by 132 mv -dropped by 87	-it went down 80mv's -our mv's has been decreasing for two days	Decreasing pattern recognition (DPR)	RQa
-our system is very unsteady	-our system was very unsteady -I don't see a pattern in our data	N/A	-our electricity has been going up and down	-The graph sometimes does not have a pattern -it went up up down down up down -how could we get a pattern	-the electricity that was decreased and increased	No pattern recognition (NPR)	

In Vivo Codes per Student							
23	30	22	12	20	4	Key Points	RQ
-I drew a line through my points	-we drew a line -our data was negative and linear	-had a negative line -our data is linear because we were able to draw a line	-I drew a positive line -I could draw a line through the dots	-the computer graph has a line -the computer graph has a pattern	-I drew a positive line -my line is linear	Linear pattern recognition (LPR)	RQa
N/A	N/A	N/A	N/A	-our graph does not have a line	N/A	Nonlinear pattern recognition (NLPR)	
*drawn in journal	*drawn in journal -x (time in days) -y (electricity in mV)	*drawn in journal -we counted by 10's on electricity side but marked by 20's -we skipped a line for each day	*drawn in journal -x axis: time (days) -y axis: electricity (mV)	*drawn in journal	*drawn in journal -x axis: time (days) -y axis: electricity (mv's)	Line of best fit Scatter plot construction (LBSPC)	RQb

In Vivo Codes per Student						Key Points	RQ
23	30	22	12	20	4		
*drawn on graph 2 -making sure the same number of points were above and below my line	*drawn on graph 2 and 3 -the line on the hand-drawn one goes all the way to the x axis -to get the dots on both sides to even amounts	*drawn on graph 2 and 3	*drawn on graph 2 and 3 -There is a total of 2 dots on each side of my line	*drawn on graph 2 *no line drawn on graph 3 -there was 2 points below the line and three above the line	*drawn on graph 2 and 3	Drawing line of best fit (DLB)	RQb
*drawn on graph 2 and 3 -by day 6 it should have reached 65mV -0 mV at day 7	*drawn on graph 2 -the trendline stops above day 7 -we would've reached 0 mV of electricity	*drawn on graph 2 and 3 -based on the line of best fit, I think it is going to hit 0 on day 9 -it will hit zero on day 9 ½	*drawn on graph 2 -I predict that day 6 is going to be 475 mV -	-I predict it will be in between 350 will be day 6 -and 500 will be day 10	*drawn on graph 2 and 3 -I predict that we will have 500 mv's on day 6	Line of best fit predictive analysis (LBPA)	
-electricity -millivolts	-Volts -millivolts -electricity	-millivolts -mv -Day	-days -electricity -millivolts	-day 0 -electiosty	-electricity -days	Variable identification (VI)	Design Decision

In Vivo Codes Per Student						Key Points	RQ
23	30	22	12	20	4		
-170mv -MV-372	*± drawn on table -375 mV -.375V	-MV: 78mv - we started off with 129 mv and now we have 85 mv	*± drawn on table -mV: 139mV	-31mv -mv 44	-135 mv -55 mv	Data collection (DC)	
*table drawn in journal	*table drawn in journal	*table drawn in journal	*table drawn in journal	*table drawn in journal	*table drawn in journal -I connected dots with a line	Data organization (DO)	
-our system may not have been set up properly and that might have caused it to go down -our system will not light a light bulb because it has a negative pattern	-which is good because that means our system is working -did not produce 2 volts to light a small light bulb	-our MFC is still bad -our MFC cannot power the light bulb	-Our electricity was not high enough to power a light bulb -if we had more bacteria we might have did it	-I think it dropped because the electrons stopped producing as much -I think it might be going down because the mu iis drying up	-I think it went down because there was less organic matter for the bacteria to eat -there is a difference from the first day to the second	Data Analysis (DA)	Design Decision

In Vivo Codes Per Student						Key Points	RQ
23	30	22	12	20	4		
-we had to drill another hole in our lid -bigger containers for the water side	-we added more open space in the lid for the water container -add more mud	-we would probably stir the mud up more often -we switched our containers from milk jugs to bowls	-we didn't change anything because our electricity is still going up -add water to our mud	-took the wire out and put it back in -bigger containers to put the mud in -get better mud	-we chose milk jugs because of the handles to make it portable -we didn't have to redesign because my system worked	Design Decision (DD)	Design Decision

Appendix N

Individual Interview: Pre-Code Frequency Counts Per Participant

Individual Interview: Frequency Counts of Pre-Codes - Participant 23

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	1	0	0	1	0
	Decreasing pattern recognition (DPR)	0	2	6	1	2	0
	No pattern recognition (NPR)	0	0	0	0	0	0
	Linear pattern recognition (LPR)	0	0	1	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0
	Summary	0	3	7	1	3	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	1	3	2	0	0
	Drawing line of best fit (DLB)	0	0	0	1	0	0
	Line of best fit predictive analysis (LBPA)	0	0	0	5	0	0
	Summary	0	1	3	8	0	0
Design Decisions	Variable identification (VI)	1	7	6	1	3	0
	Data collection (DC)	0	0	0	0	0	0
	Data organization (DO)	0	0	2	0	0	0
	Data Analysis (DA)	0	3	2	3	0	0
	Design Decision (DD)	0	0	2	0	5	0
	Summary	1	10	12	4	8	0

Individual Interview: Frequency Counts of Pre-Codes – Participant 30

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	1	0	8	0	0
	Decreasing pattern recognition (DPR)	0	2	6	6	1	0
	No pattern recognition (NPR)	0	2	5	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0
	Summary	0	5	11	14	1	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	14	4	0	0
	Drawing line of best fit (DLB)	0	0	1	14	1	0
	Line of best fit predictive analysis (LBPA)	0	3	2	11	0	0
	Summary	0	3	17	29	1	0
Design Decisions	Variable identification (VI)	0	3	5	1	6	0
	Data collection (DC)	0	4	1	0	1	0
	Data organization (DO)	0	0	8	2	5	0
	Data Analysis (DA)	1	6	4	7	3	0
	Design Decision (DD)	0	0	11	10	18	0
	Summary	1	12	29	20	33	0

Individual Interview: Frequency Counts of Pre-Codes - Participant 22

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	0	0	1	0	0
	Decreasing pattern recognition (DPR)	0	0	4	2	0	0
	No pattern recognition (NPR)	0	0	0	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0
	Summary	0	0	4	3	0	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	2	0	0	0
	Drawing line of best fit (DLB)	0	0	4	1	0	0
	Line of best fit predictive analysis (LBPA)	0	0	0	5	0	0
	Summary	0	0	6	6	0	0
Design Decisions	Variable identification (VI)	1	4	1	0	0	0
	Data collection (DC)	0	0	0	0	1	0
	Data organization (DO)	0	0	2	0	0	0
	Data Analysis (DA)	0	2	2	2	2	0
	Design Decision (DD)	1	0	3	0	3	0
	Summary	2	6	8	2	6	0

Individual Interview: Frequency Counts of Pre-Codes -Participant 12

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	2	3	1	1	0
	Decreasing pattern recognition (DPR)	0	0	0	0	2	0
	No pattern recognition (NPR)	0	0	1	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0
	Summary	0	2	4	1	3	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	0	1	0	0
	Drawing line of best fit (DLB)	0	0	1	0	0	0
	Line of best fit predictive analysis (LBPA)	0	0	0	5	0	0
	Summary	0	0	1	6	0	0
Design Decisions	Variable identification (VI)	3	1	0	0	0	0
	Data collection (DC)	0	0	0	0	0	0
	Data organization (DO)	0	0	4	0	0	0
	Data Analysis (DA)	0	4	2	3	5	0
	Design Decision (DD)	1	0	4	1	6	0
	Summary	4	5	10	4	11	0

Individual Interview: Frequency Counts of Pre-Codes - Participant 20

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	0	0	0	0	0
	Decreasing pattern recognition (DPR)	0	0	0	1	0	0
	No pattern recognition (NPR)	0	0	2	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	1	0	0
	Summary	0	0	2	2	0	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	1	0	0	0
	Drawing line of best fit (DLB)	0	0	0	0	0	0
	Line of best fit predictive analysis (LBPA)	0	0	0	2	0	0
	Summary	0	0	1	2	0	0
Design Decisions	Variable identification (VI)	0	0	2	0	1	0
	Data collection (DC)	0	0	1	0	0	0
	Data organization (DO)	0	0	1	1	2	0
	Data Analysis (DA)	0	0	0	2	0	0
	Design Decision (DD)	0	0	1	0	2	0
	Summary	0	0	5	3	5	0

Individual Interview: Frequency Counts of Pre-Codes -Participant 4

RQ	Pre-Determined Codes	Frequencies of Codes per Interview Question					
		1	2	3	4	5	6
RQa	Increasing pattern recognition (IPR)	0	1	3	2	2	0
	Decreasing pattern recognition (DPR)	0	1	0	1	3	0
	No pattern recognition (NPR)	0	0	1	0	0	0
	Linear pattern recognition (LPR)	0	0	0	0	0	0
	Nonlinear pattern recognition (NLPR)	0	0	0	0	0	0
	Summary	0	2	4	3	5	0
RQb	Line of best fit Scatter plot construction (LBSPC)	0	0	1	1	0	0
	Drawing line of best fit (DLB)	0	0	1	0	0	0
	Line of best fit predictive analysis (LBPA)	0	0	0	4	0	0
	Summary	0	0	2	5	0	0
Design Decisions	Variable identification (VI)	0	2	2	0	0	0
	Data collection (DC)	0	0	0	1	0	0
	Data organization (DO)	0	0	2	0	1	0
	Data Analysis (DA)	0	2	0	1	2	0
	Design Decision (DD)	0	0	2	0	8	0
	Summary	0	4	6	2	11	0

Appendix O

Individual Interview: In Vivo Codes and Key Points

In Vivo Code Examples per Participant							
23	30	22	12	20	4	Key Points	RQ
-our data went up	-going mostly positive -it keeps going up	-or positive	-it mostly went up -the electricity kept going up	N/A	-You could see like it rise -it would gain	Increasing pattern recognition (IPR)	
-Most of the data our data would go down -our pattern seemed to have a negative slope.	-our system it just kept going down -it would drop down alot	-ours was negative -go down just by a couple numbers	-I'd see if it was going down -ours went completely down almost	-it was going down	-it would drop more -it wasn't rising	Decreasing pattern recognition (DPR)	RQa
N/A	-and it would go up but then the next it would just go down -they went up twice and down like three times	N/A	-In the data you could see that we went up and down	-There wasn't a pattern in the data. -It went up and then it went down and then it went up again and then it went back down	-that we dropped and gained	No pattern recognition (NPR)	

In Vivo Code Examples per Participant						Key Points	RQ
23	30	22	12	20	4		
-and if it was linear we could tell for sure if it was going up or down	N/A	N/A	N/A	N/A	N/A	Linear pattern recognition (LPR)	
N/A	N/A	N/A	N/A	-It didn't have a line.	N/A	Nonlinear pattern recognition (NLPR)	RQa
-the x axis was each day we had -the y axis was every 100 millivolts -we would mark around where our millivolts were each day	-Day zero since it had 375 I would place the dot -Day one I think it had 270 so I lined up the x value of one	-plot the points of how much electricity we were generating -on what days that we would write down	-If you kept going up with like the dots	-each day we would get a new graph and point	-drawing the graph -we put a graph down	Line of best fit Scatter plot construction (LBSPC)	RQb

In Vivo Code Examples per Participant

23	30	22	12	20	4	Key Points	RQ
-By trying to find the middle point of all of our plo, all the plots on our scatter plot	-I would use a ruler to get it pretty straight -I would create it a negative trendline	-We would draw a line from the first day to the day we would place that graph -and it would tell us how many points were above and below the line	-Mostly to where you had to have points above and below the line.	N/A	-we drew like a line through like between dots	Drawing line of best fit (DLB)	RQb
- by day seven and eight our prototype had already reached zero	-whenever it reaches 2000 I would take my finger and just go down to the day	-Take a ruler and we would just continue the line past the most recent point -because eventually according the graph that we done eventually it is going to hit zero	-I think it would have went up to 2000 -If you like made the trendline keep going up	-We used the graph -By using the graph	-how fast it'll rise in how many days -following the line until it reached day 10	Line of best fit predictive analysis (LBPA)	
-for every day we would mark -we had to measure the electricity,	-electricity -day one	-generate enough electricity -check how much millivolts	-you would have more electricity -you could get the electricity going	-it was producing electricity -each day	-voltage -the millivolts	Variable identification (VI)	Design Decisions

In Vivo Code Examples per Participant						Key Points	RQ
23	30	22	12	20	4		
N/A	-we was able to look at each variable -see if it went up or down	-I would just take the data the same way	N/A	-And we would test it -see how much electricity it went up or went down	-measuring it	Data collection (DC)	
-we created a few graphs and tables to show us	-a separate table -the table it was easier to read	-wrote down in our journal -we would have a graph	-we put it in a table -or graph	-We could have a graph -and a table	-we put it in the graphs -put it on a scatter graph	Data organization (DO)	Design Decisions
-our data specifically told us that our millivolts were going down into the negatives	-just to see how it was working -see if it was doing good, bad, in between	-Well we know that it would take 2000 millivolts to light a light bulb we use a lot. Ours would never reach that. -it just tells us what we did wrong	-The data told us if it was linear, linear or non linear -cause we thought maybe the mud was the problem to where we couldn't get electricity	-I don't think it could because it was going down	-you could see how good it did -it couldn't power the light bulb	Data Analysis (DA)	

In Vivo Code Examples per Participant							
23	30	22	12	20	4	Key Points	RQ
- perhaps we would use bigger containers	-just build a whole new system -we would have to make a lot of changes	-sometimes it would be dry so we put water in it -I wouldn't really build it the same way	-we stirred the mud -use bigger containers	-to make it better -like maybe by doing more to it	-get more like bacteria in the mud -stirring the mud -moving the wires	Design Decision (DD)	Design Decision